Advances in Spatial Science

Yasuhide Okuyama
Adam Rose *Editors*

Advances in Spatial and Economic Modeling of Disaster Impacts

Springer

Advances in Spatial Science

The Regional Science Series

This series contains scientific studies focusing on spatial phenomena, utilising theoretical frameworks, analytical methods, and empirical procedures specifically designed for spatial analysis. Advances in Spatial Science brings together innovative spatial research utilising concepts, perspectives, and methods relevant to both basic science and policy making. The aim is to present advances in spatial science to an informed readership in universities, research organisations, and policy-making institutions throughout the world.

The type of material considered for publication in the series includes: Monographs of theoretical and applied research in spatial science; state-of-the-art volumes in areas of basic research; reports of innovative theories and methods in spatial science; tightly edited reports from specially organised research seminars. The series and the volumes published in it are indexed by Scopus.

More information about this series at http://www.springer.com/series/3302

Yasuhide Okuyama • Adam Rose
Editors

Advances in Spatial and Economic Modeling of Disaster Impacts

Springer

Editors
Yasuhide Okuyama
University of Kitakyushu
Kitakyushu, Japan

Adam Rose
Sol Price School of Public Policy
University of Southern California
Los Angeles, CA, USA

ISSN 1430-9602 ISSN 2197-9375 (electronic)
Advances in Spatial Science
ISBN 978-3-030-16236-8 ISBN 978-3-030-16237-5 (eBook)
https://doi.org/10.1007/978-3-030-16237-5

This Springer imprint is published by the registered company Springer Nature Switzerland AG.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

This book is dedicated to all researchers who have contributed to reducing losses from disasters.

Preface

A series of sessions on “Measuring Regional Economic Effects of Unscheduled Events” at the North American Meetings of the Regional Science Association International (RSAI), which was initiated by the late Barclay G. Jones of Cornell University in 1993, celebrated its 25th anniversary in 2017. These sessions have continued to attract a wide range of researchers from all over the world, with 162 papers presented to date. This series has been one of the longest standing and has contributed some of the most active sessions at this conference.

Many authors of this volume have participated in these sessions, while several other authors have collaborated, communicated, or networked with them. The research community of economic modeling of disasters has been rapidly expanding but is still relatively small. We hope that this volume will help expand the community, especially with regard to involving younger researchers.

Whereas the 2004 precursor book, *Modeling Spatial and Economic Impacts of Disasters*, has been considered a successful publication, this volume aims to broaden and extend the scope of and approaches to modeling the economics of disasters. The large number of catastrophes since 2004 has identified new issues and challenges, and this volume has risen to the occasion by including chapters examining a broader range of disaster types and chapters addressing policy design, as well as advancing the state of the art of modeling.

We would like to thank Geoffrey J.D. Hewings for his encouragement to initiate this project. Barbara Fess at Springer has been exceptionally helpful and patient regarding our progress. We are grateful to our respective families for their continuous support and inspiration. It is our hope that this volume can serve as a catalyst for further advancing disaster modeling, promoting its use for disaster management practices, and deepening the understanding of disasters.

Kitakyushu, Japan — Yasuhide Okuyama
Los Angeles, CA — Adam Rose
January, 2019

Contents

Editors and Contributors

About the Editors

Yasuhide Okuyama is a Professor at the University of Kitakyushu, Japan. He earned his doctoral degree in regional planning from the University of Illinois at Urbana-Champaign in 1999. He also holds master's degrees from the University of Wisconsin-Madison (urban and regional planning, 1994) and from the University of Tsukuba, Japan (environmental science, 1986). His primary research interests center on economic impact of disasters, regional science, input-output analysis, and urban and regional planning. He has published a number of articles in various academic journals and book chapters, and edited a book titled *Modeling Spatial and Economic Impacts of Disasters* in 2004 with Professor Stephanie Chang of the University of British Columbia. In addition, he has been contributing to research projects and consultation for organizations such as the World Bank, European Commission, Economic Research Institute for ASEAN and East Asia (ERIA), and Japan Bank for International Cooperation.

Adam Rose is a Research Professor in the University of Southern California Sol Price School of Public Policy, and a Research Fellow at USC's Center for Risk and Economic Analysis of Terrorism Events (CREATE). Professor Rose's primary research interest is the economics of natural disasters and terrorism. He has spearheaded the development of CREATE's comprehensive economic consequence analysis framework to include aspects of mitigation, resilience, behavioral responses, and remediation. He has done pioneering theoretical and empirical research on resilience to disasters at the level of the individual business/household, market/industry, and regional/national economy. Professor Rose is the author of several books and 250 professional papers, including most recently *Economic Consequence Analysis of Disasters: The E-CAT Software Tool* (Springer) and *Defining and Measuring Economic Resilience from a Societal, Environmental and Security Perspective* (Springer). He is a Fellow of the Regional Science Association International and President of the International Society for Integrated Disaster Risk Management.

List of Contributors

Tariq Ali School of Economics and Management, North China Technology University, Beijing, China

Andre F. T. Avelino Regional Economics Applications Laboratory, Department of Agricultural and Consumer Economics, University of Illinois, Urbana, IL, USA

Stephanie E. Chang School of Community and Regional Planning, Institute for Resources, Environment and Sustainability, University of British Columbia, Vancouver, BC, Canada

Sam Cole University at Buffalo, The State University of New York, Buffalo, NY, USA

Qi Cui School of Economics and Resource Management, Beijing Normal University, Beijing, China

Peter B. Dixon Centre of Policy Studies, Victoria University, Melbourne, Australia

Hadi Dowlatabadi Institute for Resources, Environment and Sustainability, University of British Columbia, Vancouver, BC, Canada

Stephane Hallegatte Global Facility for Disaster Reduction and Recovery (GFDRR), The World Bank, Washington, DC, USA

Geoffrey J. D. Hewings Regional Economics Applications Laboratory, University of Illinois, Urbana, IL, USA

Trond Husby PBL Netherlands Environmental Assessment Agency, The Hague, The Netherlands

Ha Hwang Division of Disaster and Safety Research, Korea Institute of Public Administration, Seoul, Republic of Korea

Michael Jerie Centre of Policy Studies, Victoria University, Melbourne, Australia

Yoshio Kajitani Faculty of Engineering and Design, Kagawa University, Takamatsu, Japan

Elco Koks Environmental Change Institute, University of Oxford, Oxford, England, UK
Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, North Holland, The Netherlands

Aditya Kusuma Victoria University of Wellington, Wellington, New Zealand

Marco Modica Gran Sasso Science Institute, L'Aquila, Italy

Cuong Nguyen Victoria University of Wellington, Wellington, New Zealand

Peter Nijkamp Tinbergen Institute, Amsterdam, The Netherlands

Ilan Noy Victoria University of Wellington, Wellington, New Zealand

Jan Oosterhaven Faculty of Economics and Business, University of Groningen, Groningen, The Netherlands

Sheree Pagsuyoin Department of Civil and Environmental Engineering, University of Massachusetts-Lowell, Lowell, MA, USA

Raghav Pant Environmental Change Institute, University of Oxford, Oxford, England, UK

Ji Young Park Department of Urban and Regional Planning, University at Buffalo, The State University of New York, Buffalo, NY, USA

Aura Reggiani Department of Economics, University of Bologna, Bologna, Italy

Maureen T. Rimmer Centre of Policy Studies, Victoria University, Melbourne, Australia

Gustavo Salcedo Department of Civil and Environmental Engineering, University of Massachusetts-Lowell, Lowell, MA, USA

Joost Santos Department of Engineering Management and Systems Engineering, George Washington University, Washington, DC, USA

Hirokazu Tatano Disaster Prevention Research Institute, Kyoto University, Uji, Japan

Johannes Többen Norwegian University of Science and Technology, Trondheim, Norway

Adrien Vogt-Schilb Climate Change Division, Inter-American Development Bank, Washington, DC, USA

Glyn Wittwer Centre of Policy Studies, Victoria University, Melbourne, Australia

Wei Xie China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China

Christian Yip Department of Engineering Management and Systems Engineering, George Washington University, Washington, DC, USA

Chapter 1
Advances in Spatial and Economic Modeling of Disaster Impacts: Introduction

Yasuhide Okuyama and Adam Rose

Abstract This chapter introduces the book, *Advances in Spatial and Economic Modeling of Disaster Impacts*, summarizes the individual chapters, and discusses further issues of such modeling theory and practice. The book is divided into three parts. The first part addresses the conceptual and broader issues of disaster modeling, offering insights for better understanding of disaster characteristics, with the aim of improving the theoretical representations and interpretations of disasters in quantitative analysis. The second part presents a series of advances in the state-of-the-art modeling frameworks using Computable General Equilibrium (CGE), Input-Output (I-O), integrated, and other economic models. The third part illustrates the use of disaster modeling in the decision-making process for recovery and reconstruction after a disaster, as well as for strategies to reduce risk from future disasters. This chapter concludes with a discussion of priorities for future research, including distributional impacts, integration with financial models, and long-run sustainability after a disaster.

1.1 Natural Hazards and Economic Modeling

Since the first edition of this volume, *Spatial and Economic Impacts of Disasters*, was published in 2004, the researchers in this field have been challenged from two fronts. One front has been the rather frequent occurrences of catastrophic events all over the world, which brought new features and issues of disaster analysis. For example, the 2004 Indian Ocean Earthquake and Tsunami created a multi-nation

Y. Okuyama (✉)
University of Kitakyushu, Kitakyushu, Japan
e-mail: okuyama@kitakyu-u.ac.jp

A. Rose
Sol Price School of Public Policy, University of Southern California, Los Angeles, CA, USA
e-mail: adamzros@price.usc.edu

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_1

disaster; the 2005 Hurricane Katrina emphasized the issues of disaster risk governance, reconstruction strategies, and migration; the 2010 Haiti Earthquake demonstrated the vulnerability of the developing country's economy; and the 2011 East Japan Earthquake and Tsunami illustrated how disasters can cascade and the reach of supply-chain disruptions in the age of globalization. Researchers have learned many lessons from these events through investigating their economic impacts and developing new modeling frameworks to tackle these issues, and some of the new findings and modeling strategies are discussed and further extended in this book. In addition to these events, continuing threats from climate change and terrorist attacks, which are somewhat different kinds of threats from the above natural hazards, have demanded a diverse range of modeling strategies, such as long-run perspectives and propagations of disaster impacts over space and time. Because one modeling framework does not fit all the features of every disaster, this book presents a wide variety of models to examine various disaster issues.

The second front of challenge came from a fellow researcher (Albala-Bertrand 2013) criticizing quantitative models, such as the ones in the 2004 volume, for being inadequate for disaster analysis due to the following three 'interactive insufficiencies': (1) the quality of disaster data; (2) inherent limitations of quantitative technique; and (3) the paramount issue of the theoretical interpretation of disaster features. As widely discussed in the disaster research community, disaster data, especially data for economic damages and losses, have been 'crude measures' (Skidmore and Toya 2002) due to the lack of their standardized definitions (Okuyama and Chang 2012). While the quality of the outcomes from a quantitative model depends heavily on the quality of input data, the input data issue remains the most crucial and unavoidable problem. Instead of using the secondary data of disasters, some researchers have devised tools to directly estimate economic damages and/or losses based on some physical data of natural hazards, such as the magnitude and depth of an earthquake (Heatwole and Rose 2013) or the intensity of projected ground motion in a particular location by an earthquake (Kajitani and Tatano 2014), or to evaluate the changes in economic activities with a set of satellite data on annual difference in nighttime light intensity (Raschky 2013). Because it is out of scope for this book, this input data issue is not discussed further in this chapter.

The issue of the limitations of quantitative analysis has been identified from many perspectives in various modeling platforms. Some of the examples on extended modeling schemes are proposed and discussed in Parts II and III of this book. The basic input-output model has been extended to cover multiple regions (Chaps. 8, 15, and 16) and/or to adopt shorter periods (Chap. 7) in order to correspond to the rapid changes in a disaster situation. The effects of resilience in production processes have been incorporated into CGE models (Chap. 5), and are further analyzed from various perspectives, such as portfolio theory (Chap. 11) or under a financial crisis (Chap. 12). While these advances of modeling features highlight some disaster characteristics, models are still the representation of one or a few particular aspects of reality (Okuyama and Santos 2014). Therefore, the results from quantitative analysis reflect only certain parts of the disaster impacts, and they should be treated as such.

Three chapters in Part I offer some insights for better understanding of disaster features, which aim to improve the theoretical interpretations of disaster situations in quantitative analysis. Because disaster influences several basic assumptions of economic analysis, such as increased uncertainty, assistance from external sources, changes in production and consumption behavior, abrupt structural changes due to damages and the reconstruction process, and so on, the empirical and theoretical investigations of how a disaster alters the economic system are necessary to enhance our understanding of such events. At the same time, even though the frequency and intensity of natural hazards appear to have been increasing recently, disasters are still rare events. Thus, it is imperative to analyze them from a broad range of perspectives and to combine such efforts to form integrated knowledge about disasters, such as this book.

1.2 Conceptual and Broader Issues

The three chapters in Part I discuss conceptual and broader issues surrounding the spatial and economic analysis of disasters.

The welfare impact of a disaster depends on its effect on consumption, not only on the direct asset losses and human losses that are usually estimated and reported after such events. In Chap. 2, Hallegatte and Vogt-Schilb propose a framework to assess disaster-related consumption losses, starting from an estimate of the asset damages. They argue that output losses after a natural hazard destroys part of the capital stock are better estimated by using the average—not the marginal—productivity of capital. A model that describes capital in the economy as a single homogeneous stock would systematically underestimate disaster output losses, compared with a model that tracks capital in different sectors with limited reallocation options. Also, the net present value of disaster-caused consumption losses decreases when reconstruction is accelerated. With standard parameters, discounted consumption losses are only 10% larger than asset losses if reconstruction is completed in one year, compared with 50% if reconstruction takes 10 years. For disasters of similar magnitude, consumption losses are expected to be lower where the productivity of capital is higher, such as in capital-scarce developing countries. This mechanism may partly compensate for the many other factors that make poor countries and poor people more vulnerable to disasters.

Insurance for disaster is one of the important and effective instruments for transferring such risks, though it is reported that insurance covers less than 10–40% of disaster damages in developing countries and developed countries, respectively. Kusuma et al. (Chap. 3) focus on the demand for insurance by residential households (for earthquakes) and by farmers (for extreme weather risk), and analyze the supply of earthquake and agricultural crop insurance and the barriers that insurance organizations (private and public) face in providing adequate coverage. In addition, the chapter discusses some of the existing insurance schemes for both risks, and continues with the very limited available descriptions of the actual performance of these schemes in the aftermath of catastrophic events. They conclude that there is little reason to doubt that a well-designed insurance system is desirable as a tool for disaster risk management. A well-designed scheme has to provide financial risk transfer products that are affordable, fairly priced and efficient, so that its contracts are widely used and penetration rates consequently are high, and that it provides an expeditious and successful claim settlement process once a catastrophe hits.

Chapter 4 by Okuyama turns to more theoretical perspectives of disaster analysis, especially on the long-run effects of disasters on economic growth. The recent empirical studies on this subject presented mixed results about whether or not disasters affect long-run economic growth of an economy. Some studies employed socio-economic indicators for disaster intensity, whereas some other and more recent studies that utilized physical intensity indices revealed statistically significant negative effects on economic growth. In order to improve the understanding of disaster's effects on economic growth, this chapter examines a set of theoretical growth models from both the neoclassical perspective and the Keynesian perspective. The insights gained from the analysis include: the speed of recovery depends on the changes in the savings rate, and cumulative changes (either growth or decline) of a damaged region can be caused by the changes in economic structure. The latter result supports the findings in the recent empirical studies that evaluated the structural changes caused by a disaster and the subsequent reconstruction process.

1.3 Modeling Variations

Part II presents a series of advances in the state-of-the-art modeling frameworks using Computable General Equilibrium (CGE) model, Input-Output (I-O) model, integrative models, and other economic models.

Rose (Chap. 5) extends his research on economic resilience as a strategy to reduce economic losses to the area of cyber-attacks on business and infrastructure. Such attacks have the potential to affect large regions, if not entire countries, in the case of airline systems, banking, power grids, and seaports. Rose provides basic definitions and metrics in this context, as well as examples for 10 resilience categories on both the supplier and customer sides. The core of the paper is a discussion of the various methods to incorporate cyber resilience into CGE models using their intrinsic features and ad hoc adjustments that he has developed, as well as those adapted from the broader literature on resilience.

Dixon et al. (Chap. 6) describe a multi-regional computable general equilibrium (CGE) tool for use in economic consequence analysis of terrorism events. The tool was designed and constructed for the Terrorism Risk Assessment (TRA) groups in the Department of Homeland Security (DHS) of the United States. CGE techniques have been applied in disaster consequence analysis for nearly 30 years. However, due to the complexity of CGE computations and security issues, the TRA groups have been reluctant to adopt CGE, preferring until recently to use in-house input-output models. This chapter explains how the authors have overcome the difficulties that the TRA groups had with CGE modeling by creating the Generalized, Regional and Dynamic Economic Consequence Analysis Tool (GRAD-ECAT), a "reduced-form" approach. Through their derivation of tables of impact elasticities based on CGE simulations relating to long-run impacts of chemical, biological, radiologic, and nuclear (CBRN) threats, they provide a solution to the problems of computational difficulty by practitioners and security. They show that CGE can be adapted to the needs of the TRA groups and can deliver insights well beyond those available from I-O.

Turning to I-O models, Avelino and Hewings (Chap. 7) analyze the time dimension of disaster impacts in various model formulations. While damages in physical capital are usually spatially concentrated in a few areas, their impacts tend to spread geographically and temporally due to the more spatially disperse nature of production chains and the timing and length of disruptions. Since the 1980s, several techniques have been proposed to model higher-order effects of disruptive events, many of which are based on the input-output framework. However, their contributions are fragmented in different models, and, still missing, is a more comprehensive accounting of production scheduling, seasonality in industrial linkages, and demographics dynamics post-event. In this chapter, the Generalized Dynamic Input-Output (GDIO) framework is presented and its theoretical basis derived. It integrates previous contributions in terms of intertemporal dynamics, explicit intratemporal modeling of production and market clearing, inventory depletion/formation, and expectations adjustment. Moreover, the chapter adds to the literature by introducing induced effects via a demo-economic extension to study the impact of displacement and unemployment post-disaster, the impact of disruption timing via seasonal input-output tables, and production chronology via the sequential interindustry model.

Spatial distribution of disaster impacts is another issue in the disaster modeling with I-O framework. Koks et al. (Chap. 8) provide an overview of several multiregional modeling approaches used for disaster impact analysis. The chapter specifically focuses on the multiregional supply-use model, the dynamic multiregional inoperability input-output model, the multiregional impact assessment model, and the non-linear programming model. Whereas the first two approaches have been applied widely over the years, the latter two are recently developed methods which aim to improve the estimation of a disruption in the economic system by, amongst others, allowing for a supply shock and spatial substitution effects. The outcomes show significantly distinct results for the demand-driven multiregional supply-use model and the dynamic multiregional inoperability input-output model on the one hand, and for the non-linear programming model and the multiregional impact assessment model on the other hand. Whereas for the former only negative impacts in all damaged regions and surrounding regions are observed, the latter also shows positive impacts in several regions that incur only indirect impacts.

In Chap. 9, Oosterhaven and Többen examine the key assumption of economic models, which are used for disaster impact analysis. Firms react to shortages in the supply of their inputs by looking for substitutes under a disaster situation. This chapter investigates the impact of finding such substitutes on estimates of the size of regional and national disaster impacts. Their analysis starts with a non-linear programming model that allows for maximum substitution possibilities. In this case, there are little to no indirect damages in the directly affected regions, whereas negative indirect impacts of a magnitude of from 5 to 34% of the direct impact occur in the surrounding regions. Adding the increasingly less-plausible fixed ratios, commonly used in standard Type I and extended Type II multiregional input-output and multiregional supply-use table (MRSUT) models, results in: (1) substantial increases in the magnitude of negative indirect impacts and (2) a significant shift in the intra-regional versus interregional and international distribution of these impacts. They conclude that both demand-driven and supply-driven input-output and MRSUT models tend to grossly overestimate the indirect impacts of negative supply shocks, which are part and parcel of most disasters.

Chang and Dowlatabadi (Chap. 10) propose a modeling framework for transportation system disruption, which is widely recognized as a major source of spatial and economic impacts in disasters. The framework focuses on a relatively simple yet vital transport system, coastal shipping, and its role in regional supply chains, particularly in the delivery of essential commodities to coastal communities in the aftermath of a disaster. Disruption to this system can quickly cause shortages of critical needs such as fuel, as modern supply chains have increasingly adopted just-in-time delivery models entailing little slack. Based on the empirical and modeling literature on the vulnerability of maritime transportation systems and supply chains to hazards, they find a need for integrated models of transportation, critical supply chains, and community demand. Such models should capture not only the physical vulnerability of key transportation assets, but also disruption modes, duration, and effects of planning and preparedness. The chapter proposes a modeling framework that is spatially explicit, functionally specified, and operationally oriented. The framework helps address a general need for disaster impact models that capture critical risk reduction and resilience-building strategies in ways that can support decision-makers in practice.

A method for modeling resilience in economic systems confronted by multiple irregular shocks is proposed by Cole in Chap. 11. Investment portfolio theory is reformulated as a protected production function. This function determines the share of output that is dedicated to protection as economic agents attempt to maintain their preferred level of consumption and safety in the face of exogenous hazards. Based on this formulation, resilience becomes the ability of production to withstand and recover from the repeated shocks. This mechanism is illustrated via a model comprising an aggregated domestic sector and a single export sector and trading with a larger regional system. Solving the model, first as a comparative static system, gives multiple stable and unstable equilibrium solutions for the level of economic activity. Equating these solutions gives the level of protection that offers greatest well-being. This production-protection relationship is then incorporated into a time-step simulation showing how the economy evolves in response to random shocks and concatenated disturbances, including irregular collapses beyond the desired resilience regime. Within this dynamic model, solutions to the static model appear as weak attractors. The analysis in this chapter bridges between equilibrium and evolutionary economics, and comparable challenges in other disciplines. The method is advanced as a closure for a social accounting-event matrix based approach.

Critical features of economic modeling, such as resilience, vulnerability, and exposure, are studied in Chap. 12 by Modica et al. The economic recession which followed the 2008 financial crisis has raised important issues on differences in the impact, especially from a spatial perspective, of the socio-economic shocks—at both the regional and the community level, especially in the European Union Member States. These differences may be due to the different levels of vulnerability, resilience, and exposure, and may arise because of dissimilarities in the intrinsic characteristics of regions or communities. While, in the scientific literature, a great deal of attention has been paid to the concept of resilience (e.g., the capacity to bounce back and/or to resist a given shock) and vulnerability (e.g., the inherent characteristics that create the potential for harm), less attention has been paid to the full set of measures of socio-economic exposure (e.g., the things affected by a shock), as well as to both the relationship between vulnerability, resilience, and exposure and the losses that ensue as a result of different external shocks and exposure. This chapter explores the above-mentioned links, since a closer analysis of these complex interrelations can produce different outcomes. It aims to review systematically the existing literature on vulnerability, resilience, and exposure in order to understand the connections between these concepts, with reference not only to economic/financial shocks but also to other catastrophic events, such as natural hazards, man-made disasters, and so on.

1.4 Economic Modeling and Decision-Making

The models for spatial and economic impacts of disasters intend inherently to be used at the decision-making stages, not only for recovery and reconstruction but also for the strategy of countermeasures against future disasters. Four chapters in Part III emphasize their use in the decision-making process.

Spatial CGE modeling is discussed in Chap. 13 by Kajitani and Tatano, focusing on the key parameters in the model. Spatial and sector classifications for the CGE model are key elements that affect the performance of the model. Although physical damages to an area by a hazard are locally concentrated, the damages lead to higher-order effects on flows that can spread to other areas. Constructing the CGE model on a fine spatial scale is necessary for describing these effects in detail. Sectoral disaggregation also improves the quality of the model if key industries that have low substitutability and cause supply chain impacts are separated from other sectors with higher substitutability. This chapter validates the spatial and sectoral disaggregation effects of the CGE model through a case study of the Great East Japan Earthquake and Tsunami in 2011. In addition, this chapter examines the extent to which the elasticity of substitution parameters relating to interregional trade contributes to improving the forecasting capability of the CGE model.

Climate change is a different kind of natural hazard from earthquakes, hurricanes, or other types of short-term events. Climate change's impact, such as temperature increases, applies globally, while the damages from other natural hazards are rather locally and unevenly concentrated. Xie et al. (Chap. 14) examine the economic impacts of extreme weather events on global grain production and analyze the contribution of different market rules, using a global CGE model. This chapter focuses on the special role of market and trade, and a specific crop—barley. Their results show that the impacts of extreme weather events on barley production are much lower than the corresponding physical yield changes when considering the domestic market response, and are even smaller when considering international trade effects. Although this study takes barley as an example, the policy implications can be applicable to other crops as well.

The impacts from climate change on regional economy have also been felt; for example, the northeastern United States has recently experienced record rainfall deficits, triggering government agencies to issue warning-level to emergency-level drought advisories. Since water is an essential resource in producing not only agricultural products but also other goods and services, droughts lead to economic losses that propagate through the interconnected sectors of an economy. Further, these sectors exhibit various levels of resilience to drought severity and duration depending on their reliance on water availability. In Chap. 15 by Pagsuyoin et al., a spatial and dynamic input-output (I-O) modeling framework is proposed to examine the adverse effects of drought events on interdependent economic sectors. A decision support system utilizing geographic information systems (GIS) was created to: (1) model the progression of drought intensity, (2) simulate the dynamic behavior of economic sectors during the drought timeline and throughout the various phases of recovery, and (3) assess the regional impacts of these behaviors on the regional economy. The resulting integrated IO-GIS model was applied to the State of Massachusetts, which experienced historic widespread drought conditions in 2016.

Hwang and Park (Chap. 16) propose an approach to assessing airport and aviation security policies, which incorporates terrorist attack behaviors with economic impacts stemming from disruption of U.S. airport systems. Terrorist attacks involve complicated strategic behaviors, while various defenders need to consider the degree of negative impacts that may occur via complicated paths. This chapter, for the first time, suggests a dynamic method to design the complicated micro-level behavioral strategies with macro-level economic impacts. By combining the micro-level model (a competitive game situation between defenders and attackers) with the macro-level model (an interstate input-output model), they developed a new framework called the Game Theoretic National Interstate Economic Model (G-NIEMO). Based on basic algorithms applied in the "attacker-defender game," this chapter explains how G-NIEMO could be achieved. Further, establishing cooperative coordination systems and collective countermeasures against terrorism is necessary to cope with much more complicated forms of terrorist attacks, such as simultaneous attacks and cyber-attacks. G-NIEMO can meet these needs through a collaborative gaming model and can be used to establish equilibrium strategies for protecting U.S. territory, creating general guidelines, and assessing government resource allocations.

1.5 Future Issues

The studies presented in this volume represent the recent advancements of philosophy, perspectives, and methodologies in modeling the spatial and economic impacts of disasters. This collective progress aims to improve the effectiveness and precision of disaster models and to promote their practical use, especially at the decision-making process. As discussed above, the standardization of the definitions, such as damages, losses, and disaster impacts, is necessary to make the results of these models comparable and useful not only for disaster policies but also for enhancing our understanding of disaster features. In addition, the balance between the further sophistication of and the practical operability of quantitative models needs to be concerned.

A few challenges that Rose (2004) pointed out as the future agenda in the 2004 volume still remain. One of such challenges is the analysis of distributional impacts of disasters. This issue has been discussed for some time (for example, Cochrane 1975; Albala-Bertrand 1993), and has been studied empirically to some extent (an excellent compilation of the literature is found in Karim and Noy 2016). The distributional impacts need to be estimated not only across income groups but also between genders and among age cohorts, since age and sex are significant factors in mortality resulting from natural hazards (United Nations 2015). Moreover, the United Nations reported that the number of countries reporting gender-specific statistics in terms of the impact of natural disasters has been minimal (United Nations 2015). Partly because of this dearth of the data, only a limited number of studies have addressed the gender issue of disaster impacts (for example, Neumayer and Plumper 2007; Bradshaw 2013). These studies show that the gender gap of disaster impacts has been significant both in developed and developing countries. While this issue is a more social than economic, an integrated approach like a demographic-economic model can potentially handle it.

Another challenge that has been raised is the sustainability of a country/region regarding the aftermath of a disaster. This can be also considered as the distributional impacts across generations, because the funding for recovery and reconstruction after a disaster could be enormous, and the repayment scheme could extend long in time. Several financial instruments for funding, such as insurance, catastrophe bond, tax increase, and so forth, and their advantages and limitations have been analyzed and discussed. Yet, the overall economic impacts of such financial instruments together with the disaster impacts have been rarely modeled. While most models for disaster analysis are for the short-run (up to five years or so), the impacts of some financial instruments, particularly catastrophe bonds, could last for a much longer time. In addition, the recovery and reconstruction activities financed by such instruments can potentially create some positive impacts, as well as unanticipated structural changes in the damaged economy. This is a complicated but crucial issue, which needs to be addressed.

References

Albala-Bertrand JM (1993) The political economy of large natural disasters: with special reference to developing countries. Clarendon Press, Oxford

Albala-Bertrand JM (2013) Disasters and the networked economy. Routledge, Oxon

Bradshaw S (2013) Gender, development, and disasters. Edward Elgar, Cheltenham

Cochrane H (1975) Natural hazards and their distributive effects. Natural Hazards Research Applications Information Center, Boulder, CO

Heatwole N, Rose A (2013) A reduced-form rapid economic consequence estimating model: application to property damage from U.S. earthquakes. Int J Disaster Risk Sci 4:20–32

Kajitani Y, Tatano H (2014) Modeling critical estimation of production capacity loss rate after the Great East Japan Earthquake and Tsunami in 2011. Econ Syst Res 26:13–38

Karim A, Noy I (2016) Poverty and natural disasters – a qualitative survey of the empirical literature. Singap Econ Rev 61(1):1–36

Neumayer E, Plumper T (2007) The gendered nature of natural disasters: The impact of catastrophic events on the gender gap in life expectancy, 1981–2002. Ann Assoc Am Geogr 97(3):551–566

Okuyama Y, Chang SE (2012) Economic and planning approaches to natural disasters. In: Brooks N, Donaghy K, Knaap GJ (eds) The Oxford handbook of urban economics and planning. Oxford University Press, New York, pp 395–418

Okuyama Y, Santos JR (2014) Disaster impact and input-output analysis. Econ Syst Res 26(1):1–12

Raschky PA (2013) Estimating the effects of West Sumatra Public Asset Insurance Program on short-term recovery after the September 2009 Earthquake, Working Papers DP-2013-35, Economic Research Institute for ASEAN and East Asia (ERIA)

Rose A (2004) Economic principles, issues, and research priorities in hazard loss estimation. In: Okuyama Y, Chang SE (eds) Modeling spatial and economic impacts of disasters. Springer, New York, pp 13–36

Skidmore M, Toya H (2002) Do natural disasters promote long-run growth? Econ Inq 40:664–687

United Nations (2015) The world's women 2015: trends and statistics. The United Nations, New York

Yasuhide Okuyama is a Professor at the University of Kitakyushu, Japan. He earned his doctoral degree in regional planning from the University of Illinois at Urbana-Champaign in 1999. He also holds master's degrees from the University of Wisconsin-Madison (urban and regional planning, 1994) and from the University of Tsukuba, Japan (environmental science, 1986). His primary research interests center on economic impact of disasters, regional science, input-output analysis, and urban and regional planning. He has published a number of articles in various academic journals and book chapters, and edited a book titled *Modeling Spatial and Economic Impacts of Disasters* in 2004 with Professor Stephanie Chang of the University of British Columbia. In addition, he has been contributing to research projects and consultation for organizations such as the World Bank, European Commission, Economic Research Institute for ASEAN and East Asia (ERIA), and Japan Bank for International Cooperation.

Adam Rose is a Research Professor in the University of Southern California Sol Price School of Public Policy, and a Research Fellow at USC's Center for Risk and Economic Analysis of Terrorism Events (CREATE). Professor Rose's primary research interest is the economics of natural disasters and terrorism. He has spearheaded the development of CREATE's comprehensive economic consequence analysis framework to include aspects of mitigation, resilience, behavioral responses, and remediation. He has done pioneering theoretical and empirical research on resilience to disasters at the level of the individual business/household, market/industry, and regional/national economy. Professor Rose is the author of several books and 250 professional papers, including most recently *Economic Consequence Analysis of Disasters: The E-CAT Software Tool* (Springer) and *Defining and Measuring Economic Resilience from a Societal, Environmental and Security Perspective* (Springer). He is a Fellow of the Regional Science Association International and President of the International Society for Integrated Disaster Risk Management.

Part I
Conceptual and Broader Issues

Chapter 2
Are Losses from Natural Disasters More Than Just Asset Losses?

The Role of Capital Aggregation, Sector Interactions, and Investment Behaviors

Stephane Hallegatte and Adrien Vogt-Schilb

Abstract The welfare impact of a natural disaster depends on its effect on consumption, not only on the direct asset losses and human losses that are usually estimated and reported after disasters. This chapter proposes a framework to assess disaster-related consumption losses, starting from an estimate of the asset losses, and leading to the following findings. First, output losses after a disaster destroys part of the capital stock are better estimated by using the average—not the marginal—productivity of capital. A model that describes capital in the economy as a single homogeneous stock would systematically underestimate disaster output losses, compared with a model that tracks capital in different sectors with limited reallocation options. Second, the net present value of disaster-caused consumption losses decreases when reconstruction is accelerated. With standard parameters, discounted consumption losses are only 10% larger than asset losses if reconstruction is completed in 1 year, compared with 50% if reconstruction takes 10 years. Third, for disasters of similar magnitude, consumption losses are expected to be lower where the productivity of capital is higher, such as in capital-scarce developing countries. This mechanism may partly compensate for the many other factors that make poor countries and poor people more vulnerable to disasters.

What is the economic cost of a natural disaster? Events such as floods or earthquakes destroy assets such as roads, plants, or office space, thus leading to losses of

S. Hallegatte (✉)
Global Facility for Disaster Reduction and Recovery (GFDRR), The World Bank, Washington, DC, USA
e-mail: shallegatte@worldbank.org

A. Vogt-Schilb
Climate Change Division, Inter-American Development Bank, Washington, DC, USA
e-mail: avogtschilb@iadb.org

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_2

economic production over the following months to years or decades. Assessing the value of this lost production is a key component of the assessment of the welfare impact of disasters.

By definition, the economic value of an asset is the net present value of its expected future production, and the output loss caused by a disaster is simply equal to the value of the lost assets. Summing asset and output (or income) losses would thus be double counting.[1] What value should be used to assess asset losses from natural disasters, then? This is no trivial task. Measuring the value of damaged or lost assets through their construction or replacement cost or through their pre-disaster market value can be inaccurate, in particular if the economic conditions when the assets were built differ from the conditions after the disaster hit, or in the presence of externality or distortion.

This issue is reminiscent of the old debate on whether using economic aggregates, and in particular an aggregated capital stock, can provide sufficient insights on the link between existing capital stock and economic production. Stiglitz (1974) summarized one aspect of this debate as follows:

> From a practical point of view, economists are always dealing with aggregates: one person's labor is aggregated with another, one piece of land is aggregated with another, one kind of steel is aggregated with another, even though they all have different properties. The condition under which these aggregates can be formed, that is, under which the aggregates act as if they were homogeneous factors of production, are very restrictive; nonetheless, I believe that, under most circumstances and for most problems, the errors introduced as a consequence of aggregation of the kind involved in standard macro- analysis are not too important; nonetheless, we must always be on our guard for situations in which this is not true. The question is, Do the problems associated with the accumulation of capital in growth processes represent one area in which properly formulated aggregates (e.g., using chain indices) are likely to lead to serious error? This, I suggest, remains a moot question.

Here, we suggest that the analysis of natural disasters may be one of these cases where aggregation can lead to errors that are too great to ignore.[2] We find that using a traditional production function would lead to a systematic underestimation of disaster output losses, and that immediate output losses after a disaster reduces the capital stock are better estimated by using the average—not the marginal—productivity of capital—leading to up to a factor three difference in estimates. The reason is that the traditional production function implicitly assumes that the capital which has not been destroyed can immediately and freely be relocated to its most productive use. Explicitly modeling several categories of putty-clay capital shows that as long as

[1]In many estimates of households' disaster losses, one can find "asset losses" and "income losses" [see for instance Patankar and Patwardhan (2014)]. However, it is often the case that "asset losses" represent the losses to the assets owned by the considered household and "income losses" represent the loss in income due to damages to other people's (or public) assets. For instance, a household can lose its house (an asset loss) and be unable to work because its firm is damaged (a loss to the firm owner's asset) or because transportation is impossible (a loss of public assets). In that case, no double counting is happening.

[2]The analysis presented in this chapter builds on previous working papers by the authors (Hallegatte 2014; Hallegatte and Vogt-Schilb 2016).

the destroyed capital does not happen to be the least productive in the economy, output losses will be higher than asset losses.

One implication is that the net present value of disaster-caused consumption losses decreases when the reconstruction is accelerated. Discounted consumption losses are only 10% larger than asset losses if reconstruction is completed in 1 year, compared with 50% if reconstruction takes 10 years. After a disaster there is an urgency to redirect resources away from new investments to concentrate them on repairs and reconstruction. This fact is consistent with the higher marginal productivity of reconstructed capital (compared to investment in new assets) that is found in the framework proposed here.

Finally, if asset and income losses are to be avoided, it is because they ultimately result in consumption losses. We thus analyze how asset losses due to natural disasters result in consumption losses. We find that for disasters that destroy a similar fraction of built capital, net present consumption losses are expected to be lower where the productivity of capital is higher, such as capital-scarce developing countries. Indeed, in economies where capital has a higher productivity, the ratio of installed capital over consumption is smaller. Thus replacing the same fraction of destroyed capital requires less forgone consumption. This mechanism may partly compensate for the many factors that make poor countries and poor people more vulnerable to disasters, such as the lower quality of their assets, their lack of access to insurance and credit, and their low level of pre-disaster consumption (Hallegatte et al. 2016).

2.1 Output Losses with a Classical Production Function

Production functions relate the inputs and the outputs in the production process. Classically, output can be represented as

$$Y = F(L, K)$$

Where L denotes the amount of labor, K the amount of capital, and Y the output. In this framework, the damage that natural disasters—such as floods, storms, earthquakes—impose on assets can be modeled as an instantaneous decrease in the stock of productive capital ($K_0 \to K_0 - \Delta K$), where ΔK is the value of the asset losses, measured as the repair or replacement cost at pre-disaster prices (this is the common metric used to measure disaster economic losses).

For small shocks, the impact on production can be estimated using the marginal productivity of capital. Denoting $r = \frac{dF}{dK}$ the marginal productivity of capital:

$$\Delta Y(t_0) = r \Delta K \tag{2.1}$$

If there is no reconstruction, the net present value of the constant output losses discounted at an unchanged rate r equals the pre-disaster replacement value of lost assets:

$$\widetilde{\Delta Y} = \Delta K \tag{2.2}$$

In a more realistic setting, however, this method to assess output losses may lead to significant underestimation. One issue is that asset losses may be too large to be considered marginal. To assess non-marginal shocks on the capital stock, one can use the full production function, and decrease the amount of capital from K_0 to $K_0 - \Delta K$. In that case, output losses are larger than in the idealized (marginal) framework and Eq. (2.1) is replaced by:

$$\Delta Y(t_0) = F(L, K) - F(L, K - \Delta K) \tag{2.3}$$

This factor alone would make the net present value of the output losses larger than the value of the damages to assets expressed with pre-disaster prices.[3]

2.2 Disasters Affect the Capital Structure, Not Only the Capital Quantity

Equation (2.3) assumes that the destruction from the disaster affects only the least productive assets, or that capital consists only in one homogeneous commodity that can be instantaneously reallocated toward its more productive usage. However, this assumption is unlikely to be valid after a disaster, because assets such as roads or offices cannot be transformed into other assets such as bridges or factories at no cost and instantaneously.

2.2.1 Accounting for Imperfect Capital Reallocation

Let us use a simple example with an economy where capital consists only of roads that produce "transport services". Roads are built starting from the most productive, that is the one used by the most people, to less productive ones, used by fewer people. At a given point in time, some roads have a high productivity, and some roads have a low productivity. Only the least productive road has the same marginal productivity as the aggregated capital stock. At equilibrium, and assuming that all roads cost the same, the construction cost of the least productive road is equal to the discounted value of its production. The other roads have a higher productivity, and the value of their production is larger than their construction cost.

[3]Note that if the value of asset losses ΔK is defined as the discounted value of the lost production, then by definition the asset losses are equal to lost production. Here, we highlight the difference between the asset losses measured by their pre-disaster value and the lost production.

If a disaster happens to destroy the segment of the road that was built last, that is the least productive segment, then the value of the destroyed road would happen to be equal to the marginal productivity of roads as an aggregate. As in Eq. (2.1), output losses ΔY would thus be the product of the value of the destroyed road (ΔK) times its productivity (r). Discounted production losses would thus equal the construction cost of the road segment, as in Eq. (2.2). But if the disaster destroys any other segment, then the productivity of destroyed capital is higher than the marginal productivity of the road network before the disaster hits. The production loss associated with the destruction of an arbitrary road segment is equal to the construction cost of that segment times the productivity of that particular segment, which is higher than the marginal productivity of the aggregated road network. To assume that the destruction of *any* road can be valued at the marginal productivity of the road network would amount to assume roads can be instantaneously reallocated to their most productive use, i.e. that roads can be moved where they are the most useful, which is of course impossible.

This example shows that the production loss can be higher than the marginal productivity of capital, and the net present value of the lost production can be larger than the construction or replacement value of the road. The replacement value of lost assets provides an underestimation of the net present value of the loss in output.

If the disaster affects more flexible forms of capital, then capital reallocation is possible. Someone whose car has been damaged could for instance buy the least productive undamaged car to its owner. However, this reallocation is (1) not instantaneous (it takes time for all the transactions to take place); (2) not costless (there are transaction and adjustment costs in capital reallocation); (3) not complete (some capital, like the roads in the previous example, cannot be reallocated, for technical, financial, institutional or behavioral reasons).

This issue links to the possibility to describe the capital stock with a single number in an aggregate production function. The question was core to the Cambridge capital theory controversy and the limits of the one-commodity model (Cohen and Harcourt 2003), and to critics on the problem of path dependence (Robinson 1974). Indeed, the capital stock can be represented unambiguously through a single number only if this capital stock is the result of a process of optimal capital accumulation, or if capital can be reallocated instantaneously and at no cost toward its optimal use. Only the assumption of optimal capital allocation allows to remove relative prices and interest rate from the valuation of the capital stock and make it possible to measure capital with a single variable K (Cohen 1989).

In what follows, we investigate the impact of capital losses on aggregate output in a model with explicit categories of capital that cannot be relocated across categories. We then demonstrate a different approach, using a model with a single stock of productive capital, where two dimensions (total capital and fraction of capital destroyed) are used to describe the stock of capital and the production process.

2.2.1.1 Modeling Disaster Impacts on Output with Layers of Capital

Let us first assume that the capital is the aggregation of many "layers" of capital:

$$K = \sum_{i=1 \ldots N} k_i$$

Layers can be broad (homes, vehicles, manufacturing equipment, etc.) or narrow (a road going from A to B, the cars in the city C, the houses of the neighborhood D, etc.). Each capital layer i has a uniform productivity π_i, such that:

$$\frac{\partial Y}{\partial k_i} = \pi_i$$

There is also a maximum amount of capital in each capital layer: $k_i \leq \overline{k_i}$. For instance, once all roads in a neighborhood are built, building more roads will not produce more mobility. This can be seen as an extreme version of decreasing returns within categories: the marginal productivity is constant until a given threshold, and then drops to zero when all opportunities for investment within that layer of capital are exhausted.

We rank the layers of capital so that their productivities are decreasing:

$$i < j \Longrightarrow \pi_i > \pi_j.$$

If the aggregated capital stock K is allocated optimally, investment goes first to the highest-productivity layer of capital until all potential is exhausted, then moves to the second-best layer of capital, and so on. Only the last layer used may have unused potential in the sense that:

$$i < i_0, \; k_i = k_i$$

$$k_{i_0} \leq \overline{k_i}$$

The production function becomes:

$$Y = F(K) = \sum_{i=1 \ldots N} \pi_i \, k_i$$

And the marginal productivity of aggregated capital is given by the productivity of the least productive used layer of capital:

$$F'(K) = \pi_{i_0(K)}$$

The production function meets classical properties. In particular, the marginal productivity of capital is decreasing with K, that is, the production function exhibits decreasing returns.

With such a production function, a destruction of capital ΔK can lead to a loss of production given by the marginal productivity of capital π_{i_0}, but only if the destruction occurs in the last layer of capital (or if capital could be reallocated from the lower- to the higher-productivity capital layers).

A more plausible case is if capital destruction is distributed uniformly over the layers of capital, that is for all i:

$$\frac{\Delta k_i}{k_i} = \frac{\Delta K}{K}$$

Assuming capital reallocation is not possible across capital layers, the impact on production is:

$$\Delta Y = \sum_{i=1\ldots N} \pi_i \, \Delta k_i = Y \frac{\Delta K}{K}$$

In other words, $\Delta Y/\Delta K$, the productivity of destroyed capital, equals Y/K, the average productivity of capital—not the marginal productivity of capital. In particular, output losses are higher than the construction value of damaged assets.

Importantly, this larger impact of capital losses does not require that reallocation of capital is entirely impossible—the result holds if reallocation of capital is possible within layers (a car or a house can be reallocated to its most efficient use), but not across layers (a house cannot replace a damaged road).

2.2.1.2 Modeling Disaster Impacts with Categories of Fully Substitutable Capital

Consider now a more generic model, in which capital still consists of a sum of different types of capital:

$$K = \sum_{i=1\ldots N} k_i$$

And that each capital category produces output with the same production function:

$$y_i = f(k_i)$$

where f has the classical properties, and in particular $f' > 0$ and $f'' < 0$. The total production is simply the sum of the output of all categories:

$$Y(K) = \sum y_i = \sum f(k_i)$$

If capital K is allocated optimally across the capital categories, there is one λ such that for all i:

$$f'(k_i) = \lambda$$

so that all k_i are equal and thus equal to K/N. Under the assumption of perfect capital allocation, we can describe the production process with the following aggregate production function:

$$Y = F(K) = Nf\left(\frac{K}{N}\right)$$

In this case, the marginal productivity of aggregate capital is given by:

$$F'(K) = f'\left(\frac{K}{N}\right)$$

And the second derivative of production is:

$$F''(K) = \frac{1}{N}f''\left(\frac{K}{N}\right)$$

So this aggregate production function meets the classical conditions of a production function.

Assume now that a shock destroys a non-marginal quantity ΔK of capital. If capital remains optimally allocated, then the impact can be approximated by:

$$\Delta Y_{opt} = \Delta K f'\left(\frac{K}{N}\right) + (\Delta K)^2 \frac{1}{N}f''\left(\frac{K}{N}\right) = \Delta K\, F'(K) + (\Delta K)^2\, F''(K)$$

If capital losses occur only in one (say, the first) category of capital, and assuming perfect reallocation within categories but not across categories, the result is:

$$\Delta Y_1 = \Delta K f'\left(\frac{K}{N}\right) + (\Delta K)^2 f''\left(\frac{K}{N}\right) = \Delta K\, F'(K) + N(\Delta K)^2\, F''(K)$$

So that:

$$\Delta Y_1 - \Delta Y_{opt} = (N-1)(\Delta K)^2 \, F''(K)$$

For marginal shocks, if $(N-1)(\Delta K)^2\, F''(K)$ is negligible, representing capital and production as aggregates only does not lead to a significant underestimation of capital losses. But if losses are large or concentrated on a few sectors, if the number of layers across which capital cannot be reallocated is large, or if the second derivative of the production function is large in absolute value, the difference can be substantial. In this case, representing the production process with an aggregate capital stock would lead to underestimating the effect of asset losses on production. And this aggregation error increases with the size and concentration of the shock: as the disaster becomes more serious, or if losses are concentrated spatially or sectorally, then the aggregated production function leads to a larger underestimation of the losses.

In such a model, whether a shock is small or marginal cannot be decided by comparing the total amount of losses ΔK to the total amount of capital K. One has to consider each category of capital (within the N categories) and compare the losses within that category to the amount of capital in that category, as well as the curvature of the production function, to compare $\Delta K\, F'(K)$ and $N(\Delta K)^2\, F''(K)$.

For instance, if a disaster destroys an entire category of capital, total capital losses are $\Delta K = K/N$, and output losses equal:

$$\Delta Y = f\left(\frac{K}{N}\right) = \frac{F(K)}{N} = \frac{F(K)}{K}\Delta K$$

Here again, the loss in output is equal to the loss in assets multiplied by the average—not the marginal—productivity of capital, even if the total amount of capital destroyed is very small. In particular, if the economy is partitioned in a very large set of categories N, and disasters tend to destroy entire categories of capital at once (for instance a bridge is usable or not), then output losses depend on the average productivity of capital. (On the other hand, if categories are only partially damaged, then losses are lower—if a bridge is only partially damaged and can accommodate 50% of peak traffic, it is likely that the service it produces is reduced by less than 50%.)

2.2.1.3 Modeling Aggregate Capital with Two Variables

Two distinct representations of the capital as the aggregation of many categories of capital lead us to conclude that output losses from natural disasters can be directly proportional to asset losses, that is depend on the average, not the marginal productive of capital. Echoing the remark by Stiglitz in the introduction, these models use several variables, not just one aggregate, to track capital. In this section, we propose an alternative model that implements as simply as possible this idea that several variables are needed to track capital: using two variables to track it.

The first variable is the total amount of capital in the absence of disaster damages K and the second variable is the amount of damaged capital K_d. We assume that in the absence of damages, the output is given by the usual production function $F(L, K)$. When a fraction of the capital is damaged, output is simply reduced proportionally to the loss in capital: if 10% of the capital stock is lost, then 10% of the instantaneous output is lost:

$$Y(K, K_d) = \left(1 - \frac{K_d}{K}\right) F(L, K) \tag{2.4}$$

In this model, asset losses ΔK add to destroyed capital, K_d instead of reducing constructed capital K. With these assumptions, lost capital has a productivity equal to the average productivity of the capital in the economy, and

$$\Delta Y(t_0) = \mu \Delta K \tag{2.5}$$

with μ equal to the average productivity of capital $F(L,K)/K$. Assuming no reconstruction, output reduction is permanent, and the net present value of output losses is:

$$\widetilde{\Delta Y} = \frac{\mu}{r} \Delta K \tag{2.6}$$

With these assumptions, the net present value of the loss in output is larger than the value of lost assets expressed as replacement value at pre-disaster prices (since average productivity is higher than marginal productivity). Assuming a Cobb-Douglas production function and using a share of capital income of 1/3, as is observed in most economies, discounted output losses are three times larger than what an estimation with a traditional production function would suggest.

This idea can be expanded to accommodate for labor. Indeed, after a disaster, either labor (through causalities and fatalities, for instance) or capital can be the binding constraint. Denoting L_d the part of labor that becomes unusable after the disaster, this model can be generalized as:

$$Y(K, L, K_d, L_d) = \overbrace{F(L, K)}^{\text{Long-term production function}} \quad \overbrace{min\left[1 - \frac{L_d}{L}, 1 - \frac{K_d}{K}\right]}^{\text{Short-term production constraint}} \tag{2.7}$$

Note that this writing also allows capturing the fact that the malleability of the production system depends on the timescale. Traditional production functions, such as Cobb-Douglas depending on labor and capital, are good representations of long-term factor allocations, when capital reallocation and technology adjustments to substitute capital and labor are possible. $F(L, K)$ can be a traditional production function. Over the short term, however, factor allocation is less flexible. The Leontief-style additional factor on the right represents that. Equation (2.7) is an example of production function that can be used to capture both the urgency to reconstruct and recover from an event, and the choice between investing in capital or labor over the long term.

2.2.2 Interactions Between Damaged and Undamaged Assets

The previous section suggests that the productivity of the lost capital may be larger than the marginal productivity of capital, but still assumed that the assets that have not been directly affected by the disaster can continue producing with an unchanged productivity.

But we also need to take into account the spill-over effects of asset losses: when assets are imperfectly substitutable, the loss of one asset affects the productivity of other assets. Output losses are not only due to forgone production from the assets that have been destroyed or damaged by the event. Assets that have not been affected by the disaster can also become unable to produce at the pre-event level because of indirect impacts. For instance, most economic activity cannot take place during a power outage, because electricity is an essential (and often non-substitutable) input in the production process.

2.2.2.1 Anecdotal Evidence

McCarty and Smith (2005) investigated the impact of the 2004 hurricane season on households in Florida, and find that among the 21% of the households who were forced to move after the disaster, 50% had to do so because of the loss of utilities (e.g., they had no running water). Only 37% of them had to move because of structural damages to the house. In most cases, the loss in the housing services produced by a house is not due to an impact on the house itself, but to impacts to complementary assets (e.g., water pipes).

Tierney (1997) and Gordon et al. (1998) investigate the impact of the Northridge earthquake in 1994 in Los Angeles; they find also that loss of utility services and transport played a key role. Tierney surveys the reasons why small businesses had to close after the earthquake. The first reason, invoked by 65% of the respondents (several answers were possible), is the need for clean-up. After that, the five most important reasons are loss of electricity, employees unable to get to work, loss of telephones, damages to owner's or manager's home, and few or no customers, with percentages ranging from 59 to 40%. These reasons are not related to structural damages to the business itself, but to offsite impacts. Gordon et al. (1998) ask businesses to assess the earthquake loss due to transportation perturbations, and find that this loss amounts to 39% of total losses. Kroll et al. (1991) find comparable results for the Loma Prieta earthquake in San Francisco in 1989: the major problems for small businesses were customer access, employee access, and shipping delays, not structural damages. Utilities (electricity, communication, etc.) caused problems, but only over the short term, since these services were restored rapidly; only transportation issues led to long lasting consequences. Rose and Wei (2013) investigate the impact of a 90-day disruption at the twin seaports of Beaumont and Port Arthur, Texas, and find that—even in the absence of other losses—regional gross output could decline by as much as $13 billion at the port region level (and that specific actions to cope with the shock can reduce these impacts by nearly 70%).

Output losses due to a disaster depend not only on interactions across sectors but also on interactions across firms (Henriet et al. 2012). Business perturbations may indeed also arise from production bottlenecks through supply chains of suppliers and producers.[4] Modern economies, with global supply chains, limited number of suppliers and small stocks, may be more vulnerable to natural disasters than traditional, close economies. The impacts of disasters on supply chains are illustrated by the large 2011 floods in Thailand. Car manufacturing in Thailand dropped by 50–80%, and Toyota was the company hit the hardest in terms of production loss, even though none of its plants got inundated: A critical supplier in the manufacturers' supply chains was affected by the floods (Haraguchi and Lall 2015). Similarly, the global production of hard drive disks (HDD) decreased by 30% in the 6 months after the floods, causing a price spike between 50 and 100% (Haraguchi and Lall 2015). This production loss was not only caused by the disruption of production facilities in Thailand, but also further HDD manufacturers outside Thailand were affected by missing parts from suppliers in flooded areas (Wai and Wongsurawat 2013).

These effects are measurable. Barrot and Sauvagnat (2016) explore the impact of natural disasters in the US on firms' sales, but also on their suppliers. They find that—unsurprisingly—the occurrence of a natural disasters decreases affected firms' sales (by about 5%), but also the sales of the affected firm's customers (by about 3%, 4 months after the disasters). They also show that this effect is not due to geographic proximity between affected firms and their customers, suggesting that the effect propagates through supplies' scarcity, and that the effect is magnified when the suppliers is "specific," i.e. when the supply is not generic and is therefore more difficult to replace. Similar effects have been observed after the 2011 earthquake in Japan, with propagation beyond Japanese borders (Boehm et al. 2019). Todo et al. (2015) shows that network firms have not only an impact on disaster impacts, but also on "firm resilience," defined as the ability of the firm to recover from the shock: among firms that were affected by the 2011 earthquake in Japan, those with suppliers and customers outside the affected areas recovered more quickly than the others.

While these effects are now well documented, they remain challenging to model and quantify. Here, we explore two specific models of firm-to-firm or sector-to-sector propagation, based on Cobb-Douglas and Leontief production functions.

[4]These ripple effects can even take place within a factory, if one segment of the production process is impossible and therefore interrupts the entire production.

2.2.2.2 The Case with Cobb-Douglas Production Functions

The framework used in Acemoglu et al. (2012) allows investigating propagation effects with Cobb-Douglas production functions. Let us assume that the production technology in sector i is described by a Cobb-Douglas function:

$$x_i = k_i^{\alpha} \prod_{i=1 \ldots n} {x_{ij}}^{(1-\alpha)w_{ij}}$$

where k_i is the capital stock in sector i, $\alpha \in (0\ 1)$ is the share of capital income, and x_{ij} is the amount of commodity j used in the production of good i, and w_{ij} represent the share of different intermediate consumption in the production process. (This is the model from the original paper, where labor has been replaced by the capital stock; an alternative representation would be to represent capital as one intermediate consumption.)

Acemoglu et al. (2012) show that with Cobb-Douglas functions, there are no propagations of a productivity shock upstream, because price and quantity effects cancel out.

Assume that a disaster reduced each sector's capital by a fraction d_i, the production function becomes:

$$x_i = ((1-d_i)k_i)^{\alpha} \prod_{i=1 \ldots n} {x_{ij}}^{(1-\alpha)w_{ij}}$$

Here, the relationship between production and capital losses is given by the Cobb-Douglas function, so that the loss of consumption is worth a fraction $(1 - d_i)^{\alpha}$ of pre-disaster capital—the losses depend on marginal productivity, like in Sect. 2.2.1.2, because it is implicitly assumed that reallocation is possible at no cost within each sector i.

Acemoglu et al. (2012) show the output in the competitive equilibrium is given by:

$$\log(Y) = v'(1-d)$$

where d is the vector of $\{d_i\}$ and v is given by:

$$v = \frac{\alpha}{n}[I - (1-\alpha)W']^{-1}\mathbf{1}$$

Where W is the input-output matrix of w_{ij}. At equilibrium, the vector v is also the "sale vector":

$$v_i = \frac{p_i x_i}{\sum_j p_j x_j}$$

where p_i is the pre-disaster competitive equilibrium price of good i. (This is consistent with Hulten's theorem linking sector-level productivity shocks to macro-level output; Hulten 1978.) If a sector that represents 2% of the total sales in the economy loses 10% of its production, the loss in output is 0.2%. Note that v is the sale vector, not the value-added vector. It gives more importance to sectors with large intermediate consumption (since intermediate consumption is the wedge between value added and sales). In this context, an economy with large intermediate consumptions will experience larger macroeconomic losses from the level sector-level shock.

2.2.2.3 Illustrative Modeling with Leontief Functions

Spill-overs across sectors can also be represented through non-homogeneous capital: capital components are not perfectly substitutable within a network of economic activities, and the relative price of different types of capital depends on the relative quantity. If the stock of capital consists of an ensemble of capital categories that have some complementarity, then the destruction of one component may reduce the productivity of other components and thus have an impact that is larger than what could be expected from the analysis of one component only. (On the other hand, if different types of capital are substitutable, the destruction of one type of capital can be compensated partially with the utilization of another type of capital. For instance one road from A to B can become more productive, that is be used by more passengers, if an alternative route from A to B is destroyed.)

One extreme example is the case of a road that is built out of a series of segments between two points: if one segment is destroyed, then the road is not usable and the other segments become useless. The output loss due to the destruction of one segment cannot be estimated based on the construction value of that segment alone, but requires an analysis of the entire system (the road). The same is true—at various degrees—of the entire economic system: the loss of one component can affect the other components and lead to losses that are higher (or lower) than the value of the asset loss suggests depending on the substitutability. This problem is disregarded if one assumes that the capital stock is always (both before and after an event) optimally allocated (in that case, road segments can be moved to their most efficient uses).

This problem can be illustrated by replacing the classical production function f(L, K) by a function with two types of capital $f(L,K_1,K_2)$. If there are decreasing returns in K_1 and K_2, the impact of a given loss $\Delta K = \Delta K_1 + \Delta K_2$ depends on how losses are distributed across the two capitals. The loss in output is larger if all losses affect only one type of capital, compared with a scenario where the two capitals are equally affected.

These two issues can be illustrated with a simple example. Assume that there are two categories of capital, K_1 and K_2, that are not substitutable. The production function is a nested Cobb-Douglas between capital services and labor, and capital services are produced using the two capital categories, through a Leontief function:

$$Y = f(L, K_1, K_2) = [\mathrm{Min}(c_1 K_1, c_2 K_2)]^{\alpha} L^{\beta}$$

K_1 and K_2 could be interpreted as two segments of a road with different construction costs, for instance: if one segment is completely destroyed, the second segment's productivity falls to zero, and the total capacity of the road is given by its segment with the lowest capacity. If one segment is damaged so that only half of the traffic can go through, then the second segment also sees half of the traffic and its productivity is also halved.

Total capital is $K = K_1 + K_2$. At the optimum, the quantities of each type of capital adjust such that $c_1 K_1 = c_2 K_2$. If we assume that capital K is always distributed optimally across K_1 and K_2, the production function becomes:

$$Y = F(K, L) = \left[\frac{c_1 c_2}{c_1 + c_2} K\right]^{\alpha} L^{\beta}$$

This production function is a classical Cobb-Douglas function, and it can be used to estimate changes in production resulting from investments or divestment, provided that the capital is optimally distributed across categories of capital (i.e. across sectors, technologies, localization, etc.), at the marginal productivity of aggregate capital:

$$\frac{\partial F(K, L)}{\partial K} = \alpha \frac{c_1 c_2}{c_1 + c_2} \left[\frac{c_1 c_2}{c_1 + c_2} K\right]^{\alpha - 1} L^{\beta}$$

If a disaster hits this economy and destroys capital K_1 and K_2 proportionally, or if the residual capital in the two categories can be reallocated, then the immediate loss of output will be given by the product of the marginal productivity of capital by the value of the damages, and the net present value of capital losses will be equal to the value of the damages, as expected.

But if only one category of capital is affected—say K_1—then $c_1 K_1 < c_2 K_2$, and if there is no possible reallocation of capital,[5] then the production becomes driven by K_1 over the short term, and the loss in output from a marginal loss of K_1 is:

[5]In growth models, the impossibility to relocate capital can be represented by a non-negativity constraint on investments: investments in capital K_1 cannot be negative, with the divestment used to consume or invest in K_2; see an example in Rozenberg et al. (2018).

$$\frac{\partial Y}{\partial K_1} = \alpha c_1^{\alpha} K_1^{\alpha-1} L^{\beta}$$

Replacing K_1 with $F'(K)$ and generalizing to n categories of capital, we get:

$$\frac{\partial Y}{\partial K_i} = \left(\frac{\sum c_j}{\sum c_j - c_i}\right) F'(K)$$

In that case, the destruction by a disaster of a (marginal) amount ΔK_i of one type of capital would lead to a loss of output with a net present value equal to:

$$\widetilde{\Delta Y} = \left(\frac{\sum c_j}{\sum c_j - c_i}\right) \Delta K_i$$

If c_i is large (if K_i is a small share of total capital), the net present value of output losses can be much larger than ΔK_i. This case is extreme because the different categories of capital are assumed non-substitutable. But recent evidence suggests that at least over the short-term, elasticities in the production system are close to zero (Boehm et al. 2019; Farhi and Baqaee 2017). Typically, it is the case that if all electricity generation is impossible, most other production processes are interrupted. Even though electricity generation represents a small share of GDP, the impact of such an event on total output can be very large (Rose et al. 2007; Farhi and Baqaee 2017).

The qualitative result remains valid with higher substitutability: considering disaggregated capital categories with imperfect substitutability, a disaster would break the assumption that the total amount of capital is optimally distributed across these categories, increasing the marginal productivity of destroyed capital and the value of output losses (and as a result, the marginal productivity of reconstruction).

Recent papers have explored the impact of microeconomic shocks on aggregate consumption of GDP, using production function with constant elasticity of substitution (Farhi and Baqaee 2017; Baqaee 2018; Taschereau-Dumouchel 2017). Unsurprisingly, they find that smaller elasticity in the production function tends to increase the aggregate losses due to a negative shock, and that a large shock to a small sector can have a large impact on macroeconomic aggregates.

2.2.3 Externalities

Output losses need to be estimated from a social point of view. The equality between market value (for the owner) and expected output (for society) is valid only in the absence of externalities. Some assets that are destroyed by disasters may exhibit positive externality. It means that their value to society is larger than the value of the owner's expected output. Public goods have this characteristic, among which include infrastructure projects, health services, and education services.[6]

One example is the health care system in New Orleans. Beyond the immediate economic value of the service it provides, a functioning health care system is necessary for a region to attract workers (in other terms, it creates a positive externality). After Katrina's landfall on the city in 2005, the lack of health care services made it more difficult to attract construction workers to the region, and thus slowed down the reconstruction; as a result, the cost for the region of the loss in health care services was larger than the direct value of this service.

To account for these effects, lost assets (ΔK) should be valued taking into account externalities. Below, we explore two particular cases: the stimulus effect of reconstruction; and productivity spill-overs from reconstruction.

2.2.3.1 The Stimulus Effect

Disasters lead to a reduction of production capacity, but also to an increase in the demand for the reconstruction sector and goods. Thus, the reconstruction acts in theory as a stimulus. For instance, Albala-Bertrand (2013) assumes that reconstruction spending has a Keynesian multiplier equal to two (each dollar spent in reconstruction increases GDP by two dollars). However, as for any stimulus, its consequences depend on the pre-existing economic situation, such as the phase of the business cycle and the existence of distortions that lead to under-utilization of production capacities (Hallegatte and Ghil 2008). If the economy is efficient and in a phase of high growth, in which all resources are fully used, the net effect of a stimulus on the economy will be negative, for instance through diverted resources, production capacity scarcity, and accelerated inflation. If the pre-disaster economy is depressed, on the other hand, the stimulus effect can yield benefits to the economy by mobilizing idle capacities. For instance, the 1999 earthquake in Turkey caused direct destruction amounting to 1.5–3% of Turkey's GDP, but consequences on growth remained limited, probably because the economy had significant unused resources at that time (the Turkish GDP contracted by 7% in the year preceding the earthquake). In this case, therefore, the earthquake may have acted as a stimulus and increased economic activity in spite of its human consequences. In 1992, the economy in Florida was depressed and only 50% of the construction workers were employed (West and Lenze 1994) when Hurricane Andrew made landfall on south Florida. Reconstruction had a stimulus effect on the construction sector, which would have been impossible in a better economic situation (e.g., in 2004 when four hurricanes hit Florida during a housing construction boom).

---

[6]Other assets may exhibit negative externality, e.g. air pollution from a coal power plant.

2.2.3.2 Productivity Spill-Overs

Disasters damage old and low-quality capital, and the reconstruction may allow to "build back better" and to reach an endpoint that is superior in some aspects to the pre-disaster situation. For instance, an earthquake may destroy old, low-quality, buildings, making it possible to rebuild with improved building norms (and higher energy efficiency leading to better comfort and lower energy bills); this possibility has been mentioned for the Christchurch earthquake in New Zealand in 2011. And Hornbeck and Keniston (2014) show that the Great Fire in Boston in 1872 led to a large increase in land values, suggesting that reconstruction created positive local externalities that were difficult to capture through normal building turnover. More general exploration of this effect, hereafter referred to as the "productivity effect" (closely linked to the "Schumpeterian creative destruction effect"), can be found in Albala-Bertrand (2013), Stewart and Fitzgerald (2001), Okuyama (2003) and Benson and Clay (2004).

When a natural disaster damages productive capital (e.g., production plants, houses, bridges), the destroyed capital can be replaced using the most recent technologies, which have higher productivities. Capital losses can, therefore, be compensated by a higher productivity of the economy in the event aftermath, with associated welfare benefits that could compensate for the disaster's direct consequences. This process, if present, could increase the pace of technical change and accelerate economic growth, and could therefore represent a positive consequence of disasters. This effect is often cited to explain why some studies find a positive impact of disasters (Skidmore and Toya 2002, Toya and Skidmore 2007). However, the productivity effect is probably not fully effective, for several reasons. First, when a disaster occurs, producers have to restore their production as soon as possible. This is especially true for small businesses, which cannot afford long production interruptions (see Kroll et al. 1991; Tierney 1997), and in poor countries, in which people have no means of subsistence while production is interrupted. Second, even when destructions are quite extensive, they are never complete. Some part of the capital can, in most cases, still be used, or repaired at lower costs than replacement cost. In such a situation, it is possible to save a part of the capital if, and only if, the production system is reconstructed identical to what it was before the disaster. This technological "inheritance" acts as a major constraint to prevent a reconstruction based on the most recent technologies and needs, especially in the infrastructure sector. This effect is investigated in Hallegatte and Dumas (2009) using a simple economic model with embodied technical change. In this framework, disasters are found to influence the production level but cannot influence the economic growth rate, in the same way as the saving ratio in a Solow growth model. Depending on how reconstruction is carried out (with more or less improvement in technologies and capital), moreover, accounting for the productivity effect can either decrease or increase disaster costs, but this effect is never able to turn disasters into positive events.

2.3 Reconstruction Dynamics and Consumption Impacts

In the previous section, it was assumed that the output losses were permanent, i.e. that there is no investment or reconstruction taking place. In practice, of course, damaged assets are replaced or repaired, often as fast as possible. If the lost capital has a productivity that is higher than the pre-disaster marginal productivity of capital, the rationale to reconstruct and repair is stronger than the pre-disaster rationale to invest, possibly leading to higher investments. This section investigates these dynamics.

2.3.1 Modeling the Reconstruction Phase

Consider the production function proposed in Sect. 2.2.1.3, where capital is described by two variables; total amount of capital, and amount of capital destroyed. In this model, investment needs to be described by two variables too: investment towards reconstruction of damaged capital (i_R); and the investment into new capital, which is not linked to reconstruction (i_N):

$$\frac{dK_d}{dt} = -i_R$$
$$\frac{dK}{dt} = i_N$$

The marginal return on expanding the total capital stock I_N is $\left(1 - \frac{K_d}{K}\right)\partial_K F(K, L) + \frac{K_d}{K}\frac{F(K,L)}{K}$ while the marginal return on reconstruction I_R is $F(K, L)/K$. With decreasing return, marginal productivity is lower than average productivity of capital, and the return on I_N is lower than the return on I_R.[7]

In this theoretical setting, all post-disaster investments should be dedicated toward the reconstruction instead of damages. For instance, construction of any new house would be postponed to focus efforts toward rebuilding and repairing damaged houses. Similarly, construction of new roads and bridges should be delayed to focus on repairing damaged roads and bridges.

If that was the case, if output could be entirely directly toward reconstruction, damages from disasters would be repaired extremely rapidly. Damages from hurricane Katrina represented less than 1 month of US investments, so the return to the pre-disaster situation could have happened in a matter of months.

[7] One limitation of using only two variables is that we have to assume that the return on reconstruction is constant, which is obviously an oversimplification. One way to include priorities for reconstruction (more productive destroyed assets can be rebuilt before less productive destroyed assets), is to keep a disaggregated production function.

But in actuality, investment in reconstruction is limited by financial and technical constraints. First, the people who lost their assets may not have access to savings or borrowing to pay for reconstruction and repair, and may not be insured, so that they cannot make corresponding investments in spite of their large returns. Second, the economic sectors that are involved in the reconstruction have limited production capacity. For instance, the construction sector usually struggles to cope with the surge in demand seen after disasters, which leads to rationing and increased prices (see Appendix). These constraints mean that I_R cannot usually represent more than a limited share of total investment (and total output), leading to reconstruction periods that are much longer than what the amount of losses would suggest.

The length of the reconstruction period depends on many characteristics of the affected economy, including (1) the capacity of the sectors involved in the reconstruction process (especially the construction sector); (2) the flexibility of the economy and its ability to mobilize resources for reconstruction [e.g., the ability of workers to move to the construction sector, see Stéphane Hallegatte (2008)]; (3) the openness of the economy and its ability to access resources (e.g., skilled workers and materials for reconstruction); (4) the financial strength of private actors, households and firms, and their ability to access financial resources for reconstruction, through savings, insurance claims, or credit; and (5) the financial strength of the public sector and its ability to access financial resources to reconstruct (see the very thorough analysis of financing options in developing countries in (Mechler 2004).[8]

As shown in Appendix, one consequence of the limited capacity of the reconstruction sector is that the price of reconstruction services hikes in the aftermath of a disaster.

2.3.2 Consequence on Consumption

If we assume that all investment goes to reconstruction and that output losses are reduced to zero exponentially with a characteristic time T, then output losses after t_0 are given by (Fig. 2.1)[9]:

---

[8]Specific instruments such as contingent credit lines help with reconstruction financing. See for instance on the World Bank's Cat-DDO, http://treasury.worldbank.org/bdm/pdf/Handouts_Finance/CatDDO_Product_Note.pdf

[9]One difficulty is the fact that an economy affected by a disaster may never return to its initial situation: some activities may disappear permanently, while new sectors may appear. Hurricanes in La Réunion, a French island off the coast of Madagascar, in 1806 and 1807 led to a shift from coffee to sugar cane production, for instance. Also, "good" reconstruction may improve the quality and resilience of infrastructure and productive capital (Benson and Clay 2004; Skidmore and Toya 2002). In this rule of thumb, however, we assess the cost of the disaster as the losses that occur if the economy returns to its initial state, leaving economic growth aside. A modeling exercise with an endogenous growth model (Hallegatte and Dumas 2009) suggests that introducing even an optimistic version of this effect would not change results dramatically. Moreover, even if there is no "return to the initial situation," defining the "cost" as "the cost to return to the initial situation" provides a useful (and comparable) benchmark.

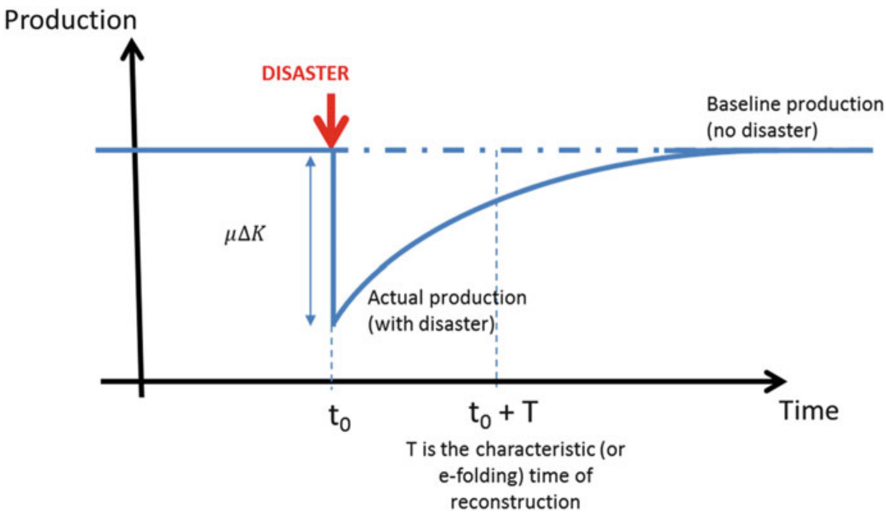


Fig. 2.1 Simplified representation of the return to "initial state" after a disaster. This figure assumes a stable (no-growth) baseline

$$\Delta Y(t) = \mu \Delta K e^{-\frac{t-t_0}{T}}$$

Where μ represents the average productivity of capital as before. With discounting at a rate ρ, the net present value of output losses is:

$$\widetilde{\Delta Y} = \int_{t_0}^{+\infty} \mu \Delta K e^{-\frac{t-t_0}{T}} e^{-\rho(t-t_0)} dt = \frac{\mu \, \Delta K}{\rho + \frac{1}{T}}$$

Consider first a case where all losses are repaired instantaneously by reducing consumption and directing all the goods and services that are not consumed toward reconstruction investments (this is a scenario where reconstruction capacity is infinite, and T is equal to zero). In this limit case, there is no output loss since all asset damages are instantaneously repaired. There are however consumption losses, since consumption has to be reduced to reconstruct, and this reduction is equal to the reconstruction value (i.e. the replacement cost of damaged capital). In that case, the net present value of consumption losses ($\widetilde{\Delta C}$) is simply equal to the reconstruction cost. With unchanged prices, this is equal to the pre-disaster value of damaged assets ΔK. (If the prices of goods and services needed for the reconstruction change, as discussed in Appendix, then the reduction in consumption can be larger than the initial assessment of asset losses, a mechanism known as "demand surge" in the insurance industry.)

Consider now another case with no reconstruction, in which output losses are permanent and all losses in output are absorbed by a reduction in consumption (but no share of income is used for reconstruction). In that case, consumption losses are equal to output losses (with no reconstruction), and T is equal to infinity. The loss in consumption at t_0 is thus equal to $\mu\Delta K$, and the net present value (discounted at the rate ρ) of consumption losses is $(\mu/\rho)\Delta K$, as in the previous section. Consumption losses and welfare losses are thus larger than the value of lost assets in a no-reconstruction case (given that the average productivity of capital is larger than the discount rate).

In the instantaneous reconstruction scenario, consumption losses are equal to the share of consumption needed to repair and rebuild, i.e. to asset losses ΔK. In the no-reconstruction scenario, consumption losses are equal to output losses $(\mu/\rho)\Delta K$, i.e. larger than direct losses ΔK.[10] As a result, consumption (and welfare) losses are magnified when reconstruction is delayed or slowed down. And in all realistic scenarios where reconstruction takes some time (from months for small events to years for large-scale disasters), consumption losses are larger than direct losses.

For intermediate scenarios, with reconstruction over a given period, the duration of the reconstruction phase determines the welfare cost of natural disasters. The net present value of consumption losses is equal to:

$$\widetilde{\Delta C} = \int_{t_0}^{+\infty} \left(\mu \Delta K e^{-\frac{t-t_0}{T}} + \Delta K e^{-\frac{t-t_0}{T}} \frac{1}{T} \right) e^{-\rho(t-t_0)} dt = \Delta K \frac{\mu + {}^1\!/_T}{\rho + {}^1\!/_T}$$

This result depends crucially on the fact that the productivity of destroyed capital is equal to the average pre-disaster productivity of capital. If the productivity of the lost capital was assumed equal to the marginal productivity of capital, i.e. if μ is replaced by ρ in the equation, then the loss of consumption is simply equal to the loss of capital and is thus independent of the reconstruction duration. There would be no urgency in reconstructing, and accelerating the reconstruction process would not bring any benefit. With the framework proposed here, consumption losses are increasing with the duration of the reconstruction period, a finding that is consistent with the urgency to reconstruct that is easily observable after a disaster.

The framework also suggests that the relative impact on consumption of a disaster is smaller in developing countries than in developed countries. Express annual consumption as the product of propensity to consume (1-s), average capital productivity, and aggregate capital: $C = (1\text{-}s)\mu K$. Then, the ratio of the net present value of consumption losses to the annual consumption is:

$$\frac{\widetilde{\Delta C}}{C} = \frac{\Delta K}{K} \frac{1}{1-s} \frac{1 + {}^1\!/_{\mu T}}{(\rho + {}^1\!/_T)}$$

If a disaster destroys 15% of the capital in an economy, the relative loss in consumption $\frac{\widetilde{\Delta C}}{C}$ decreases with μ: it tends to infinity for $\mu = 0$, and decreases to

[10] The reality is more complex than what has been described here because not all output losses are translated into consumption losses. In practice, the loss in output changes the terms of the intertemporal investment-consumption trade-off and translates into ambiguous instantaneous changes in consumption and investment. But the main conclusions of the analysis are not affected by this complexity.

zero as μ tends to infinity. Since the average productivity of capital μ is expected to decrease as countries develop and accumulate capital (Lucas 1990), rich countries will tend to suffer larger relative consumption losses than poor countries with higher productivity of capital. Where capital has a higher productivity, replacing destroyed capital requires a lower share of consumption.

This effect contribute to the resilience of poor countries (compared with higher income ones): low-income countries can reconstruct without giving up a large share of their consumption, because the amount at stake is lower, even relative to their income. This factor partly rebalances the many other factors that make poor countries and poor people more vulnerable to natural disaster, such as the higher vulnerability of their capital stock (leading to higher $\Delta K/K$) and the high impact on welfare of the same relative loss in consumption [for a full analysis of the multiple determinants of resilience, see Hallegatte et al. (2016)].

This result also suggests that the consumption and welfare impact of natural disasters can be reduced by accelerating reconstruction, for instance by removing some of the financial or technical constraints discussed earlier. Higher penetration of market insurance or better access to borrowing can make reconstruction easier for all economic actors. Higher trade openness helps bring the equipment and materials needed for the reconstruction. Higher openness to workers also helps accelerate reconstruction and reduce the reconstruction cost. For instance, using classical calibration for parameters, reducing a reconstruction period from 5 to 2 years reduces consumption losses by 20% (Fig. 2.2).

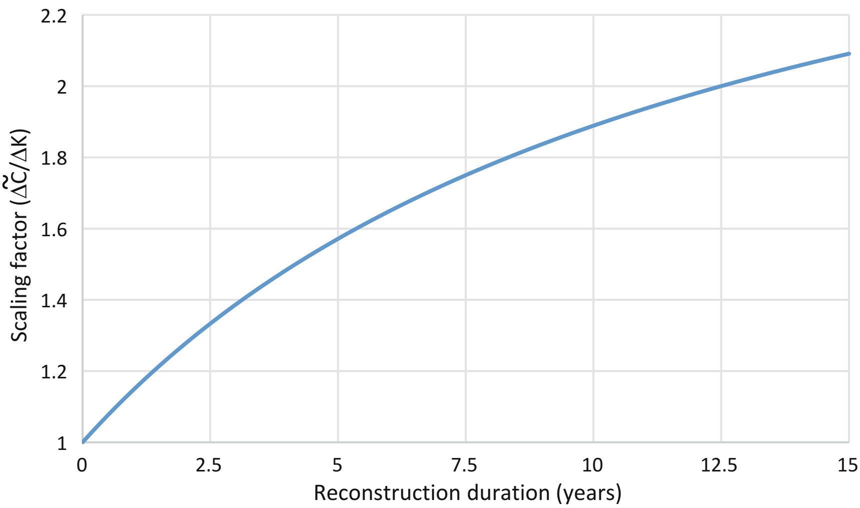


Fig. 2.2 The scaling factor between consumption and asset losses ($\widetilde{\Delta C}/\Delta K$) as a function of the reconstruction duration (defined as the time needed to repair 95% of the losses)

2.4 Conclusion

The modeling of the macroeconomic impacts of natural disasters that is proposed here is extremely simple. It is not meant to replace more sophisticated representations of the impacts of natural disasters, such as those based on input-output models (Okuyama 2004; Hallegatte 2008, 2014) or calculable general equilibrium models (Rose et al. 2007; Rose and Wei 2013). It is meant to highlight the risk of underestimating the cost of natural disasters (and the value of rapid reconstruction) in simple models used for the cost-benefit analysis of disaster risk management investments or for climate change analyses.

First, it shows that using an aggregate production function may lead to underestimating the immediate impact of asset losses due to disasters on the economic output flow. It also proposes an alternative modeling to avoid this bias, by using the average—and not the marginal—productivity of capital to estimate the effect of asset losses on output. This results in an immediate reduction in output flow that is about three times larger than estimates based on the value of asset losses (and an aggregated capital stock). A better estimate of the impact on output is a critical input into the assessment of the benefits of risk reduction measures.

Second, this paper highlights the critical role of the reconstruction capacity and speed in the consumption (and welfare) impact of disasters. Again, the bias created when using only one aggregated capital stock in the production function leads to underestimating the output impact of natural disaster, and to disregard the importance of reconstruction capacity as a critical determinant of welfare losses. This paper provides a simple way to estimate total consumption losses due to a disaster. It suggests that the (discounted) consumption losses due to a disaster are 10% larger than asset losses if reconstruction takes place in 1 year, and up to 50% if reconstruction takes place in 10 years. This provides the required inputs to estimate the economic benefits from improved reconstruction capacity (e.g., thanks to insurance or rainy-day funds).

Acknowledgements This paper is a background paper for the World Bank report "Unbreakable: Building the resilience of the poor in the face of natural disasters." It benefited from comments and feedback from many people, including Jinqiang Chen and the participants to the ENGAGE workshop hosted by the Potsdam Institute for Climate Impact Research in Potsdam, Germany, on June 20–21, 2016.

Appendix: Price Impacts and the Cost of Reconstruction

The equality of asset value and output is valid only for marginal changes, i.e. for small shocks that do not affect the structure of the economy and the relative prices of different goods and services. The impact is different for large shocks. Such non-marginal shocks affect prices, while asset and output losses are often estimated assuming unchanged (pre-disaster) prices (e.g., assuming that if a house is destroyed, the family who owns the house can rent another house at the pre-disaster price). But this assumption is unrealistic if the disaster causes more than a small shock. In post-disaster situations, indeed, a significant fraction of houses may be destroyed, leading to changes in the relative price structure. In this case, the price of alternative housing can be much higher than the pre-disaster price, as a consequence of the disaster-related scarcity in the housing market.[11]

For large shocks, estimating the value of lost output service should take into account the price change. Compared with an assessment based on the pre-disaster prices, it can lead to a significant increase in the assessed disaster cost.

Post-disaster price is especially sensible in the construction sector, which sees final demand soar after a disaster. For instance, Fig. 2.3 shows the large increase in wages for roofers and carpenters in two areas heavily affected by hurricane losses in Florida in 2004. This inflation affects the replacement cost of capital and is referred to as "demand surge" in the insurance industry.

Post-disaster price inflation is often considered as resulting from unethical behavior from businesses, justifying anti-gouging legislation (e.g., Rapp 2005). But it also has positive consequences by supporting the optimal allocation of the remaining capital (e.g., housing) and by incentivizing quick reconstruction. This inflation, indeed, helps attract qualified workers where they are most needed and creates an incentive for all workers to work longer hours, therefore compensating for damaged assets and accelerating reconstruction. It is likely, for instance, that higher prices after hurricane landfalls are useful to make roofers from neighboring unaffected regions move to the landfall region, therefore increasing the local production capacity and reducing the reconstruction duration. Demand surge, as a consequence, may also reduce the total economic cost of a disaster, even though it increases its financial burden on the affected population.

In extreme cases, or where price adjustment is constrained by ethical considerations or anti-gouging regulations, there may be rationing, i.e. the price cannot clear the market and supply is not equal to demand: there is no available house for rent at any price, there is no qualified worker to repair a roof. In these situations, even using the post-disaster price underestimates the losses.

[11]Conversely, if a disaster makes a large fraction of the population leave the city (such as Katrina in New Orleans) or if many jobs disappear as a result, then the cost of housing may decrease because of the shock. Changes in risk perceptions could also lead to a decrease in home values, as illustrated in Bin and Polasky (2004)).

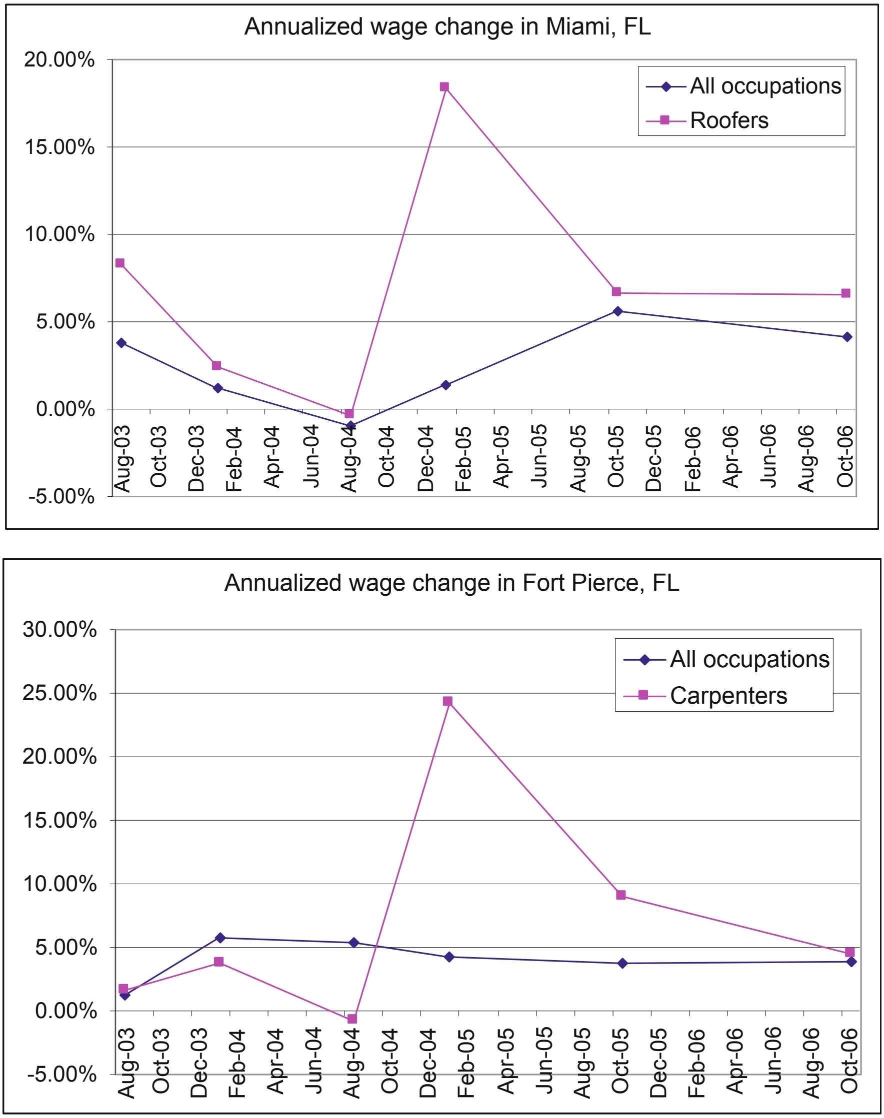


Fig. 2.3 Wages for qualified workers involved in the reconstruction process (roofer and carpenter), in two areas where losses have been significant after the 2004 hurricane season in Florida. Data from the Bureau of Labor Statistics, Occupational Employment Surveys in May 03, Nov 03, May 04, Nov 04, May 05, May 06, May 07

References

Acemoglu D, Carvalho VM, Ozdaglar A, Tahbaz-Salehi A (2012) The network origins of aggregate fluctuations. Econometrica 80(5):1977–2016. https://doi.org/10.3982/ECTA9623

Albala-Bertrand JM (2013) Disasters and the networked economy. Routledge, New York

Baqaee DR (2018) Cascading failures in production networks. Econometrica 86:1819–1838

Barrot J-N, Sauvagnat J (2016) Input specificity and the propagation of idiosyncratic shocks in production networks. Q J Econ 131(3):1543–1592

Benson C, Clay EJ (2004) Understanding the economic and financial impacts of natural disasters. World Bank, Washington, DC

Bin O, Polasky S (2004) Effects of flood hazards on property values: evidence before and after Hurricane Floyd. Land Econ 80(4):490–500

Boehm C, Flaaen A, Pandalai-Nayar N (2019) Input linkages and the transmission of shocks: firm-level evidence from the 2011 Tōhoku earthquake. Rev Econ Stat 101:60–75

Cohen AJ (1989) Prices, capital, and the one-commodity model in neoclassical and classical theories. Hist Polit Econ 21(2):231–251

Cohen AJ, Harcourt GC (2003) Retrospectives: whatever happened to the Cambridge capital theory controversies? J Econ Perspect 17:199–214

Farhi E, Baqaee D (2017) The macroeconomic impact of microeconomic shocks: beyond Hulten's Theorem. In: 2017 Meeting Papers. Society for Economic Dynamics

Gordon P, Richardson HW, Davis B (1998) Transport-related impacts of the Northridge earthquake. National Emergency Training Center

Hallegatte S (2008) An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. Risk Anal 28(3):779–799

Hallegatte S (2014) Economic resilience: definition and measurement. The World Bank, Washington, DC

Hallegatte S, Dumas P (2009) Can natural disasters have positive consequences? Investigating the role of embodied technical change. Ecol Econ 68(3):777–786

Hallegatte S, Ghil M (2008) Natural disasters impacting a macroeconomic model with endogenous dynamics. Ecol Econ 68(1):582–592

Hallegatte S, Vogt-Schilb A (2016) Are losses from natural disasters more than just asset losses? The role of capital aggregation, sector interactions, and investment behaviors

Hallegatte S, Bangalore M, Vogt-Schilb A (2016) Socioeconomic resilience: multihazard assessments in 117 countries. World Bank Group, Washington, DC

Haraguchi M, Lall U (2015) Flood risks and impacts: a case study of Thailand's floods in 2011 and research questions for supply chain decision making. Int J Disaster Risk Reduct 14 (December):256–272. https://doi.org/10.1016/j.ijdrr.2014.09.005

Henriet F, Hallegatte S, Tabourier L (2012) Firm-network characteristics and economic robustness to natural disasters. J Econ Dyn Control 36(1):150–167. https://doi.org/10.1016/j.jedc.2011.10.001

Hornbeck R, Keniston D (2014) Creative destruction: barriers to urban growth and the great Boston fire of 1872. Working Paper 20467. National Bureau of Economic Research. http://www.nber.org/papers/w20467

Hulten CR (1978) Growth accounting with intermediate inputs. Rev Econ Stud 45(3):511–518

Kroll CA, Landis JD, Shen Q, Stryker S (1991) Economic impacts of the Loma Prieta earthquake: a focus on small businesses. Berkeley Plann J 5(1). https://doi.org/10.5070/BP35113132

Lucas RE (1990) Why doesn't capital flow from rich to poor countries? Am Econ Rev 80(2):92–96

McCarty C, Smith S (2005) Florida's 2004 Hurricane season: local effects. Florida Focus, BEBR University of Florida 1

Mechler R (2004) Natural disaster risk management and financing disaster losses in developing countries, vol 1. Verlag Versicherungswirtsch

Okuyama Y (2003) Economics of natural disasters: a critical review. Research Paper 2003–12, Regional Research Institute, West Virginia University, USA

Okuyama Y (2004) Modeling spatial economic impacts of an earthquake: input-output approaches. Disaster Prev Manag: Int J 13(4):297–306. https://doi.org/10.1108/09653560410556519
Patankar A, Patwardhan A (2014) Estimating the uninsured losses due to extreme weather events and implications for informal sector vulnerability: a case study of Mumbai, India. Mimeo
Rapp GC (2005) Gouging: terrorist attacks, hurricanes, and the legal and economic aspects of post-disaster price regulation. KY Law J 94:535–560
Robinson J (1974) History versus equilibrium. Thames Polytechnic, London
Rose A, Wei D (2013) Estimating the economic consequences of a port shutdown: the special role of resilience. Econ Syst Res 25(2):212–232
Rose A, Oladosu G, Liao S-Y (2007) Business interruption impacts of a terrorist attack on the electric power system of Los Angeles: customer resilience to a total blackout. Risk Anal 27 (3):513–531
Rozenberg J, Vogt-Schilb A, Hallegatte S (2018) Instrument choice and stranded assets in the transition to clean capital. J Environ Econ Manag, November. https://doi.org/10.1016/j.jeem.2018.10.005
Skidmore M, Toya H (2002) Do natural disasters promote long-run growth? Econ Inq 40 (4):664–687
Stewart F, Fitzgerald EVK (2001) War and underdevelopment. Oxford University Press, Oxford
Stiglitz JE (1974) The Cambridge-Cambridge controversy in the theory of capital; a view from New Haven: a review article. J Polit Econ 82(4):893–903
Taschereau-Dumouchel M (2017) Cascades and fluctuations in an economy with an endogenous production network
Tierney KJ (1997) Business impacts of the Northridge earthquake. J Conting Crisis Manag 5 (2):87–97. https://doi.org/10.1111/1468-5973.00040
Todo Y, Nakajima K, Matous P (2015) How do supply chain networks affect the resilience of firms to natural disasters? Evidence from the Great East Japan earthquake. J Reg Sci 55(2):209–229. https://doi.org/10.1111/jors.12119
Toya H, Skidmore M (2007) Economic development and the impacts of natural disasters. Econ Lett 94(1):20–25. https://doi.org/10.1016/j.econlet.2006.06.020
Wai LC, Wongsurawat W (2013) Crisis management: western digital's 46-day recovery from the 2011 flood disaster in Thailand. Strateg Leadersh 41(1):34–38
West CT, Lenze DG (1994) Modeling the regional impact of natural disaster and recovery: a general framework and an application to Hurricane Andrew. Int Reg Sci Rev 17(2):121–150

Stephane Hallegatte is the lead economist with the Global Facility for Disaster Reduction and Recovery (GFDRR) at the World Bank. Dr. Hallegatte is a lead author of the IPCC, author of dozens of articles and several books. He led several World Bank reports including Shock Waves in 2015, and Unbreakable in 2016. He was team leader for the World Bank Group Climate Change Action Plan, a planning exercise to determine how to support countries in their implementation of the Paris Agreement. In 2018, he received the Burtoni Award for his work on the link between climate change adaptation and poverty reduction. Dr. Hallegatte holds an engineering degree from the Ecole Polytechnique (Paris) and a Ph.D in economics from the Ecole des Hautes Etudes en Sciences Sociales (Paris).

Adrien Vogt-Schilb is a senior climate change economist at the Inter-American Development Bank. His work focuses on the design of effective and politically-acceptable long-term emission-reduction strategies: how to align the Paris Agreement's Nationally Determined Contribution implementation with local development goals and the long-term decarbonization imperative while navigating the political economy. He also works on quantifying the effect of policies that build socio-economic resilience to natural disasters and climate change, and on methods to facilitate decision making under deep uncertainty. Dr. Vogt-Schilb is a trained engineer, holds a PhD in climate economics and is the author of three books and many academic papers.

Chapter 3
Insurance for Catastrophes: Why Are Natural Hazards Underinsured, and Does It Matter?

Aditya Kusuma, Cuong Nguyen, and Ilan Noy

Abstract This chapter describes the state of our knowledge about the impacts of disaster insurance. To narrow our discussion, we concentrate on agricultural insurance (for droughts and floods) and earthquake insurance (for buildings and infrastructure) and describe the current state of these two markets globally. We then briefly discuss the more commonly investigated puzzles about the demand and supply of insurance in these domains. Potential purchasers of insurance (households, commercial firms, infrastructure owners, local and central governments) appear to undervalue catastrophic insurance and thus the demand for insurance is typically below what standard economic models with risk averse agents would predict. Equally, the supply of insurance contracts also appears to be limited in both of these markets. Both of these puzzles have been surveyed before. Our main focus is to describe the more sparse literature about the impacts of having these insurance covers. We ask how the presence of insurance may change the ways the insured assess risk, and how its presence changes outcomes following catastrophic events. We end with some directions for future research on the impacts of disaster insurance.

3.1 Introduction

Natural disasters have adverse consequences on people and the economy. A combination of effective mitigation and coping strategies, decreasing both exposure and vulnerability to disasters, can reduce their detrimental impact. Further policy choices can reduce the consequent losses to the economy in the aftermath of catastrophic events. Although constituting no panacea, the evidence suggests that insurance and

A. Kusuma · C. Nguyen · I. Noy (✉)
Victoria University of Wellington, Wellington, New Zealand
e-mail: aditya.kusuma@vuw.ac.nz; cuong.nguyen@vuw.ac.nz; ilan.noy@vuw.ac.nz

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_3

similar financial risk transfer instruments enable improved recovery and thus increase resilience (IPCC 2012; UNFCCC 2008).[1]

However, the literature also suggests that insuring catastrophic risks is complex and not easily achieved (Hazell 2001; Kunreuther and Michel-Kerjan 2014; Skees and Barnett 1999). A recent evaluation, for example, suggests that if a 50% of insurance coverage were in place, disaster impact on growth caused by a very severe (1 in 250 years) disaster can be reduced by as much as 40% (S&P 2015a, b). Still, a survey commissioned by the World Bank in 2009 reported that insurance covers less than 10% of disaster losses in developing countries (Cummins and Mahul 2009). In developed countries, the figure is higher, though only about 40% of disaster damages are typically insured.

Here, we aim to elucidate the obstacles that appear to reduce both the supply and demand for insurance and that may explain the current low levels of disaster insurance coverage globally, and the evidence that supports these hypotheses. We describe the formal insurance programs implemented by governments, the private sector and multilateral/regional organizations that aim to address several of these impediments to insurance adoption.

In addition to investigating the availability of insurance products, we also analyse the limited evidence about the performance of insurance systems in the aftermath of disaster events. We end by summarising some of the many questions that we think are necessary to answer in order to expand insurance coverage globally, and specifically in lower income countries where insurance is largely absent.

Different types of disaster insurance products are available globally. Some examples are government supported flood insurance in the United States and in the UK, micro-insurance for crop losses in Bangladesh and India, earthquake insurance in New Zealand and Turkey, tropical cyclone sovereign insurance for the Caribbean and Pacific island countries, drought sovereign insurance in Sub-Saharan Africa, and agricultural insurance in Europe. To narrow our discussion, we focus in this chapter on only two types of insured catastrophic hazards: residential earthquake insurance and agricultural crop insurance for floods and droughts. With this focus, we seek to provide examples of the complexity of catastrophic-risk sharing mechanisms in urban areas (earthquake insurance), and in rural areas (agricultural insurance), and in higher and lower income countries.

Earthquakes are a very significant hazard in many countries, in particular around the rim of the Pacific Ocean, in mountainous Central Asia and the Northern South Asian subcontinent, and in the Mediterranean. Other regions may not experience very strong earthquakes but in some areas very high vulnerability make them equally risky (e.g., Haiti in 2010). Coastal regions elsewhere are exposed to tsunamis generated by earthquakes (even if far away). Mortality from earthquakes can be very high, with more than half a million casualties in the three most lethal events since the turn of the century (2004 in Indonesia, 2008 in China, 2010 in Haiti).

[1] A previous version of this paper is publicly available as Noy et al. (2017).

Earthquakes also destroy large amounts of assets, as the costliest disaster in recorded history, the 2011 earthquake in Japan, demonstrates.[2]

Equally, weather events such as droughts and floods have adverse consequences for the overall economy and particularly for agriculture. Many middle- and low-income countries are especially reliant the agricultural sector as an important export sector and a mainstay of domestic economic activity. As such, these countries are more affected by adverse weather events that damage agricultural production. Many high-income countries also have important agricultural sectors (e.g., United States, New Zealand, France). In high-income countries, agriculture typically has powerful interest groups supporting it, even if the size of the labour force employed in agriculture in these countries is fairly small.

Given these observations, it is not surprising that risk transfer tools, and especially insurance, play a significant part in policies dealing with earthquake risk and weather-related risk to agriculture. Here we focus on these two sectors and describe the reasons that are still impeding the many ways in which insurance can provide on its promise to reduce and transfer risk. Floods, perhaps the most widely experienced and damaging natural hazard, is not covered here, as the variety of flood insurance arrangements globally makes it difficult to summarise in this chapter. Owen and Noy (2017) provide a brief overview of public flood insurance schemes globally.

We start by focusing on the demand for insurance by residential households (for earthquake cover) and by farmers (for extreme weather risk). We then analyse the supply of earthquake and agricultural crop insurance and the barriers that insurance organisations (private and public) face in providing adequate coverage. We then describe some of the existing insurance schemes for both risks, and continue with the very limited available descriptions of the actual performance of these schemes in the aftermath of catastrophic events. We conclude with some thoughts about future research directions.

3.2 Demand for Insurance

3.2.1 Demand for Agricultural Insurance

Globally, market penetration of agricultural insurance remains low. Slow market development of agricultural insurance, especially those products that directly insure crop and/or livestock production, is typically attributed to low demand because of under-estimated risks, and financial illiteracy, as well as limited supply (Kunreuther and Pauly 2009; Mahul and Stutley 2010; Smith and Watts 2009). This is true especially in low- and middle-income countries where agricultural insurance is

[2]The cost of the earthquake in Japan was mostly associated with damage from the tsunami that was generated by the earthquake, and to a lesser extent by the Fukushima nuclear meltdown that was triggered by the loss of power caused by the earthquake and tsunami damage.

almost non-existent, in spite of the importance of the sector in the economies of many of these countries. Elsewhere, catastrophic risk management in agriculture in high-income countries is often reliant on public interventions such as ex-post payments or price guarantees rather than explicit insurance tools (Skees et al. 2006; Smith and Glauber 2012).

Studies of willingness-to-pay for insurance consistently show evidence that farmers are not willing to pay for the full actuarial cost of the insurance (Hazell et al. 1986; McCarthy 2003; Sarris et al. 2006). The evidence suggests this is not because they are not risk-averse; farmers think there are cheaper ways to manage risks (Smith and Glauber 2012). Many farmers are also simply constrained by their budget. Kunreuther and Michel-Kerjan (2014) explain this willingness-to-pay puzzle with behavioural economics, by examining the implications of prospect theory models and goal-based models of choice.[3]

Another reason for low demand for insurance may be the availability of aid and financial assistance following a disaster. These responses, triggered by principles of solidarity and shared responsibility, contribute to underinsurance as they weaken the incentives to take ex-ante measures to reduce financial risk. Heavy reliance on government or private assistance is referred to as "Charity hazard" while the same from the donors' perspective is typically termed the "Samaritan's dilemma" (Coate 1995). Raschky and Weck-Hannemann (2007), for example, identify empirical evidence that reliance on private charity has adverse efficiency effects.

3.2.2 Demand for Earthquake Insurance

Historically in California, a region very exposed to earthquake risk, there has been very little earthquake insurance. For the 1971 San Fernando earthquake, for example, none of the damaged residential properties had insurance cover (Anderson and Weinrobe 1986). Rates of earthquake insurance coverage today are still very low; with the most recent data suggesting only about 13% of residential properties have cover. Prices for earthquake insurance are high, and local homeowners appear unwilling to purchase cover because of ambiguity in prices, disaster losses, and the probability of occurrence (Kunreuther and Pauly 2004; Palm 1981; Palm and Hodgson 1992). Underinsurance, though, is not unique to California, and is found in other high risk places (Gurenko et al. 2006).

The decision whether to purchase insurance is influenced by people's perceptions of risk, which is often formed by their personal experience. For very low frequency but destructive events, this leads to an underestimation of risk before a disaster occurs, and over-estimation of such risks in the immediate aftermath of a disaster (Hertwig et al. 2004). Browne and Hoyt (2000) estimate people's risk perception

[3] In contrast with the neo-classical/expected utility theory– the model that is often used to assess the optimal demand for insurance.

based on previous experience with floods, and concluded that there is a positive relationship between risk perception and demand for insurance. This mechanism is especially important for earthquake events, and is somewhat distinct from insurance for more frequent events that are covered by agricultural insurance (or floods). For example, there was a 72% increase in earthquake insurance purchases following the 1989 Loma Prieta earthquake (Palm 1995).

Behavioural economics suggests several reasons why we observe this. People assess the probability of an event by how often examples of disaster occurrence they can remember; i.e., ‘availability bias’ (Tversky and Kahneman 1991). Additionally, following a disaster, people focus more on pursuing emotion-related goals such consolation, reduction in anxiety and avoidance of regret (Finucane et al. 2000; Loewenstein et al. 2001). The purchase of an insurance policy can satisfy these goals, but eventually these interests in reducing anxiety and avoiding regret weaken and homeowners become, once again, less inclined to purchase cover. Some individuals even cancel their insurance policy after several years because they find it difficult to justify the spending on premiums that have not been paid on (Hogarth and Kunreuther 1995). Policyholder, in a sense, tends not to follow the maxim that “the best return on one‘s insurance policy is no return at all”.

3.3 Supply of Insurance

3.3.1 Supply of Agricultural Insurance

Agricultural insurance has a long history in developed countries. Crop insurance was first offered to cover a natural hazard peril (hail) in Germany as early as the late 1700s. In the nineteenth century, crop and livestock insurance were already available in rural areas in many European countries and in the United States (Mahul and Stutley 2010; Smith and Glauber 2012).

In developing countries, agricultural insurance of any type has only been offered for less than 20 years (Mahul and Stutley 2010); and the data suggests it is very slowly spreading. Empirical evidence suggests that the increase in insurance penetration rates is correlated with the introduction of publicly subsidized schemes and when insurance is either made compulsory or a condition for provision of credit (FAO 2011; Mahul and Stutley 2010). This is not unique to low- and middle-income countries; a review by Smith and Glauber (2012) about agricultural insurance in high-income countries concluded that the expansion of crop insurance programs in the last 50 years has been largely accomplished because of public budgetary support.

Covariate risks, and asymmetric information—which lead to moral hazard and adverse selection, can both make insurance firms reluctant to offer insurance products for any catastrophic event. Previous research has identified several additional reasons for the under-supply of agricultural insurance, especially in low- and middle-income countries: limited domestic technical, actuarial, and financial expertise, limited financial capacity, limited access to reinsurance markets, lack of infrastructure support for agricultural risk management such as weather database or crop modelling research, and regulatory impediments (Mahul and Stutley 2010).

In agriculture, maybe one of the highest obstacles is the covariate nature of weather risks, when adverse events such as drought and flood can affect very large areas and thus a very large number of policyholders at the same time. Classic capacity problems such as lack of actuarial data (weather data, risk modelling, disaster statistics), low penetrations rates and knowledge of general insurance practices, and the absence of enabling regulations contribute to the limited availability (Hazell 1992; Hazell et al. 1986).

Lastly, climate change increases the uncertainty about the frequency, location, and severity of weather disaster events and thus may intensify the informational barriers that lead to under-supply of agricultural insurance. This is especially true since most climate modellers predict more and more intense disasters, but there is little agreement on magnitudes (Botzen et al. 2010; Deschenes and Greenstone 2007; Warner et al. 2013).

3.3.2 Supply of Earthquake Insurance

As is true for any type of insurance, insurers need to make sufficient profit to generate returns to their shareholders in order to attract capital. Kunreuther and Michel-Kerjan (2014) state that one condition must be satisfied to ensure the availability of coverage against a natural catastrophe: the ability to evaluate the probability of event's occurrence and predict the loss in the case of adverse trigger event. Although there are constantly advancements in seismic science and loss estimation modelling, these forecast tools are yet to reduce the uncertainty to an acceptable level (from an insurance perspective) so that insurance can be offered without major subsidies but priced affordably.

Nevertheless, insurance companies may be reluctant to offer earthquake coverage even when both insurability conditions are met. Following the 1994 Northridge earthquake, insurers suffered losses of $US21.7 billion. After this costly event, affected private insurers decided not to offer earthquake coverage at any price, despite the existence of a significant demand for this insurance product in California.

Even risk information that is potentially available is very costly to collect. For example, in most cases the quality of soil/rock base on which housing is located is largely unknown, as is the likelihood of earthquake-induced liquefaction. This information is very costly to collect, so insurers (private or public) have to rely on very limited information and find it difficult to set risk-informed insurance premiums. This problem is maybe uniquely significant for earthquake insurance. For instance, California public earthquake insurance scheme (CEA) charges the same premium rates for areas with different seismic risks (as do most other public schemes). This creates adverse selection. Homeowners who live in earthquake-prone areas are more likely to purchase the CEA policy. This forces the CEA to charge high premiums and drive take-up rates down (Lin 2014).

Correlated risk, a problem we already identified as plaguing agricultural insurance, is also significant for earthquake risk. Some of the largest insurance events in the past few decades were associated with earthquakes (in particular the 2011 East Japan earthquake, the 2010–2011 earthquakes in New Zealand and the 1994 one in California). Because of this correlated risk, insurers are required to hold additional liquid capital, and thus significantly increase their costs.[4]

3.4 Existing Insurance Markets

Agricultural insurance is largely underwritten in high-income countries. Agricultural insurance contracts mainly consist of crop insurance (90%), despite long history of livestock insurance (Mahul and Stutley 2010; Smith and Glauber 2012). Agricultural insurance is now growing fast, at an average of 20% annual growth rate, with an estimated globally-collected insurance premiums in 2014 reaching US$31 billion (Boissonnade 2015). In developed countries, contributing factors to this growth are increasing subsidies and the introduction of new products such as revenue-based crop insurance which is easier to observe. The same trend is observed in large middle-income countries such as in China, Turkey, and Brazil where governments encourage major expansion of agricultural insurance by offering premium subsidies and reinsurance protection (Mahul and Stutley 2010). In low-income countries, provision of agricultural insurance is slowly increasing with support from multilateral organization (e.g., the World Bank).

The United States is by far the largest market for agricultural insurance. Adding up the US market with agricultural insurance premiums collected in Canada, the total for these two countries accounts for 55% of the total global premium. The second largest market for agricultural insurance is China, but market penetration rate there is still very low (Boissonnade 2015).

The market for earthquake insurance is even less developed than in agriculture for almost all countries (except, maybe, in New Zealand). The impact of an earthquake can be enormous, but there is still limited coverage for earthquake risk even in very earthquake prone places like Japan and the West Coast of the United States. In middle- and low-income countries, almost no earthquake insurance is available. For instance, the 2008 Sichuan earthquake in China caused $US125 billion in losses but less than half a per cent of that was insured. In the 2010 Haiti earthquake, only 3% of disaster losses were covered by insurance.

[4]AMI Insurance (AMI) was the second largest residential insurer in New Zealand. Because of its high market share in the affected region (35%), the private insurer was exposed to a loss of $NZ1.8 billion following the 2010–2011 Canterbury earthquake sequence. However, AMI only had $NZ300 million in capital reserves. Consequently, New Zealand Government had to bail out AMI by settling $NZ 1.5 billion of AMI earthquake claims, administrated through a state-owned entity, Southern Response.

Kunreuther (2015) argues that the market failures in the case of disaster risks can be remedied through the design of Public-Private Partnerships (PPP) in insurance market. In these arrangements, the private insurance companies can be providing claim services, marketing/distribution, responsibility for some tranches of the cover capacity, or some combination of these. The government may act as the primary insurer (e.g., Australia, Denmark, Mexico, and Poland) or by offering reinsurance coverage for larger losses (e.g., Japan, France and Indonesia). In addition, some governments take a "last resort" guarantor role that ensures the insuring entities will always meet all their obligations to cover the disaster risks (e.g., Spain and New Zealand).

PPP insurance systems can overcome some of the issues associated with asymmetric information if they are carefully designed, and by making cover mandatory (or near enough to it), they can also overcome some of the demand constraints. A PPP insurance scheme can charge risk-based premiums, set official standards and regulations, introduce education and applied research programs that help enhance resilience in the community, and also reduce costs through economies of scale and cheaper access to capital.

The main rationale for large public investment is usually to overcome market failures in insurance markets. These include: covariate risk, asymmetric information, limited access to reinsurance market due to small scale, and lack of public databases and risk models to support actuarial calculations.

The question that then needs to be asked is whether it is in the public interest to overcome these market failures. Only if the answer is positive, should one then consider what are the exact failures that matter, and what would be the best way for the public sector to overcome them. The answer to this primary question is not necessarily obvious.

We chose to focus on agricultural and residential earthquake insurance because the public interest in these two cases is somewhat easier to determine. In the case of agriculture, there is a widely-perceived need for national food security (even if the term itself is ambiguous). Governments, when they can afford it, typically find myriad ways of supporting their agricultural sectors. The provision of insurance coverage is only one of these methods of assisting and growing the agricultural sector for this perceived (though ill-defined) national interest.

The 'family' home is typically by far the largest asset that households own, so that the public interest in sustaining this investment and insuring it in the face of catastrophic risks might be easier to identify. If an earthquake insurance scheme supports this goal of financially protecting the largest asset owned by (most) homeowners, then it also prevents this homeowners from impoverishment if a catastrophic event occurs.

Clearly, however, homeowners are not the most vulnerable part of society, and therefore a decision to provide a public-sector-financed insurance scheme also has distributional implications. For earthquake (and flood) publicly-provided residential insurance, these distributional impacts are distinctly regressive, though the extent of this regressiveness is rarely measured or even acknowledged (Owen and Noy 2017). The distributional implications are overlooked in most discussions of hazard insurance, and apply equally to agricultural insurance as they do to earthquake insurance schemes, at least in so much as these are subsidized.

A related question is whether the government itself needs to purchase insurance for the assets it owns (or for other liabilities it might incur if a catastrophic event were to occur). Again, there are distributional concerns here, especially with respect to who will pay for the indemnified damages, and what is the spatial distribution of the risk. If the risk is localized sufficiently, the central government has no need to further diversify its portfolio of assets, though that may be different for a local government entity that owns assets.

3.4.1 Examples of Agricultural Insurance

In agricultural insurance markets, governments typically intervene with premium subsidies, including administrative and operational costs. Crop insurance programs in China, Japan, India and South Korea receive significant subsidies. These programs account for 94% of the total volume of the agricultural insurance premium in Asia. FAO (2011) reports that agricultural insurance penetration rates are very low in other countries in Asia—Bangladesh, Indonesia, Malaysia, Nepal, Pakistan, Thailand and Vietnam.

Apart from premium subsidy, several governments support actuarial capacity building and resolve other supply-side issues through: insurance pools (e.g. in Mongolia, Spain, and Turkey), reinsurance protection (in China, Mexico, Brazil, Turkey, Spain, and the United States), by building and maintaining free access to reliable weather databases (e.g., the Caribbean Island States), or indirectly by commissioning regular risk modelling research, and enacting supportive regulations (Mahul and Stutley 2010).

Government support for ex-ante risk transfer instruments like agricultural insurance is typically viewed as more cost effective than post disaster contingency assistance that can drain the public budget. Some critics, however, argue that agricultural insurance is relatively inefficient due to the high cost of delivery of the required subsidies, if compared to other government support programs such as direct payments (Babcock and Hart 2015; Glauber 2013; Mahul and Stutley 2010).

A survey of existing schemes, FAO (2011), finds that the heavily subsidized public sector insurance schemes have mostly performed very poorly. Many of these programmes have ceased (Bangladesh), were reformed (e.g. Philippines and India) or replaced by public-private partnerships (PPP) schemes. PPP models have been increasingly popular across the region especially in China and South Korea. A private insurance approach has long been operating in Australia and New Zealand. Lastly, new forms of small-scale initiatives are appearing, usually offered by microfinance institutions. Yet, the FAO study suggests that these more traditional or informal risk management practices cannot provide protection against infrequent catastrophic risks [see also IPCC (2012), Janvry et al. (2016), Skees et al. (2004)]

Public sector agricultural insurance schemes are usually characterized by a full government control of risk underwriting with one single insurance product that is exclusively delivered by a state-owned agency. Other features are deep subsidies (for premiums and for other delivery expenses) and the government acting as the main (or only) reinsurer. A major advantage of this model is its high penetration rate and therefore geographically-diversified portfolios (Iturrioz 2009). Major drawbacks include: high operating costs with little market pressure to reduce them, financial pressure for the government to assume full liability, and significant fiscal liability.

One of the most cited success stories of a public scheme is the AgriInsurance program in Canada. The financial performance of AgriInsurance has been sound: the average loss ratio (proportion of payable claims to premiums collected) in the period 2003–2007 was 73% (Porth and Tan 2015). The AgriInsurance program is managed by 10 provincial governments that formed crop insurance corporations in the early 1960. The program insures production or quality losses for specific crops such as wheat, corn, oats and barley as well as horticultural crops such as lettuce, strawberries, carrots and eggplants. The federal government fully backs up the program by subsidizing the premium (farmers pays 40% of the actuarial cost of the premiums and administrative and operational costs), and provides reinsurance protection to some of the provinces. As we noted earlier, this program therefore constitutes a significant (and possibly regressive) redistributive transfer from taxpayers to farmers.

Another example is India's modified National Agricultural Insurance Scheme (mNAIS), which is the world's largest crop insurance program in terms of area and number of policies under cover (195 million hectare/14% of arable land and 20 million policies/15% of all Indian farmers). This is a reformed version after failures of several public-sector schemes. This large subsidized program insures production from losses against multi perils and is implemented by the Agricultural Insurance Company of India (AIC), a state-owned agricultural crop insurance company. The government makes this program compulsory for all farmers taking agricultural loans from any bank or another financial institution. The premium is subsidized for farmers who own less than 2 ha. The agricultural insurance scheme however does not underwrite individual farmers' risks rather it insures designated production areas against crops losses due to floods, drought, landslide, hails, storms and inundation. The mNAIS program offers area-yield index-based insurance and weather index based Insurance for crops and livestock insurance. The losses for the NAIS program have been reinsured by the Indian government under a 50:50 excess of loss agreement between the federal government and participating states. In the period of 2003–2007, financial performances statistics of NAIS' crop insurance products show that premium collected was on average US$103.4 million/year (where premium subsidies on average of US$6.7 million/year and A/O subsidies were on average US$3.3 million/year) and payable claims were on average US$ 324.3 million/year of which US$ 228 million/year were paid by the Indian government (FAO 2011). The loss ratio in that period was 314% per year. To date the NAIS program still operates at a loss, and the Indian government is reportedly considering changing the scheme into a more actuarially sound model.

A similar recent program was introduced in Indonesia in 2015; where the government offers crop insurance for rice farmers having less than 2 ha land to reduce the impact of revenue shocks following droughts and floods. The scheme applies multi perils crop insurance (MPCI) concept, therefore it also protects production risk because of pests, and as long as the adverse event reduced the harvest by 75% (the harvest failure threshold set by the government). The main feature is premium subsidy of 80% that is paid by the government, and is implemented by a state-owned insurance company.

Following well-publicized failures of public schemes due to very high operational costs and very high loss ratios, some reforms have been introduced to strengthen such schemes. Reforms include combining operational management with private entities. These public-private partnership models ideally implement sharing mechanism of gains and losses in underwriting natural hazard risk between participating private companies and the government. Mahul and Stutley (2010) categorize PPP models into three types: (1) National agricultural insurance schemes with monopoly agricultural insurer (typically state-owned); (2) Commercial competition with high level of control; and, (3) Commercial competition with less control. The most comprehensive PPP arrangements, which fall into type 1, are Agroseguro Pool program in Spain and the Tarsim Pool in Turkey. Type 2 schemes are ones where competition among participating private companies, with subsidization, is allowed under strict compliance with the regulatory regime. This group includes the United States Federal Crop Insurance Program (FCIP) and the Portuguese Protection of Climatic Risks program. The last model is the one where the PPP arrangements allow private insurers to operate under a loose partnership, with governments providing premium subsidies and/or reinsurance to the private insurers.

In terms of uptake, the FCIP has one of the highest uptake rates in the world—in 2014 it covered 119 million hectares (almost 90% of total area). Participating farmers will get, on average, about 62% premium subsidy from the federal government and the insurers receive A/O payment for delivering the FCIP products as well as reinsurance compensation if they experience losses (Shields 2015).

There are several PPP arrangements in Latin America. The Seguro Agrícola Catastrófico is a subsidized agricultural insurance program in Peru implemented by private insurance companies to protect small to medium-size farms from catastrophic weather events. Uniquely, farmers do not directly enroll, instead community leaders suggest lists of beneficiary farmers who have suffered losses (Solana 2015). The Component of Assistance against Natural Disasters (CADENA) program in Mexico is another PPP example. The CADENA program facilitates catastrophic risk sharing mechanism between private insurance and reinsurance companies with federal and state government agencies through a federally coordinated scheme to protect agricultural losses (Solana 2015). CADENA covers almost all perils from meteorological (drought, frost, hail, snow, torrential rain, floods, tornadoes and cyclones) to geological-seismic events (earthquakes, volcanic eruptions, tsunamis and landslides). Janvry et al. (2016) evaluate CADENA's implementation and conclude that despite some drawbacks the program's benefits outweigh its costs.

In pure market-based agricultural insurance systems, government intervention is minimal and schemes do not receive government subsidies. Yet, some government provision of supports such as an appropriate regulatory framework and supporting public goods and services (research, education, weather information) are still required as they provide the enabling environment. Government in these markets also sometime still provide support in the case of catastrophic disaster events. Obviously, one of the major advantages of private systems is the absence of a fiscal obligation. However, private agricultural insurance systems are constrained by high start-up and operational costs, which can lead to a monopolistic market with very few suppliers, high premiums, vulnerabilities to systemic risk exposure, and low penetration rates. Beyond the high-income markets, some private schemes are offered in middle-income countries such as Argentina and South Africa, but in most cases only some risks are covered. Often, risk to agricultural production due to weather shocks is not included.

3.4.2 *Earthquake Insurance Schemes*

The risk of earthquakes is higher only in some specific regions, especially the Pacific Rim (on both sides of the Pacific), the Alpide belt which stretches through the Mediterranean and the Middle East to the Himalayas, and the Western edge of Indonesia. In order to contribute to their seismic resilience, many countries in these higher risk regions introduced earthquake insurance systems. In low risk and high income areas, the private insurance sector is typically willing to sell earthquake insurance (e.g., Israel), but in higher risk locations the earthquake insurance programs have deep public sector involvement. Here, we focus on the biggest programs to date: in Japan, Turkey, California, and New Zealand.[5] Other high-risk regions do not yet have very well developed earthquake insurance markets (e.g., the North-West Coast of the United States). We describe these arrangements chronologically based on the time they were introduced.

3.4.2.1 New Zealand Earthquake Commission (EQC)

New Zealand is seismologically very active. There are 15,000 earthquakes in New Zealand every year, although most are not large enough to be felt. Following two major earthquakes in 1931 and 1942, the Earthquake and War Damage Commission was establishes in 1945. It was established as a State Owned Entity owned by New Zealand Government and managed by a board of commissioners. It became

[5]Nguyen and Noy (2017) compares the three programs in high-income countries (US, Japan, and New Zealand), and calculates how much each one would have hypothetically paid had they experienced an event similar to the Christchurch (NZ) 2011 earthquake sequence.

the Earthquake Commission (EQC) in the 1993 EQC Act, the last time the law was revised.

EQCover is the seismic insurance cover provided by the EQC. It provides capped insurance to residential buildings, land and personal contents against the risk of earthquakes, volcanic eruptions, landslips, hydrothermal activity and tsunamis. It only covers residential properties and the land on which they are sited; commercial, industrial, and agricultural properties are excluded from EQCover but are typically covered by private insurers. The EQCover insurance is a de-facto compulsory addendum to standard fire insurance policies (that are typically required by lenders for home loans). Homes without standard fire insurance are not covered by EQCover, but in practice more than 90% of residential properties in New Zealand have it.

The EQCover has strict caps on both structural and contents cover, but anything above the cap has to be insured by the private insurer; the same insurer that issued the fire insurance policy through which the EQCover premiums are collected. Uniquely, EQCover also insures the land beneath the residential properties.[6] The deductible excess is much lower than other international schemes. The EQC buys reinsurance internationally, and also purchases annually a government full 'last resort' guarantee. Any collected premiums that are not used annually are accumulated and transferred to a Natural Disaster Fund (NDF). By 2011, the NDF had accumulated almost $NZ6 billion.

In February 2011, a strong and shallow earthquake very close to the Central Business District of Christchurch, New Zealand's second largest city, damaged much of the city. In the aftermath of this event, the cost of reconstruction was very high, and even though the EQC had about $NZ4 billion in re-insurance coverage, it also had to use practically all of the $NZ6 billion that previously accumulated in the NDF over the last few decades.

The EQCover has a flat premium rate irrespective of evaluated risk, and it is significantly more affordable than other international earthquake insurance schemes. Coverage costs 15 cents for every $NZ100 of cover.[7] Maybe not coincidently, New Zealand also has one of the highest take-up rates of residential insurance cover for natural disasters in the world. In the above-mentioned 2011 Christchurch earthquake, practically all residential damages were covered by insurance.

[6] The insured amount is the lower value of either the damaged land's market value or the cost to repair the land to its pre-event condition. This proved to be a contentious issue in cases where the 2011 earthquake caused liquefaction.

[7] The cost was tripled from 5 cents after international reinsurers increased their premiums in the aftermath of the 2011 earthquake. It is scheduled to rise again to 20 cents at the end of 2017, as a consequence of another damaging earthquake in November 2016.

3.4.2.2 Japanese Earthquake Reinsurance (JER)

Japan is the world's most earthquake afflicted country. Following the 1964 Niigata Earthquake,[8] the government and general insurance organizations decided to establish an earthquake insurance system. In 1966, Japanese Earthquake Reinsurance (JER) scheme was initiated and the Government of Japan undertook the role of reinsurer for earthquake risk.

JER offers coverage on buildings for residential use and their contents. The JER coverage per insurance policy varies between 30 and 50% of the property value. The claim payment is dependent on the degree of loss. "The Act Concerning Earthquake Insurance" defines the earthquake damage on property and content to three levels: total loss, half loss and partial loss. According to the "Insurance Claim Total Payment Limit", JER system sets the maximum insured amount to ¥JP50 million for residential property and ¥JP10 million for content for a single event. The deductible fee equals the annual premium paid by policyholder with the maximum amount of ¥JP50,000 per policy.

The JER insurance was at first compulsory but has become optional since 1979. Private insurers must enrol in JER scheme which offer optional earthquake insurance as part of a comprehensive fire insurance policy. The earthquake insurance premiums paid by policyholders are passed-on from the private insurer and managed by the government and the JER system. Both institutions are responsible for reinsurance and providing a limited state guarantee. The maximum liability of the government, JER and private insurance are 87%, 10% and 3%, respectively.

The Tohoku earthquake in 2011 was the costliest earthquake in history. Marsh (2014) reports that the earthquake caused an economics loss of $US210 billion of which only about $US35.7 billion was insured. This devastating disaster wiped out half of the insurance program's reserves (Paudel 2012).

JER sets the annual basic premium rate for every ¥JP1000 of amount insured. The premium rate varies across zones, classified by their seismic exposure and building structures. The premiums paid by homeowners are between 0.05% (risk zone 1 and wooden) and 0.35% (risk zone 4 and non-wooden). The epicentre of 2011 Tohoku earthquake was located in the risk zone 1 which was thought to be associated with the lowest earthquake risk. The penetration rate for the JER scheme is not very high; according to 2015 Japan's Insurance market report, it is increasing but still below 30%.

[8]The Niigata Earthquake (M 7.5) happened on June 16, 1964, and damaged nine prefectures. The earthquake, ground liquefaction and flooding caused significant damages to infrastructures and residential properties in the region.

3.4.2.3 California Earthquake Authority (CEA)

As is true for New Zealand and Japan, California is also very exposed to earthquakes. In 1985, California policymakers required that insurers offer earthquake insurance coverage to dwellings with one- to four-units. The Northridge earthquake of 1994, damaged more than 40,000 buildings, and caused losses of $US21.7 billion to insurers. This created a surge in demand for earthquake insurance. However, Roth (1998) maintains that after paying claims and re-evaluating earthquake exposures, private insurers decided to reduce their earthquake risk underwriting and had placed restricting terms on the remaining polices. As a result, the California Earthquake Authority (CEA) was established in 1996.

In California, private insurers now provide earthquake insurance coverage to homeowners by ceding their exposure to the CEA. The CEA provides coverage to both residential structures and content. The scheme allocates 14% of premium revenue to the participating insurers for distributing and administering the policies and handling claims. Insurance companies that do not participate must offer their own earthquake coverage to their customers. About 30% of the collected premium goes toward purchasing reinsurance and other financial risk transfer products. The rest is pooled in a CEA Fund as reserves. The CEA's overall claim-payment capacity is approximately $US12.1 billion. The components of this capacity include CEA accumulated capital ($US5.1 billion), reinsurance ($US4.37 billion), bond revenues and insurer assessments ($US2.6 billion) (CEA 2016).

The CEA premium rates are calculated based on the property's construction type, the year it was built, and the earthquake risk for its location (19 different rating zones). The high premium rates and the low collectable claim-payment (deductible excess is often 15% of the claimed amount), makes homeowners reluctant to purchase the CEA coverage. Only 10% of California households have seismic coverage (Marshall 2017).

3.4.2.4 The Turkish Catastrophe Insurance Pool (TCIP)

The Turkish Catastrophe Insurance Pool (TCIP) is a compulsory earthquake insurance scheme that, as in all the other previous cases, commenced its operations following the devastating Marmara earthquake in 1999. The TCIP focus is on high-risk urban dwellings as these proved to be very vulnerable in the 1999 catastrophe. The TCIP insurance is mandatory for residential buildings located within municipal boundaries; properties in smaller villages can purchase coverage on a voluntary basis. Households in rural areas who cannot afford insurance are eligible to receive direct financial assistance from the government following a disaster event.

The policy covers dwelling damages with no cover offered for household contents. Similar to the other insurance systems described above, commercial and public buildings are not covered. The sum insured for each claim depends on the construction type (steel, concrete, masonry or others) and the size of the property. The TCIP coverage is capped for dwellings with value over $US83,500 (as of January 2013). More expensive dwellings can typically purchase additional coverage from private insurers.

The General Directorate of Insurance (GDI) of the Turkish Treasury plays the leading role in creating, operating, and implementing changes in the TCIP's policies. A private insurance company manages the program, and is responsible for information systems, claim management and reinsurance. Domestic insurers collect premiums, and take a 17.5% commission. Revenue is also used to purchase international reinsurance. In 2015, the total payment capacity of TCIP, including the available reinsurance, was $US6 billion. The TCIP scheme aims to settle claims within a month and also provide partial fast payment following an earthquake; but this has not yet been tested in a large event (Başbuğ-Erkan 2007).

The TCIP sets 15 premium tariffs, which are calculated using the level of local earthquake risk (5 zones) and the type of building structure (3 types). The premium rate varies from 0.44 to 5.50% of the insured property value, depending on the seismic resistance and geographic location of the property (Gurenko et al. 2006). There is a 2% deductible fee (of the sum insured) for each claim. The earthquake policy is sold separately from the standard household insurance. Başbuğ-Erkan and Yilmaz (2015) show that there was dramatic increase in the TCIP penetration rate from 4.6% in 2000 to 38.9% in 2015. Regulations are applied to encourage wider participation in the TCIP scheme such as the requirement for TCIP policy documentation to buy/sell a house or to register for water and electricity services.

3.4.2.5 Multi-national Risk Pools: CCRIF and PCRAFI

Caribbean Countries (CCs) and Pacific Island Countries (PICs) are both highly exposed and vulnerable to adverse natural events, especially to tropical storms (cyclones/hurricanes) or earthquakes and their associated tsunami risk (Noy 2016). Both CCs and PICs have very limited financial resilience to catastrophes due to their small size, inadequate building code, limited reinsurance access and borrowing capacity. Lack of economic diversification between countries also makes cross-subsidization for recovery efforts more difficult (especially in the Caribbean, where a single event can easily hit multiple countries). In 2007, the Caribbean Catastrophe Insurance Facility (CCRIF) was established following the collaborative work between the Caribbean Common Market and Community, donor partners and the World Bank. Currently, 17 out of 20 CCs participate in this multi-national risk pool (CCRIF 2015).

Following the establishment of CCRIF, the Pacific Catastrophe Risk Assessment and Financing Initiative insurance pilot program (PCRAFI) was launched in 2013. The scheme was managed by the Secretariat of the Pacific Community (SOPAC), supported by the Asian Development Bank and the World Bank, and financed by donor countries (in particular Japan) and the Global Facility for Disaster Reduction and Recovery (GFDRR). Five PICs are currently participating in the insurance component of the program.

The insurance programs in both the Caribbean and the Pacific function as a not-for-profit risk pool facility, providing coverage against earthquakes and cyclones (CCRIF also has a separate program for excess rainfall). In the Caribbean case, a portion of the collected premium is retained in the risk pool as reserves. The rest is used to purchase reinsurance and catastrophe financial derivatives. For instance, according to the World Bank's analysis, CCRIF's claim payment capacity is such that it can pay for a 1-in-1125 years event—an unusually conservative threshold. Each participating country has its owned attachment point (deductible), and exhaustion point (capped payout).[9]

Both schemes provide parametric coverage. While traditional insurance requires assessments of individual disaster damage, the parametric insurance claim payment in both schemes is based on the estimated (modelled) emergency costs associated with the disaster. Since the parametric coverage does not require on-the-ground inspections, it reduces the insurance cost, makes quick claim payment possible, and provides the affected government liquidity in the disaster's emergency aftermath. For example, Vanuatu received from PCRAFI a claim payment of $US1.9 million less than a month after Tropical Cyclone Pam in early 2015. The parametric aspect of these schemes was essentially borrowed from agricultural index insurance.

Parametric insurance also reduces moral hazard because the pay-out only depends on the intensity of the event. The most significant disadvantage of parametric coverage is the possibility of divergence between the incurred damages and the estimated/modelled ones (so-called basis risk). Since the modelling in both these schemes is very conservative, it appears that the most plausible discrepancy is for the model to underestimate the level of damage, rather than to overestimate it. For instance, the Solomon Islands government discontinued its participation in the PCRAFI scheme after the modelling did not trigger payments after an earthquake in the Santa Cruz archipelago and floods in the capital of Honiara—the model underestimated the emergency costs associated with the earthquake and the floods were an uncovered hazard (Mahul et al. 2015). Similar examples of recent perceived type II errors in the sovereign insurance pools were the Bahamas in the CCRIF, and Malawi in the African Risk Capacity program.

[9]For the 2014/2015 policy year, for example, member countries selected attachment point return periods in the range 10–30 years for tropical cyclones; 20–100 years for earthquakes and 5 years for excess rainfall events. CCRIF member countries also selected exhaustion point return periods in the range of 75–180 years for tropical cyclones; 100–250 years for earthquakes and 25 years for excess rainfall events, with maximum coverage of approximately US$100M currently available for each peril (CCRIF SPC 2016).

3.4.2.6 Private Earthquake Insurance: Indonesia

More than 12 million people live in earthquake-prone areas in Indonesia. The estimated economics exposure to seismic risk is $US79 billion. The Indonesia government established a reinsurance scheme against earthquake exposure in 2003 (PT Asuransi MAIPARK). Its shareholders are 82 non-life insurance and reinsurance companies. MAIPARK functions as a reinsurer and shareholders' clearing-house for earthquake risk. The Indonesian private scheme sets a benchmark for earthquake insurance pricing. It also invests in public education, research, risk mitigation and risk management activities.

Private insurers offer coverage for agriculture, commercial, industrial and residential properties. The insured objects are comprised of the material damage (building, foundation, stock) and business interruption (gross profit, wages, increase working cost). Earthquake coverage is provided as a voluntary extension of fire policies. The insurance cost is classified based on the property location and its structure type. In 2011–2015, the highest insurance exposure to earthquakes was for commercial policies (41% of total risks), while 47% of the collected premiums were from industrial properties. More than 90% of the incurred claim value in this time period has been allocated to the commercial sector (MAIPARK 2015).

3.5 Barriers to Take-Up of Existing Schemes

In the last decade, agricultural insurance has grown substantially, marked by a sizeable increase of global agricultural insurance premiums from an estimate of US$8 billion in 2005 to $31 billion in 2014. Nevertheless, the penetration rate—defined as the ratio of agricultural insurance premiums to agricultural output—in emerging markets and developing countries is still very low. Even in successful programs the penetration is quite low; most recent publicly available data, for example, suggests the take up rate in the index-based Mongolian Livestock scheme is about 10% of herding households. Overall, the penetration rate is probably 0.2–0.4%.

The average penetration rate in developed economies is much larger; but is still quite low. Studies suggest that the recent expansion of agricultural insurance in both developed and developing countries is largely driven by increasing government subsidies, and by the introduction of new insurance products such as index-based or revenue-based crop insurance (Boissonnade 2015; FAO 2011; Mahul and Stutley 2010).

However, experiences in countries such as Canada, the Netherlands and Spain show that subsidies cannot solve many of the demand and supply constraints we identified earlier (OECD 2011). Attempts to address these market failures should focus on reducing asymmetric information in the agricultural insurance market through the development of supporting infrastructure (e.g. risk databases and models), and improving the incentives in insurance contracts (e.g. incentivising risk reduction through premium discounts).

The increasing creation of public-private partnership schemes has to some extent addressed poor financial performance of public insurance since the involvement of private partners usually improves the application of actuarial principles, and overcomes market failures facing private insurers by enlarging market uptake (sometime even mandating it) and insurance capacity. However, Smith and Glauber (2012) warn that private partners can use the political process to gain benefits from the public support in partnership schemes (see also Smith et al. 2016).

Another development in the agricultural insurance landscape is the index-based insurance, as a response to information asymmetries and high verification costs faced by conventional indemnity-based agricultural insurance. Rapid growth of index insurance is largely predicated on the availability of public goods such as weather data, improved real-time meteorological measurement systems (i.e. automated rain-gauge stations) and remote-sensing and satellite technology as well as computational modelling that analyses the quantitative relationship between agricultural losses and natural hazard events. Since index-based insurance applies more transparent procedures, access to reinsurance is cheaper. The public-sector role is initially in the provision of this data (whose collection incur a very high fixed cost), and also in facilitating and standardizing the written insurance contracts, and sometime also in its marketing.

Demand and uptake for index-based insurance is still relatively low as new products are challenged by lack of trust. An exception is an index insurance program in India, the world's largest index insurance program. It has higher uptake as farmers are required to take this insurance when they apply for farm credit (FAO 2011). Other than in India, large index-based insurance programs are operating in Canada and US (for forage crops), drought insurance for African countries (Africa Risk Capacity—ARC), and the previously mentioned livestock insurance in Mongolia. Smaller pilot programs include a typhoon-based index in the Philippines for rice, flood index insurance in Peru, and weather–indexed crop insurance in China.

A challenge in designing an effective agricultural insurance scheme is the development of actuarial models based on the quantitative links between crop losses and natural hazard indices. The development of catastrophic risk modellings has been limited, and is mostly done by a small set of specialized firms using proprietary models. Government can facilitate this knowledge acquisition through research funding and pilot projects, as an effective insurance market needs a range of agricultural catastrophe risk models. Modelling biological dynamics such as agricultural production in association with its exposure to natural hazards (e.g. drought, flood, frost, hail, storms) is a complex spatial task. These agricultural models are extremely useful for insurers and reinsurers (as well as government) in underwriting the risks. Further, these models can assist in the development of risk-based pricing approaches.

Lastly, supporting regulations in insurance market are considerably underdeveloped, especially for agricultural insurance. This is especially true for many low- to middle-income countries that have little history of agricultural insurance. On the other hand, product innovations in agricultural insurance (e.g., weather index insurance) require specific enabling regulatory frameworks, or supporting policies to encourage wider access to weather databases.

The picture is not very different for earthquake insurance, even if the constraints are even more binding. Most insurance schemes have low market penetration even in high seismic risk countries and even with government involvement. This is even the case when insurance is mandatory, but the requirement is not adequately enforced by the authority (as is the case in Turkey). The New Zealand scheme, with its very high penetration rate is the one successful outlier. The reasons for this are unclear; one potential issue is the automatic, 'nudge-like' tie-in between standard fire insurance and earthquake insurance, and the traditionally very aggressive marketing of insurance contracts by the commercial and retail banks (marketing that is not allowed in some countries). An additional reason for the high coverage rates in New Zealand is the low price charged for this coverage relative to other jurisdictions. State guarantee and public reinsurance are not a panacea, however, as they create 'hidden' financial obligations for governments and may end up placing significant costs on taxpayers.

3.6 The Consequences of Having Insurance

It is well recognized that disasters caused by natural hazards could result in substantial damage and losses to a specific sector like agriculture (FAO 2015) and eventually affect economic growth (Felbermayr and Gröschl 2014; Strobl 2012), while the magnitude of the impact may depend on country's socio-economic structures (Noy 2009).

There is only limited evidence to suggest that insurance may help a country reduce spill-overs of physical destruction of stocks into the flow of economic activity, and that with insurance the dynamic impacts are smaller and of shorter duration. Some indirect evidence is provided by Warner et al. (2013), who find that general insurance availability (but not necessarily take-up) is associated with better economic recovery after weather-related hazard events. Similarly, Melecky and Raddatz (2011) find that, following a large weather catastrophe, GDP recovers better when the general insurance penetration rate is high. These findings are instructive and relevant only if general insurance takeup is correlated with the penetration rates of insurance for natural hazard risks and is not correlated with other growth-inducing variables (such as the rule-of-law).

Evidence from crop insurance in the United States show that availability of insurance schemes provides farmers with effective risk management tool to recover from natural disasters as well as functions as a farm safety net (Shields 2015). As an example, a multiple-peril crop insurance that cover about 90% of corn and soybean total acreage in Nebraska and Iowa helped farmers smooth the revenue losses from floods in 2010 (Edwards 2011) and reinsurance protection helped both crop insurer and farmers deal with the huge losses of severe drought incidence in the US Midwest (Porth and Tan 2015). Still, critics argue the US Federal government over-subsidises the insurance premium for farmers and the costs for the private operators (Babcock and Hart 2015; Glauber 2013; Shields 2015).

A recent World Bank study analysed the ex-post effects of the large scale crop insurance program in Mexico implemented between 2005 and 2013, and found that income and expenditures of participating households increased during the survey period or few years after the insurance program starts (Janvry et al. 2016). Bertram-Hümmer (2015) evaluated the impact of commercial Index-Based Livestock Insurance program in Mongolia and finds that asset recovery (herds) of households participating in the program was much better than those who were not participating, 1–2 years following a severe winter in 2009/2010. The study also suggests that the program contributed to recovery since payouts prevented herders from selling or slaughtering their animals. Participation in the program also reportedly allowed households better access to credit; probably as it increased the credit-worthiness of insured household.

Tadesse et al. (2015) review several pilot projects for weather-based crop insurance in drought-affected areas in Northern Sub-Saharan Africa (Ethiopia, Kenya and Malawi). The review finds that actual net benefits of the insurance schemes are not so easy to identify, but suggest some ways these programs can be improved and net benefits manifest better.

A study of the Munich Climate Insurance Initiative (MCII) conducted by Warner et al. (2013) suggests that another potential benefit of agricultural insurance programs, a benefit realized in some countries, is the incentivising of loss reduction and resilience building behaviour [e.g., the India NAIS program as discussed in Surminski and Oramas-Dorta (2011)], provide tools for decision-making support [refer to experience in Ghana rainfall crop insurance as discussed in Cutter et al. (2012) and Karlan et al. (2012)]. The spending on loss reduction and protection is evident in the Swiss scheme, but is found to be implemented only in regions (cantons) covered by a public insurer and not in those covered by private insurance companies (Schwarze and Croonenbroeck 2017).

3.6.1 Case Study: The Great East Japan Earthquake (GEJE)

The Tohoku Region was hit by a M9.0 earthquake on 11/3/2011. The resultant tsunami was the main cause of causalities and damages, though the earthquake also led to meltdown of the nuclear reactors in the power plants in Fukushima Prefecture. 88,000 residents were evacuated, with some unlikely to ever be able to return to their homes. The disruption to many manufacturing facilities and supply chains led to slowdowns or stoppages in some production lines and adversely affected manufacturing plants in faraway countries. The electric power shortages due to the stopping of all nuclear power plants in Japan caused difficulties for many industries, and potentially led to a nationwide economic slowdown.

The insurance loss was estimated at $US35.7 billion. Nevertheless, the impact of the catastrophe on insurance companies was limited because of the Japanese

Earthquake Insurance mechanism. The total limit of liability the Japanese government assumes, as the reinsurer of JER, is $US54 billion out of a capped liability of $US69 billion for JER. The JER's loss from the GEJE was approximately $US15 billion. There was thus limited impact on the balance-sheets of insurance companies. There is no government support for commercial earthquake insurance coverage. Due to the confidential nature of private insurance deals, it is hard to estimate the effect of the catastrophe on this sector, and we are not aware of (English language) reports describing the performance of this sector in this case.

Based on the lessons from 1995 Kobe earthquake, the General Insurance Association of Japan (GIAJ) had collaborated in efforts to settle claim payments rapidly. Eleven months after the GEJE, JER scheme has settled 99% of reported claims—885,000 of them (GIAJ 2012). The JER rapid insurance payments likely allowed local residents to rebuild damaged structures, repurchase necessary living appliances and stimulate production for this demand. We are not aware, however, of any systematic analysis of the impacts insurance coverage and rapid settlement of claims had on the insured households' and firms' recovery trajectories, their patterns of investment and consumption spending, and their other decisions—for example, whether to stay in the affected area or move elsewhere.

Nagamura (2012) states that the residential insurance take-up rate in the affected regions was approximately 33.6%, which was much higher than the national average of 23.7% because of the local government efforts to encourage it. Overall, and in spite of the higher than typical take-up, no insurance company was made insolvent after the costliest insurance loss in Japanese history.

3.6.2 Case Study: The Christchurch Earthquake Sequence (2010–2011)

The September 2010 earthquake caused over 150,000 residential property claims to the public insurer (the EQC) and 5000 commercial and business interruption claims to private insurers. On 22th February 2011, a M6.3 earthquake struck closer to Christchurch's center, and led to significantly more damage. The Canterbury earthquake sequence was the most devastating catastrophe in New Zealand's history (Simpson 2013), and damage was very high (especially relative to the size of the economy). The severe seismic damages resulted in over 500,000 residential insurance claims (buildings, land and contents from 160,000 properties in and around Christchurch) and more than 30,000 commercial and business interruption claims. The number of submitted claims was twice as large as the EQC's expectation of the worst foreseeable event (King et al. 2014).

To stimulate the region's recovery post event, the government decided to require the insurance industry (including the EQC) to offer their customers a repair or rebuild settlement rather than the typical cash payment. The Canterbury Home Repair Programme was introduced by EQC and has been operating since 2012.

The process of repairs and the closing of insurance claims has been slow, for numerous technical, legislative, legal, institutional, administrative, and practical reasons. It is not yet finished more than 6 years after the event. These delays in insurance settlements following the earthquakes have been reported as a major cause anxiety and stress among delay-impacted households. In some cases, residents were unable to live in their partially ruined dwelling but also unable to have it fixed or sell it for extended periods of time (King et al. 2014). The duration and persistence of these negative impacts on residents' psychological wellbeing are largely unknown.

Similarly to residential claims, the commercial insurance claim settlement process also faced significant delays, even though the legal and institutional issues deferring claims were different. As elsewhere, however, the details of commercial claim settlements often remain confidential so research about its impact is much more limited. Based on firm surveys, Stevenson et al. (2011) find that affected organisations financed their recovery primarily by their cash-flow instead of claim payment as these were delayed. A further complicating factor for any speeding of claim resolution and recovery was the cordon placed around the city centre for more than 2 years because of the fear of aftershocks leading for further destruction.[10]

Using the same firm surveys, Poontirakul et al. (2016) find that in the short-term, business survival was not any different between the insured and uninsured firms as payments were anyway paid slowly. In the medium-term, firms which were paid promptly and in full experienced better recovery in term of performance and profitability than those that had incomplete or delayed claim settlements. Interestingly, the latter performed marginally worse than firms that had no insurance.

3.7 Conclusions

To summarise, there is little reason to doubt that a well-designed insurance system is desirable as a tool for disaster risk management. A well-designed scheme has to provide financial risk transfer products that are affordable, fairly priced and efficient, that its contracts are widely used and penetration rates consequently are high, and that provides an efficient and successful claim settlement process once a catastrophe hit. The potential role for insurance as a risk transfer mechanism was therefore acknowledged and encouraged in the most recent international agreement on disaster risk reduction (the Sendai Agreement signed in March 2015).

Insurance by itself is not a panacea, and only a prudent combination of various financial risk transfer tools and relevant disaster risk reduction measures such as early warning system, risk education and communication, and defensive infrastructure, can minimize disruptions and losses to societies when catastrophic hazards

[10]Businesses were not entitled to full business interruption insurance if their building was located inside the cordon but was unaffected by the earthquakes.

occur (Warner et al. 2013). Insurance, however, can strengthen incentives for some of these other risk mitigating behaviours (Surminski et al. 2016).

Insurance is the most common financial risk transfer tool, but other informal and formal risk sharing arrangements also exist (e.g., mutual (informal) insurance, micro- and macro-contingent loans, catastrophic bonds, and contingent sovereign credit).

Despite these clear potential benefits and prospects, insurance is yet to deliver on this promise in most cases. For agricultural insurance, there are numerous challenges in designing adequate insurance products that can serve the very diverse needs of different crops and livestock, different natural environments (soil conditions and weather patterns), different institutional and governance details, and very different farming practices. There are very few cases where insurance contracts that are successfully sold are not heavily subsidized by governments. Without high level of support, agricultural insurance remains expensive and largely unavailable for very vulnerable groups like poor farmers (Surminski et al. 2016). Equally, challenges of local implementation, and in particular the low interest in these products from farmers in middle- and especially low-income countries, are major hurdle.

These challenges in the supply and demand for insurance are not unique to agricultural insurance. Earthquake insurance markets, however, face additional hurdles as damaging earthquakes are frequently very large-scale events and designing effective processes for the speedy resolution of claims in such large events remains a challenge.

Governments and the international community can and should actively facilitate the dissemination of insurance tools and products through the design of appropriate legal and institutional tools, in conjunction with private insurance entities. Governments should also ensure that the insurance markets that are present operate effectively and indeed deliver on their promises if a triggering event occurs. Much of the details about how these goals can be achieved, however, are not very well understood. There is a real and surprising scarcity of careful research about markets for natural catastrophe insurance. The only corner of this issue that is researched intensively is the demand for agricultural (micro) insurance in low-income countries. And in that corner, results are regrettably not very encouraging.

In any case, it is important to remember that insurance only transfers the financial component of risk. It most certainly does not save lives directly and may only indirectly improve people's wellbeing after catastrophic events. It should therefore only follow important risk reduction measures and mitigation strategies that could and should be prioritized. These measures and strategies can be facilitated and incentivized through insurance markets, but that is another area where both research and policy are still in their infancy.

References

Anderson D, Weinrobe M (1986) Mortgage default risks and the 1971 San Fernando Earthquake. Am Real Estate Urban Econ Assoc 14(1):110–135

Babcock BA, Hart CE (2015) Crop insurance: a good deal for taxpayers? Iowa Ag Rev 12(3)

Başbuğ-Erkan BB (2007) The modelling of the Turkish Catastrophe insurance pool data between 2000–2003. PhD thesis, London School of Economics and Political Science, London

Başbuğ-Erkan BB, Yilmaz O (2015) Successes and failures of compulsory risk mitigation: re-evaluating the Turkish Catastrophe insurance pool, vol 4. Wiley, Oxford

Bertram-Hümmer V (2015) Does index insurance help households recover from disaster? Evidence from IBLI Mongolia. DIW & Leibniz University, Berlin

Boissonnade A (2015) New frontiers in agricultural insurance. Retrieved from TheActuary.com. http://www.theactuary.com/features/2015/03/new-frontiers-in-agriculture/

Botzen WJW, van den Bergh JCJM, Bouwer LM (2010) Climate change and increased risk for the insurance sector: a global perspective and an assessment for the Netherlands. Nat Hazards 52 (3):577–598

Browne M, Hoyt R (2000) The demand for flood insurance: empirical evidence. J Risk Uncertain 20 (3):291–306

CCRIF (2015) Strategy plan 2015–2018. Grand Cayman, KY1 – 1102 Cayman Islands

CEA (2016) The strenght to rebuild: financial foundations of the California Earthquake authority, California

Coate S (1995) Altruism, the Samaritan's dilemma, and government transfer policy. Am Econ Rev 85:46–57

Cummins JD, Mahul O (2009) Catastrophe risk financing in developing countries: principles for public intervention. World Bank, Washington, DC

Cutter S, Osman-Elasha B, Campbell J, Cheong S, McCormick S, Pulwarty R et al (2012) Managing the risks from climate extremes at the local level. In: Managing the risks of extreme events and disasters to advance climate change adaptation. Cambridge University Press, Cambridge, pp 291–338

De Janvry A, Ritchie ER, Sadoulet E (2016) Weather index insurance and shock coping, evidence from Mexico's CADENA program. World Bank Policy Research Working paper, 7715, 37

Deschenes O, Greenstone M (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Am Econ Rev 97(1):354–385

Edwards W (2011) Flood damaged crops, crop insurance payments, and lease contracts. Retrieved from http://www.extension.iastate.edu/sites/www.extension.iastate.edu/files/files/ISU-UNL-Flood-Crop-Insurance-Lease.pdf

FAO (2011) Agricultural insurance in Asia and the Pacific Region (RAP PUBLICATION 2011/12). http://www.fao.org/docrep/015/i2344e/i2344e00.htm

FAO (2015) The impact of natural hazards and disasters on agriculture and nutrition and food security. Roma, Italy

Felbermayr G, Gröschl J (2014) Naturally negative: the growth effects of natural disasters. J Dev Econ 111:92–106

Finucane M, Alhakami A, Slovic P, Johnson S (2000) The affect heuristic in judgments of risks and benefits. J Behav Decis Mak 13:1–17

GIAJ (2012) Number and amount of earthquake insurance payments pertaining to the Great East Japan Earthquake. Tokyo, Japan

Glauber JW (2013) The growth of the federal crop insurance program, 1990–2011. Am J Agric Econ 95(2):482–488

Gurenko E, Lester R, Mahul O, Gonulal SO (2006) Earthquake insurance in Turkey: history of the Turkish Catastrophe insurance pool. World Bank, Washington, DC

Hazell PB (1992) The appropriate role of agricultural insurance in developing countries. J Int Dev 4 (6):567–581

Hazell P (2001) Potential role for insurance in managing catastrophic risk in developing countries. International Food Policy Research Institute
Hazell PB, Pomareda C, Valdes A (1986) Crop insurance for agricultural development: issues and experience. IICA Biblioteca Venezuela
Hertwig R, Barron G, Weber E, Erev I (2004) Decisions from experience and the effect of rare events in risky choice. Am Psychol Soc 15(8):534–539
Hogarth R, Kunreuther H (1995) Decision making under ignorance: arguing with yourself. J Risk Uncertain 20:149–159
IPCC (2012) Managing the risks of extreme events and disasters to advance climate change adaptation
Iturrioz R (2009) Agricultural Insurance. Washington
Karlan D, Osei RD, Osei-Akoto I, Udry C (2012) Agricultural decisions after relaxing credit and risk constraints. NBER Working paper Series, 18463
King A, Middleton D, Brown C, Johnston D, Johal S (2014) Insurance: its role in recovery from the 2010–2011 Canterbury Earthquake sequence. Earthquake Spectra 30(1):475–491
Kunreuther H (2015) The role of insurance in reducing losses from extreme events: the need for public-private partnerships. Genevar Pap 40:1–22
Kunreuther H, Michel-Kerjan E (2014) Economics of natural catastrophe risk insurance. In: Handbook of the economics of risk and uncertainty. Elsevier B.V, Amsterdam
Kunreuther H, Pauly M (2004) Neglecting disaster: why don’t people insure against large losses? J Risk Uncertain 28(1):5–21
Kunreuther H, Pauly M (2009) Insuring against catastrophes. In: Diebold FX, Doherty NJ, Herring RJ (eds) The known, the unknown and the unknowable in financial risk management. Princeton University Press, Princeton
Lin X (2014) Essays on the demand for catastrophe insurance: evidence from California’s residential earthquake insurance market (PhD), University of Wisconsin-Madison
Loewenstein G, Weber E, Hsee C, Welch N (2001) Risk as feelings. Psychol Bull 127(2):267–286
Mahul O, Stutley CJ (2010) Government support to agricultural insurance: challenges and options for developing countries. World Bank, Washington, DC
Mahul O, Cook S, Bailey B (2015) Advancing disaster risk financing and insurance in the Pacific. World Bank, Washington, DC
MAIPARK (2015) Indonesian Earthquake insurance statistic. PT Reasuransi MAIPARK Indonesia
Marsh (2014) Comparing claims from catastrophic earthquakes. Marsh Risk Management Research
Marshall D (2017) The California Earthquake authority. Resources for the future, 17(05)
McCarthy NA (2003) Demand for rainfall-index based insurance: a case study from Morocco (vol. 106). International Food Policy Research Institute, Washington, DC
Melecky M, Raddatz CE (2011) How do governments respond after catastrophes? Natural-disaster shocks and the fiscal stance. World Bank Policy Research Working Paper Series, 5564
Nagamura M (2012) 11 March Japanses Earthquake, Tsunami and nuclear emergency: how insurance responded in post-disaster recevery. The Geneva Reports: Risk and Insurance – Research Extreme Events and Insurance: 2011 Annus Horribilis: Geneva
Nguyen C, Noy I (2017) Insuring Earthquakes: how would the Californian and Japanese insurance programs have fared down under (after the 2011 New Zealand Earthquake)? Working paper – School of Economics and Finance, Victoria Business School
Noy I (2009) The macroeconomic consequences of disasters. J Dev Econ 88(2):221–231
Noy I (2016) Natural disasters in the Pacific Island countries: new measurements of impacts. Nat Hazards 84(1):7–18
Noy I, Kusuma A, Nguyen C (2017) Insuring disasters: a survey of the economics of insurance programs for earthquakes and droughts. Working paper – School of Economics and Finance, Victoria Business School
OECD (2011) Managing risk in agriculture. OECD, Paris

Owen S, Noy I (2017) The unfortunate regressivity of public disaster insurance: a quantitative analysis of a New Zealand case. Working paper – School of Economics and Finance, Victoria Business School
Palm R (1981) Public response to earthquake hazard information. Ann Assoc Am Geogr 71:389–399
Palm R (1995) Earthquake insurance: a longitudinal study of California homeowners. Westview Press, Boulder
Palm R, Hodgson M (1992) Earthquake insurance: mandated disclosure and homeowner response in California. Ann Assoc Am Geogr 82(2):207–222
Paudel Y (2012) A comparative study of public—private catastrophe insurance systems: lessons from current practices. Geneva Pap 37:257–285
Poontirakul P, Brown C, Noy I, Seville E, Vargo J (2016) The role of commercial insurance in post-disaster recovery: quantitative evidence from the 2011 Christchurch Earthquake. Working paper – School of Economics and Finance, Victoria Business School
Porth L, Tan KS (2015) Aricultural insurance: more room to grow? The Actuary Magazine 12
Raschky PA, Weck-Hannemann H (2007) Charity hazard—a real hazard to natural disaster insurance? Environmental Hazards 7(4):321–329
Roth R (1998) Earthquake insurance protection in California. In: Kunreuther H, Roth R Sr (eds) Paying the price: the status and role of insurance against natural disasters in the United States. Joseph Henry, Washington, DC
S&P (2015a) The heat is on: how climate change can impact sovereign ratings (Report). RatingsDirect. Standard and Poors
S&P (2015b) Storm alert: natural disasters can damage sovereign creditworthiness (Report). RatingsDirect. Standard & Poors
Sarris A, Karfakis P, Christiaensen L (2006) Producer demand and welfare benefits of rainfall insurance in Tanzania. FAO Commodities and Trade Policy Research Working Paper Series, 18, Rome
Schwarze R, Croonenbroeck C (2017) Economies of integrated risk management? An empirical analysis of the swiss public insurance approach to natural hazard prevention. Econ Disasters Clim Chang 1(2):167–178
Shields DA (2015) Federal crop insurance: background. Congressional Research Service, 7-5700
Simpson I (2013) Earthquake lessons from the New Zealand earthquake recovery. Paper presented at the NZ Society of Actuaries General Insurance Seminar
Skees JR, Barnett BJ (1999) Conceptual and practical considerations for sharing catastrophic/systemic risks. Rev Agric Econ 21(2):424–441
Skees JR, Varangis D, Larson D, Siegel P (2004) Can financial markets be tapped to help poor people cope with weather risks? Insurance against poverty. WIDER Studies in Development Economics
Skees JR, Barnett BJ, Hartell J (2006) Innovations in government responses to catastrophic risk sharing for agriculture in developing countries. Paper presented at the International Association of Agricultural Economists Conference, Gold Coast, Australia
Smith VH, Glauber JW (2012) Agricultural insurance in developed countries: where have we been and where are we going? Appl Econ Perspect Policy 34(3):363–390
Smith V, Watts M (2009) Index based agricultural insurance in developing countries: feasibility, scalability and sustainability. Gates Foundation, pp 1–40
Smith VH, Glauber JW, Dismukes R (2016) Rent dispersion in the US agricultural insurance industry. IFPRI Discussion Paper, 1532
Solana M (2015) Making public-private partnerships work in insurance, Geneva
Stevenson JR, Seville E, Kachali H, Vargo J, Whitman Z (2011) Post-disaster organisational recovery in a central business district context: the 2010 & 2011 Canterbury Earthquakes. Resilient Organisations Research

Strobl E (2012) The economic growth impact of natural disasters in developing countries: evidence from Hurricane strikes in the Central American and Caribbean Regions. J Dev Econ 97 (1):130–141
Surminski S, Oramas-Dorta D (2011) Building effective and sustainable risk transfer initiatives in low-and middle-income economies: what can we learn from existing insurance schemes? Centre for climate change economics and policy
Surminski S, Bouwer LM, Linnerooth-Bayer J (2016) How insurance can support climate resilience. Nat Clim Chang 6(4):333–334
Tadesse MA, Shiferaw BA, Erenstein O (2015) Weather index insurance for managing drought risk in smallholder agriculture: lessons and policy implications for Sub_Saharan Africa. Agric Food Econ 3(1):26
Tversky A, Kahneman D (1991) Loss eversion in riskless choice: a reference-dependent model. Q J Econ 106:1039–1061
UNFCCC (2008) Mechanisms to manage financial risks from direct impacts of climate change in developing countries (FCCC/TP/2008/9)
Warner K, Yuzva K, Zissener M, Gille S, Voss J, Wanczeck S (2013) Innovative insurance solutions for climate change: how to integrate climate risk insurance into a comprehensive climate risk management approach. United Nations University Institute for Environment and Human Security (UNU-EHS), Bonn

Aditya Kusuma is a PhD candidate at the School of Economics and Finance, Victoria University of Wellington, New Zealand. He obtained his M.Sc. from Wageningen University, the Netherlands. His research interests are in the areas of social and economic impact of natural disasters, disaster risk and insurance, and spatial and temporal analysis of weather events. Earlier, he worked as a research and advisory manager of Rabobank International and as senior policy advisor for the Dutch Ministry of Agriculture, Nature and Food Quality.

Cuong Nguyen is PhD candidate at the School of Economics and Finance, Victoria University of Wellington, New Zealand. He obtained his M.Sc. from Queen Mary University in London. His dissertation is about the recovery from the 2010–2011 Canterbury earthquakes, earthquake insurance, property market, and risk perception.

Ilan Noy is the Chair in the Economics of Disasters and a Professor of Economics at Victoria University of Wellington, New Zealand. His research and teaching focus on the economic aspects of natural hazards and disasters, and other related topics in environmental, development, and international economics. He is also the founding Editor-in-Chief of *Economics of Disasters and Climate Change*, a journal published by SpringerNature. He previously worked at the University of Hawaii.

Chapter 4
Disaster and Economic Growth: Theoretical Perspectives

Yasuhide Okuyama

Abstract The long-run effects of disasters on economic growth have been studied since the pioneering work of Dacy and Kunreuther (The economics of natural disasters: implications for federal policy. The Free Press, New York, 1969). The recent empirical studies on this subject presented mixed results about whether or not disasters affect economic growth. Some studies that employed socio-economic indicators for disaster intensity, such as the number of casualties and/or the value of economic damages, to analyze the effects on growth found inconsistent or inconclusive results among them. Some more recent studies that utilized physical intensity indices, such as the Richter scale for earthquakes and the maximum wind speed for storms, revealed statistically significant negative effects on economic growth. In order to improve our understanding of disaster's effects on economic growth and to evaluate these empirical results, this chapter examines a set of theoretical growth models from both the neoclassical perspective and the Keynesian perspective. The insights gained from the analysis include: the speed of recovery depends on the changes in saving rate, which can be raised through more patient preference toward future (lower rate of time preference and higher intertemporal elasticity of substitution); and cumulative changes (either growth or decline) of a damaged region can be caused by the changes in economic structure through either elasticities of demand for imports or of demand for exports from the damaged region. The latter result supports the findings in the recent empirical studies that evaluated the structural changes caused by a disaster and the subsequent reconstruction process.

This chapter is a significantly extended and revised version of Okuyama (2003).

Y. Okuyama (✉)
University of Kitakyushu, Kitakyushu, Japan
e-mail: okuyama@kitakyu-u.ac.jp

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_4

4.1 Introduction

The book, *The Economics of Natural Disasters*, by Douglas C. Dacy and Howard Kunreuther was published in 1969, following the 1968 National Flood Insurance Act of the United States and devastating losses from the 1964 Alaska earthquake. Chapter 3 of the book is titled "Economic Theory and Natural Disaster Behavior," and discusses the theoretical analysis of behavior under natural disasters with the following two sub-sections: (1) a short-run recuperation phase and (2) long-run recovery problems. In their analysis, the short-run recuperation phase is dealt with through microeconomic theory, such as decision-making theory and laws of demand and supply, whereas the long-run recovery problems are investigated using macroeconomic theory, such as economic growth theory. In particular, they defined the long-run recovery as "the rebuilding process that brings the community back to its pre-disaster economic level" (page 70).

In order to analyze the long-run recovery problems, Dacy and Kunreuther employed a simplified version of the Solow-Swan growth model (Solow 1956; Swan 1956). They divide capital stock, K, into three-fold in terms of their use: public capital, K_p, business capital, K_b, and residential capital, K_r. Then, the production function of an economy becomes as follows:

$$Y = f\left(K_p, K_b, K_r, L\right) \tag{4.1}$$

After a disaster, capital stock is reduced to K_p^*, K_b^*, and K_r^* for each type of capital stock. For simplicity, it is assumed that the levels of labor and outside aid for capital recovery are fixed at $\bar{L}$ and $\bar{K}$, respectively. During the recovery from disaster damages, the production function, Eq. (4.1), is transformed to the following form:

$$Y = f\left(K_p^*, K_b^*, K_r^* | \bar{L}, \bar{K}\right) \tag{4.2}$$

The labor and outside aid, $\bar{L}$ and $\bar{K}$, need to be allocated to recover damaged capital in order to maximize the total output, Y.

With this formulation, it is possible to investigate the resource allocation of aid across the different types of capital stock so that, as they claimed, the optimum path of recovery can be analyzed. Unfortunately, they did not elaborate the model any further theoretically or analytically. It may have become more useful if their model specified the relationships of productivity between the different types of capital. For example, public capital, K_p, such as infrastructure and lifelines, can have a meaningful improvement to the productivity of undamaged business capital, K_b, and to the recovery process (accumulation process after a disaster) of both damaged business capital and residential capital, K_b and K_r.

To complement and extend Dacy and Kunreuther's pioneering work in this regard, this chapter examines the long-run effects of a disaster, namely the effects on economic growth, using two distinctive perspectives with their theoretical models: one is the neoclassical growth model from the supply side, as Dacy and Kunreuther did; and the other is the Keynesian growth model from the demand side. These theoretical models can provide insights about how a disaster affects the economic growth of a nation or a region, focusing on the transitional dynamics of the recovery and reconstruction process. In Sect. 4.2, the empirical studies on long-run effects of disasters are reviewed and discussed in order to pave the way to the theoretical models through highlighting whether or not disasters affect the trajectory of economic growth empirically. Section 4.3 presents the analysis from the neoclassical perspective, utilizing various models, from Solow-Swan's to the open economy models. Section 4.4 turns to the Keynesian perspective and discusses the Kaldor-Dixon-Thirlwall (KDT) model and its use in disaster analysis. Finally, Sect. 4.5 concludes this chapter with some discussions on policy implications, making connection with the empirical studies discussed in Sect. 4.2, and presents a few potential extensions.

4.2 Macroeconomic Analysis of Disaster Impacts

The long-run effects of disasters on economic growth have been investigated empirically, using cross-country macroeconomic statistics and disaster data, which are oftentimes extracted from the EM-DAT database. While most studies employ some form of econometric models with various techniques to test the relationship between economic growth (usually the growth rate of per capita GDP) and disaster impact (number of casualties, damages in monetary value, etc.), their conclusions do not agree with each other. For example, Albala-Bertrand (1993a) used Latin American disaster cases and found that capital damages are unlikely to cause significant effects on growth. This conclusion is echoed by Cavallo et al. (2013) that even extremely large disasters do not display any significant effect on economic growth when political changes of the country are controlled. On the other hand, various other studies concluded that some types of disasters cause negative or positive impacts on economic growth of a national economy. For instance, the findings in Noy (2009) indicate that disasters have a statistically observable impact on economic growth when they are measured by the amount of property damage incurred. Some other studies estimated the effects from different disaster types and found some mixed results. Skidmore and Toya (2002) showed no effect by geophysical hazards but a positive effect from climatic hazards, while Fomby et al. (2013) found positive effect of floods, negative effect of storms and droughts, and mixed results from earthquakes.

One of the reasons that these studies provide conflicting results is that disaster impact data, such as the number of casualties and damages in monetary value, as an independent variable creates an endogeneity problem,[1] in which such an independent variable may correlate with the error term in regression models, violating the basic assumption of regression analysis. Moreover, socio-economic data on disaster impacts, such as economic damage, are typically much harder to find, let alone the data being consistent, as Skidmore and Toya (2002) claimed that "disaster variables are somewhat crude measures." In order to overcome this problem, Hsiang and Jina (2014) employed the physical intensity index, i.e., wind speed exposure and energy dissipation, for analyzing the effects of cyclones on economic growth. They found robust evidence that national incomes decline relative to their pre-disaster trend and do not recover within 20 years to the pre-disaster level, and that income losses arise from a small but tenacious suppression of annual growth rates over the 15 years following a disaster, generating significant cumulative negative effects. Strobl (2012) also studied the effect from hurricanes in the Central American and Caribbean regions using a physical intensity index, called the hurricane destruction index, and found that the average hurricane strike caused GDP growth rate to fall by around 0.84 percentage points. Using the rainfall and GDP data of 153 countries during the period of 1960–2002, Berlemann and Wendzel (2016) examined the economic effects of drought, and their results show significantly negative long-run growth effects of droughts in both developed and developing countries. Furthermore, Felbermayr and Gröschl (2014) covered a few types of natural hazards and used corresponding physical indicators as disaster intensity. For example, they used the disaster intensity index of the Richter scale value for earthquakes, the maximum wind speed for storms, the maximum difference in monthly precipitation for drought or flooding events, and so forth. Their analysis reveals that disasters lower GDP per capita temporarily. It is interesting to observe that all the studies using physical intensity indicators of disaster intensity found negative effects of disaster on economic growth, whereas the studies using socio-economic disaster indicators provide somewhat mixed results. In fact, these results with physical intensity indicators vindicate the use of a simple neoclassical growth model, such as the above Dacy and Kunreuther's, for the analysis of long-run effects of disasters, since the neoclassical growth model predicts the lower per capita output when a disaster destroys a part of capital accumulation.[2]

While the above empirical studies investigate the long-run effects of a disaster based on cross-country data, there are a series of case studies that trace the effects of a particular disaster over time to examine the long-run effects on a regional economy, including Odell and Weidenmier (2002), Baade et al. (2007), Hornbeck (2009), and Coffman and Noy (2011). In particular, the 1995 Kobe earthquake in Japan has been receiving more attention, partly because of the data availability and

[1]The excellent summary and discussions on this endogeneity problem in regression analysis on climate change-related literatures are found in Dell et al. (2014). Much of the recent research in that field has applied panel methods for the analysis.

[2]While Felbermayr and Gröschl (2014) found the decline in per capita output by disasters, they did not find the faster growth after the disaster that the neoclassical model foresees toward the convergence to a steady state.

the well-documented reconstruction process. For instance, Chang (2010) employed simple indicators to measure the recovery process of the City of Kobe after the earthquake, and the results illustrate a 3–4-year temporary gain of production from the reconstruction demand injection, followed by a decline of around 10% below pre-disaster levels. DuPont and Noy (2015) analyzed the long-run economic trend of the Hyogo Prefecture, instead of the City of Kobe, after the 1995 earthquake, using econometric models with the synthetic control methodology to examine the earthquake's effect on Gross Regional Products (GRP) and local government expenditures. Their results show a persistent and continuing adverse impact of the event after 15 years. They also obtained the similar level of long-run decline to Chang's study, where GRP per capita in 2007 was 13% less than the projected economic trend without the earthquake. In contrast, Okuyama (2016) employed the GRP per capita of the City of Kobe with a general form of linear autoregressive-distributed lag model to examine the long-run trend of the Kobe economy before and after the event. The results are consistent with the aforementioned two studies, displaying a steady decline of Kobe's GRP per capita following the reconstruction boost of only 3 years. On the other hand, Fujiki and Hsiao (2013) did not find such persistent declining trends in the Hyogo Prefecture, utilizing econometric models based on macroeconomic data between 1955 and 2009. Their results indicate that the stimulation effects from the recovery and reconstruction activities occurred from 1995 to 1998, while smaller negative impacts from the end of the intense demand injections were found between 1999 and 2000. They concluded that the long-run decline of the Hyogo Prefecture resulted from the underlying structural change of the economy rather than from the earthquake and its related activities.

In order to investigate the structural changes caused by the 1995 Kobe Earthquake in a more detailed manner, Okuyama (2014, 2015) performed structural analyses of the Kobe economy before and after the Kobe Earthquake based on a time series of the Kobe regional input-output tables. Changes in gross output of the Kobe economy are decomposed into different factors, such as changes in final demand, in the technological coefficient matrix, and in the regional purchase coefficient matrix, while the changes specific to Kobe are set apart from the macroeconomic disturbances through the shift-share analysis. The results pointed out the significant structural changes that occurred in the Kobe economy after the event, and the most influential factor for such changes appears to be the decline of regional final demand, while the changes in regional interindustry relationships also acted as a crucial role but to a smaller degree.

While the above empirical studies shed light on how an economy is affected by and responds to a disaster, theoretical considerations based on various growth models can provide some insights that can explain these empirical observations and lead to policy implications for mitigating negative effects. The following sections deal with two distinctive perspectives for theoretical investigation: the neoclassical perspective and the Keynesian perspective.

4.3 Investigation from the Neoclassical Perspective

Catastrophic disasters can create significant and intense damages to capital stocks, and sometimes to labor. These damages become quite serious in the context of sub-national regions and of developing countries (Albala-Bertrand 1993b). In this section, the long-run effects of a disaster are investigated based on neoclassical growth models.

4.3.1 The Solow-Swan Model

The basic but popular neoclassical Solow-Swan growth model (Solow 1956; Swan 1956) is examined first to see how disasters affect the growth path of an economy. Consider, for a moment, if technological progress can be neglected,[3] the production function of an economy can be set as:

$$Y = F(K,\ L) \tag{4.3}$$

where Y is the total output, K is the level of capital accumulation, and L is the level of labor population. The use of per capita terms for output and capital makes Eq. (4.3) the intensive form:

$$y = f(k) \tag{4.4}$$

where $y = {}^{Y}\!/_{L}$, and $k = {}^{K}\!/_{L}$. Suppose that the constant saving rate is s, the constant capital depreciation rate is δ, and the constant population growth rate is n. The changes in per capita capital stock over time become as follows:

$$\dot{k} = s \cdot f(k) - (n + \delta) \cdot k \tag{4.5}$$

where $\dot{k} = {}^{dk}\!/_{dt}$. Thus, the steady-state level of capital accumulation, k^*, where $\dot{k} = 0$, satisfies the following condition:

$$s \cdot f(k^*) = (n + \delta) \cdot k^* \tag{4.6}$$

This steady-state condition can be seen as the point A in Fig. 4.1. Now, assume that an economy is at the steady state[4] and that a catastrophic natural hazard, such as a large earthquake, occurred and the capital stocks were severely damaged, but with no or minimal casualties to the labor population. The damages from the natural hazard can

[3]This assumption of ‘no technological progress’ will be relaxed and discussed later in this section.

[4]Even if an economy is not at the steady state, the results of the following analysis still apply.

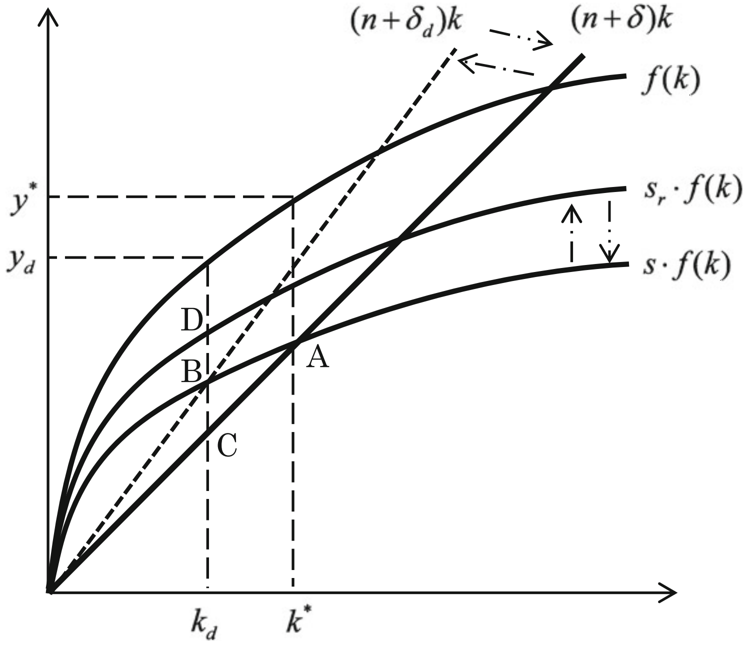


Fig. 4.1 Solow-Swan model and disaster situation

be reflected as a temporal increase in the depreciation rate, from δ to δ_d, where δ_d is the increased depreciation rate accounting for the damages, seen as the move from $(n + \delta)k$ to the broken line of $(n + \delta_d)k$. Consequently, the per capita capital level goes down to the decreased level, k_d, where $k_d < k^*$. However, this increase in the depreciation rate is instantaneous, just reflecting the damages on capital stock, thus it momentarily moves back to the pre-disaster depreciation rate of δ. The economy's production level decreases due to the damages from the steady-state level, y^*, to the damaged level, y_d. Because of the lower level of per capita capital, the economy is now out of its steady state, and returning to the steady-state production level requires an increase in capital accumulation, from k_d to k^*.

The transitional dynamics of recovery can be further illustrated by the use of the growth rate of k. The growth rate of per capita capital, γ_k, can be given based on Eq. (4.5):

$$\gamma_k \equiv \dot{k}\Big/_k = s \cdot f(k)/k - (n + \delta) \tag{4.7}$$

Figure 4.2 illustrates the transitional dynamics around the steady state. At the steady state, the growth rate becomes zero, thus $s \cdot f(k)/k = (n + \delta)$. Due to the disaster damages, the level of per capita capital becomes k_d, and because of this deviation from the steady state, the growth rate of per capita capital becomes positive

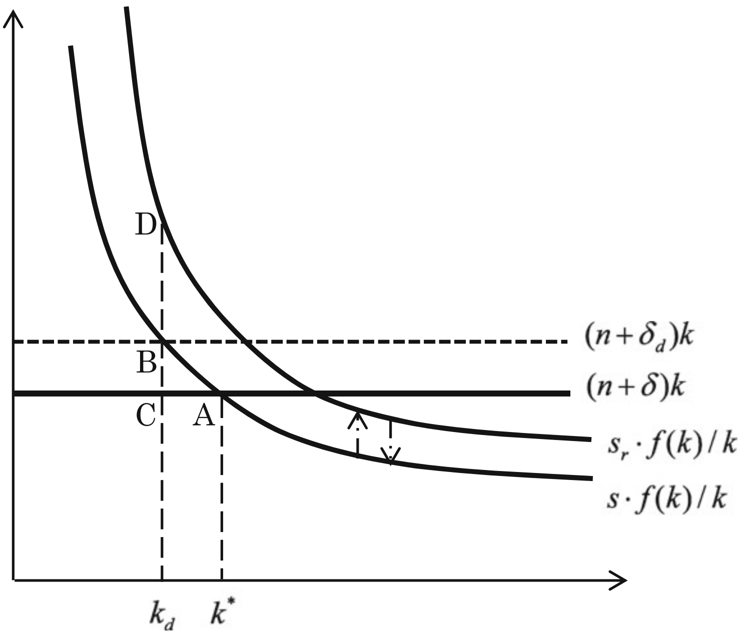


Fig. 4.2 Dynamics of recovery

(the distance between B and C in Fig. 4.2). Thus, the economy starts re-accumulating capital stock toward the previous steady-state level. The speed of re-accumulation is determined by Eq. (4.7). If the economy desires to return to the previous level of per capita income as soon as possible, the respective government may introduce some temporary measures to finance reconstruction activities for a faster recovery. In this modeling framework, savings are equal to investment as shown in Eq. (4.5), thus the reconstruction activities as investment can be established as a temporary increase of the saving rate for accelerating the growth rate, as the saving rate becomes s_r (where $s_r > s$) in Figs. 4.1 and 4.2. Consequently, the growth rate of per capita capital becomes much higher (the distance between D and C, which is much wider than between B and C with the original saving rate in Fig. 4.2), thus the recovery of per capita income becomes faster. As the reconstruction progresses, the government makes the saving rate gradually return to the previous level, s, and the economy returns to the original steady state (from D to A in Figs. 4.1 and 4.2). It can be concluded that the more resources are allocated to the recovery and reconstruction, the faster the speed of recovery (capital re-accumulation) becomes. At the same time, since a sizable increase in the saving rate leads to a severe decrease in current consumption, this will become a difficult option for policy makers. As Healy and Malhotra (2009) suggested, ex-ante mitigation strategies and/or disaster insurance against future disaster damages require much less cost than the ex-post reconstruction projects. Therefore, in order to allocate resources effectively and efficiently, the saving rate will be a bit higher for including such mitigation investment to countermeasures, and it leads to a slightly lower per capita production level over the years.

4.3.2 Technology Update in the Solow-Swan Model

As discussed in Okuyama (2003), the damages of a catastrophic disaster tend to be found more often at older and outdated facilities and equipment than newer and retrofitted ones, mainly because of having weaker structure and being fitted to outdated regulations (for instance, building codes) that are applied for older capital stocks. Through the recovery activities, these damaged older facilities and equipment are replaced with updated and/or upgraded newer facilities and equipment with more advanced technologies. Thus, this technology update during the recovery and reconstruction period has some potential to influence the speed of recovery and/or the growth path. In order to examine the effect from the technology update during reconstruction, we need first to introduce variable technology in the above Solow-Swan model of Eq. (4.3). Suppose the level of labor-augmented technology, A_t, and the progress of the technology is determined by $A_t = e^{xt}$, where x is the rate of technological progress. The production function of the above Eq. (4.3) becomes:

$$Y_t = F(K_t,\ A_t L_t) \tag{4.8}$$

The changes in per capita capital over time is written as:

$$\dot{\hat{k}} = s \cdot f\left(\hat{k}\right) - (n + x + \delta) \cdot \hat{k} \tag{4.9}$$

where $\hat{k} = {}^{K}\!/_{AL}$. As long as x is the constant value, the results of the above analysis also hold with this specification.

Hallegatte and Dumas (2009) examined the effect of these technological updates on growth based on their extended Solow-Swan growth model. Their model, called the Non-Equilibrium Dynamic Model (NEDyM), not only reproduces the behavior of the Solow-Swan model over the long-run but also allows disequilibria during transition phases, which is a suitable feature under a disaster and during a recovery situation. Whereas the detailed descriptions of the NEDyM can be found in Hallegatte et al. (2007), Hallegatte and Dumas (2009) extend the NEDyM to evaluate the effects of technological updates in a neoclassical framework.[5] They set the latest technology level in an economy at time t as A_t, while the installed capital for production has a mixture of current and various levels of old technology. Thus, the technology level of the installed capital at time t can be measured as a mean

[5]NEDyM in Hallegatte and Dumas (2009) is based on the neoclassical growth model in Solow (1962), while the one in Hallegatte et al. (2007) and the above analysis in this section are based on the model in Solow (1956).

technology level, Λ_t, which is $\Lambda_t < A_t$. While newly installed capital has the latest technology, the mean technology level can be determined as the weighted average of technology levels as follows:

$$\Lambda_t = \frac{sY_tA_t + (1-\delta)K_{t-1}\Lambda_{t-1}}{sY_t + (1-\delta)K_{t-1}} = \frac{sY_tA_t + (1-\delta)K_{t-1}\Lambda_{t-1}}{K_t} \tag{4.10}$$

Based on this, the growth of technology level becomes:

$$\dot{\Lambda}_t = \frac{sY_t}{K_t}(A_t - \Lambda_t) \tag{4.11}$$

If a natural hazard damages a part of the existing capital stocks (higher depreciation rate in (4.10) at the time of the natural hazard) and the economy tries to reconstruct them with the latest technology, the above mean technology level becomes higher than the case without such a disaster. In this way, the technology updates can be dealt more realistically than just raising the overall technology level of an economy. Based on a series of simulations using NEDyM, it is concluded that because the growth rate is only determined by the rate of technological progress, not by the average level of technology that does not influence the rate of technological progress, disasters can only boost production levels through updates of damaged capital but cannot lead to the overall technological progress, thus cannot increase the long-run growth rate. Empirical studies on this issue found conflicting results, however. Based on the cross-country analysis, Skidmore and Toya (2002) concluded that climatic disasters are positively correlated with economic growth, investment in human capital, and total factor productivity growth through technology updates, whereas geophysical disasters are negatively correlated with economic growth. Meanwhile, Cuaresma et al. (2008) employed the cross-country and panel data among developing countries for examining the relationship between technological transfer and disaster risk. Their results show that disaster risk is negatively correlated with the extent of technological transfer, while only countries with higher levels of per capita income can benefit from technological transfer after a disaster. Their analysis indicates that the reconstruction period after disasters are not considered as a good trigger to install newer technologies in developing countries, whereas it cannot be compared directly with the Skidmore and Toya's. Further empirical studies and theoretical development are needed to evaluate this issue.

4.3.3 Determining the Behavior of the Saving Rate: Ramsey Model[6]

The above analyses guide toward a policy implication that the speed of recovery depends on the resource allocation for recovery activities, *i.e.* changes in saving rate. However, an increase in saving rate implies a decline in current consumption level, while the changes in consumption level are determined by the consumers' preference. In this context, the analysis should extend to employ the Ramsey model with consumer optimization (Ramsey 1928; Cass 1965; Koopmans 1965). In this way, the optimum allocation of resources for recovery and reconstruction can be explored.

In the Ramsey model, each household wishes to maximize overall utility, U, as follows:

$$U = \int_0^\infty u[c(t)] \cdot e^{nt} \cdot e^{-\rho t} \; dt \tag{4.12}$$

where $c(t)$ is per capita consumption at t, ρ is the rate of time preference and $\rho > 0$. The utility function, $u(c)$, is assumed to have the following form:

$$u(c) = \frac{c^{(1-\theta)} - 1}{(1-\theta)} \tag{4.13}$$

where $-\theta$ is the constant elasticity of marginal utility and $\theta > 0$. The households' utility maximization problem of (4.12), subject to (4.9), will derive the optimal path of consumption as:

$$\dot{\hat{c}}/\hat{c} = \frac{\dot{c}}{c} - x = \frac{1}{\theta} \cdot \left[f'\left(\hat{k}\right) - \delta - \rho - \theta x\right] \tag{4.14}$$

Equation (4.14) and the steady-state consumption growth, $\dot{\hat{c}} = 0$, imply:

$$f'\left(\hat{k}^*\right) = \delta + \rho + \theta x \tag{4.15}$$

where $\hat{k}^*$ is the steady-state level of capital per effective labor. In order to analyze the transitional behavior of the saving rate, the production function is assumed to be a Cobb-Douglas form as follows:

$$f\left(\hat{k}\right) = A\hat{k}^\alpha \tag{4.16}$$

[6] The detailed formation of the model and the derivation of its solution can be found, for example, in Barro and Sala-i-Martin (2004).

At the steady state, $\dot{\hat{k}} = f(\hat{k}) - \hat{c} - (x + n + \delta)\hat{k}$ and $\dot{\hat{c}}/\hat{c}$ from Eq. (4.14) above are each equal to zero. These and $f(\hat{k})/\hat{k} = f'(\hat{k})/\alpha$ from (4.16) yield the steady-state saving rate as:

$$s^* = \alpha \cdot (x + n + \delta)/(\delta + \rho + \theta x) \tag{4.17}$$

The transversality condition of this system implies that the steady-state rate of return, $f'(\hat{k}^*) - \delta$, exceeds the steady-state growth rate, $x + n$ (Barro and Sala-i-Martin 2004). This condition can be rewritten based on Eq. (4.15):

$$\rho > n + (1 - \theta)x \tag{4.18}$$

This can be transformed to $\rho + \theta x > x + n$, and with Eq. (4.17), it leads to $s^* < \alpha$. This indicates that the steady-state gross saving rate is smaller than the gross capital share.

Based on the above Ramsey model, especially with (4.17), the behavior of the saving rate[7] under the recovery and reconstruction period after a disaster can be examined. Since α, x, n, and ρ are assumed not to be affected by a disaster, the changes in other parameters in (4.17) are considered. First, the depreciation rate, δ, momentarily increases to indicate the damages on capital stock, leading to a lower level of capital accumulation, as above. However, it will return to the original level, and the long-run depreciation rate remains the same as before. Second, the reciprocal of θ is determined as the intertemporal elasticity of substitution, $\sigma = 1/\theta$. Under a disaster situation, current consumption is reduced for a faster growth in order to accelerate the recovery and reconstruction activities to return to the steady-state capital and income levels, and the intertemporal preference becomes more toward the increase in future consumptions during the recovery period, leading to a higher σ. This can be realized as a higher saving rate. The increase in saving rate during the recovery and reconstruction period is consistent with the above discussion using the Solow-Swan model, in which the saving rate is determined exogenously.

Calzadilla et al. (2007) carried out a simulation analysis, adapting a standard Ramsey model to examine the impact of an extreme event's damages on a regional economy. The basic structure of the model is similar to the one described above, and the parameter values are set at the ones consistent with the GTAP 5 data set for the U.S. economy in 1997. The simulation is completed with terminal conditions for the final simulation year to make the results consistent with their theoretical model with an infinite horizon. The simulation period was set from 1997 to 2050, and it is assumed that some disaster will occur during the simulation period, but the specific timing of its occurrence is not determined. Since the economy faces a positive probability of the event occurrence each year, the economy prepares for the unexpected happening of such event through a slightly higher saving rate. An unexpected

[7] More detailed discussion about behavior of saving rate in general can be found at pages 106–110 in Barro and Sala-i-Martin (2004).

disaster is assumed to occur in 2030. Their simulation results illustrate that at 2030, a part of capital stock is destroyed, and the levels of production and consumption fall. Moreover, the level of consumption further falls due to the higher return from capital that now becomes scarce. This also implies a higher interest rate, leading to a higher saving rate. In their simulation, after 2030, the accumulations of capital and consumption become steeper with this new saving plan, reaching higher levels than the ones without such an event.

The conclusion of Calzadilla et al. (2007) about a higher saving rate and faster growth (recovery) after the event is consistent with the analysis in this section, but it is not coherent with the empirical evidence from the recent studies on the 1995 Kobe earthquake, as discussed in the previous section. One of the reasons for such inconsistency can be that the models presented in this section are closed models, whereas economies are open in terms of capital and labor, especially in the regional context. The next sub-section discusses such open models.

4.3.4 Interregional Considerations: Open Economy Models[8]

In the age of globalized economic activities, industrial clustering, and vertical specialization of production, economies have become more open and interdependent on each other than before. While disaster impacts are mostly localized (Albala-Bertrand 2007), recovery and reconstruction activities after a disaster rely more on interregional trade, such as importing capital and labor from other regions (sometimes from other countries in the case of small island nations). Therefore, analyzing the growth path of a regional economy after a disaster necessitates the use of open economy models in order to take into account its relationships (constraints) with trade, capital flows, and migration with other regions.[9]

In the neoclassical perspective, regional growth models are assumed to have the features that the economy is perfectly competitive, that the production factors are paid according to their marginal products, and that the production factors are perfectly mobile across regions (Harris 2008; McCann 2013). As in the Solow-Swan model for a closed economy, it is assumed that capital and labor are complementary inputs for production, and their relative quantities are defined as a capital-labor ratio, K/L. Suppose that two regions comprise a nation, and the relationship of their capital-labor ratios between two regions are as follows:

[8]The term regions, used for the discussion in this and following sections, implies sub-national areas, rather than regional blocs consisting of multiple countries. Therefore, the effects of currency exchange rate, trade restrictions, and so on can be neglected in the analysis below.

[9]This depends on the availability of production factors in other regions, as well as on interregional trade patterns. Examining such trade relationships requires a multi-sectoral model, but it is out of the scope of this chapter. Interested readers can consult with such literatures, for recent example, Koks et al. (2016) and Koks and Thissen (2016).

$$\frac{K_1}{L_1} > \frac{K_2}{L_2} \tag{4.19}$$

Because the marginal product of capital in region 1 is lower than in region 2, capital in region 1 will move to region 2 to seek higher marginal profits from capital. Meanwhile, because the marginal product of labor in region 2 is lower than in region 1, labor in region 2 will migrate to region 1 for higher wages. In the long-run, these factor migrations will continue until the capital-labor ratios in both regions reach the following equilibrium[10]:

$$\frac{K_1}{L_1} = \frac{K_2}{L_2} \tag{4.20}$$

If a catastrophic natural hazard destroyed the capital in region 1, the capital-labor ratio of region 1 becomes smaller than in region 2. Hence, while labor in region 1 will migrate to region 2, capital in region 2 tends to move to region 1, a part of which can be considered as reconstruction of capital in region 1. Overall production level of this nation is determined by the level of total factors, $K = K_1 + K_2$ and $L = L_1 + L_2$. Since the amount of labor is assumed not to change by the disaster, the total production level after a disaster can be decreased in the short-run due to the damaged capital in region 1. While the production factors are reallocated to reach a new equilibrium in the long-run, there will be further capital accumulation in this nation as in the Solow-Swan model, and the economy will return to the original growth path under this framework. Empirical evidences discussed in Sect. 4.2, such as DuPont and Noy (2015) and Okuyama (2016), found contradictory evidence that the regions with a catastrophic disaster appear not to return to the previous growth path, but rather move toward a different growth path. This contradiction can be attributed to the assumptions of the neoclassical perspective, such as perfect competition, perfect mobility of factors, and marginal returns, and/or to the lack of spatial and internal externalities (McCann 2013).

The open-economy version of the Ramsey model can be formulated to analyze how factor mobility interacts with the saving rate. As Barro and Sala-i-Martin (2004) presented, however, an open-economy Ramsey model, with the assumption of perfect capital mobility and immobile labor, exhibits some paradoxical conclusions, such as per effective labor capital, income, and wages converge instantaneously to their steady-state level (*i.e.* the speed of convergence is infinite), per effective labor consumption tends to be zero for all but the most patient country (with small θ), and the per effective labor asset becomes negative. There are various modifications to avoid these counterfactual results, whereas they become rather too complicated for applying to disaster cases. Nijkamp and Poot (1998) criticized the open-economy Ramsey model because, in general, the assumption of perfect capital mobility is not

[10]This interregional adjustment model is refereed as the 'one-sector' neoclassical model of factor allocation and migration (McCann 2013).

realistic, and suggest to consider labor mobility instead. However, in the disaster context, the research question is more about the effect of changes in the level of capital accumulation, decreases by destruction, and increases through reconstruction, rather than changes in the labor population.[11]

4.4 Analysis from the Keynesian Perspective

The studies on the long-run effects of disasters have been dominated using the neoclassical growth models, as in Dacy and Kunreuther (1969). This is mainly because natural hazards bring destruction on both physical and human capitals. Thus, the production-side analysis based on the neoclassical growth models is straightforward to capture the effects of such shocks. Meanwhile, the demand-side analysis on the long-run effects of disasters based on the Keynesian growth models has been quite limited, due mostly to the ambiguity of demand-side changes in a disaster situation.[12] Nevertheless, the demand-side analysis is valuable, since the recovery and reconstruction process after a disaster can be considered as an intense demand injection, and because the impact from the disaster can create demand-side effects, such as an adverse effect on demand based on rumors, decreased consumption due to self-restraint, decreased demand from lower incomes, and so forth. Furthermore, in the regional context, the Keynesian models can deal with interregional trade relatively well, so that the relationship with other regions can be investigated. The discussion in this section focuses on the Keynesian growth models.

In order to analyze the regional growth process from the demand side, the Kaldor-Dixon-Thirlwall (KDT) model was proposed (Dixon and Thirlwall 1975; Thirlwall 1980; McCombie and Thirlwall 1994). Suppose that a general long-run regional import demand function is as follows:

$$M_r = aY_r^{\pi}\left(\frac{P_f}{P_r}\right)^{\mu} \tag{4.21}$$

where M_r is the level of regional imports to region r, Y_r is the regional income level, π is the regional income elasticity of demand for imports, P_f is the nominal price of goods produced in other regions, P_r is the nominal price of goods produced in region r,

[11] The analysis of long-run changes in migration pattern becomes important if a disaster leads to a negative net migration rate in the damaged region. Such cases include widespread terrorist attacks in a region, the surrounding areas in a nuclear accident case, and so forth.

[12] Short-run analysis of disaster impact has been performed with demand-side changes using a multi-sector model, such as input-output and computable general equilibrium (CGE) models. For example, Rose et al. (2017) utilized a CGE model with a 'Keynesian closure rule' with the account balance constraint, allowing for unemployment equilibrium to examine the impact of terrorist attacks on U.S. air travel target.

and μ is the price elasticity of demand for imports. Similarly, set a general long-run regional export demand function as:

$$X_r = bZ^{\varepsilon}\left(\frac{P_r}{P_f}\right)^{\eta} \tag{4.22}$$

where X_r is the level of regional exports from region r, Z is the sum of other regions' income, ε is other regions' income elasticity of demand for exports of region r, and η is the price elasticity of demand for the exports from region r by the other regions. These demand functions denote that the levels of imports and exports depend on the price and income elasticities of the goods, and on the relative prices of regional and externally produced goods.[13] Based on (4.21) and (4.22), the growth rates of import and export become:

$$\dot{M}_r = \pi\dot{Y}_r + \mu\left[\dot{P}_f - \dot{P}_r\right] \tag{4.23}$$

and

$$\dot{X}_r = \varepsilon\dot{Z} + \eta\left[\dot{P}_r - \dot{P}_f\right] \tag{4.24}$$

In the long-run, a region cannot sustain a balance of payments deficit. Consequently, the level of long-run regional import growth depends on the region's growth in exports, and the relative changes in regional and external production costs and prices. This implies:

$$\dot{M}_r = \dot{X}_r + \left[\dot{P}_r - \dot{P}_f\right] \tag{4.25}$$

Plugging (4.23) and (4.24) into (4.25) yields:

$$\dot{Y}_r = \frac{1}{\pi}\left\{\varepsilon\dot{Z} + (1 + \eta + \mu)\left[\dot{P}_r - \dot{P}_f\right]\right\} \tag{4.26}$$

It is assumed that the relative price effects, $\left[\dot{P}_r - \dot{P}_f\right]$, are relatively unimportant and can be set to null, when the balance-of-payments model like this is applied to domestic regions (McCann 2013).[14] Thus, Eq. (4.26) becomes:

[13] These expressions apply for sub-national regions in a closed nation. When this model is applied to an international case, the exchange rate should be included in both Eqs. (4.21) and (4.22).

[14] McCann (2013) elucidated the reasons for this assumption, including the one that transportation costs and spatial competition over regions suggest that differences in nominal prices among regions remain relatively stable in the long-run.

$$\dot{Y}_r = \frac{\varepsilon\dot{Z}}{\pi} = \frac{\dot{X}_r}{\pi} \tag{4.27}$$

This represents that the balance-of-payments constrained long-run growth rate of a region is equal to the long-run rate of the other regions' income multiplied by the ratio of the other regions' income elasticity of demand for exports from region r over the regional income elasticity of demand for imports. This turns out to be the long-run rate of growth of exports from region r divided by the regional income elasticity of demand for imports. In this formulation, when a disaster occurs and during the reconstruction period, the region becomes more reliant on imports for reconstruction and the production of goods, and also faces declines in exports due to the damaged production capacity within the region. The increase in imports can be expressed as an increase in the regional income elasticity of demand for imports, π. Meanwhile, the decrease in exports leads to a lower or negative growth rate of exports, $\dot{X}_r$. Both of these changes direct to a smaller or negative growth rate of regional income, $\dot{Y}_r$.

Another component in the Keynesian growth model concerns the issue of economies of scale. As in Dixon and Thirlwall (1975), the analysis of economies of scale centers on the Verdoorn's Law, in which a positive relationship between the growth rate of labor productivity and the growth rate of output (income) is assumed as follows:

$$\dot{\rho} = a + b\dot{Y} \tag{4.28}$$

where $\dot{\rho}$ represents the growth rate of labor productivity, a and b are constants, and b is called the Verdoorn coefficient. If Verdoorn's Law on dynamic economies of scale is included in the above Keynesian growth model, various regional growth trajectories can be traced through the diagrammatic approach of Dixon and Thirlwall (1975).[15]

Figure 4.3 exhibits a steady-state regional growth based on the Keynesian growth model. In the upper right-hand quadrant, given the export growth of x, and the income elasticity of regional demand for imports, π, the balance-of-payments constrained output growth rate is q. Through the Verdoorn effect, the output growth rate of q results in the regional labor productivity of h, in the upper left-hand quadrant. This leads to quality-adjusted real-price reductions at a rate of s. For the given relative output price, the productivity growth h leads to real quality improvements, which in turn result in regional export growth of x, the actual extent of which will depend on the income elasticity of demand for exports, ε (McCann 2013). In Fig. 4.3, the relationship between $\dot{X}$ and $\dot{Y}$ is at a steady state. It can be seen from this figure that different regions can have different growth rates, depending on the ratio of the income elasticities of demand for exports and for imports, as seen in Eq. (4.27).

[15]Because of the simultaneity problem in Eq. (4.28), the solution of the above Keynesian growth model with the Verdoorn relationship cannot be solved analytically (McCann 2013). Thus, the diagrammatic approach is utilized in Dixon and Thirlwall (1975) and here.

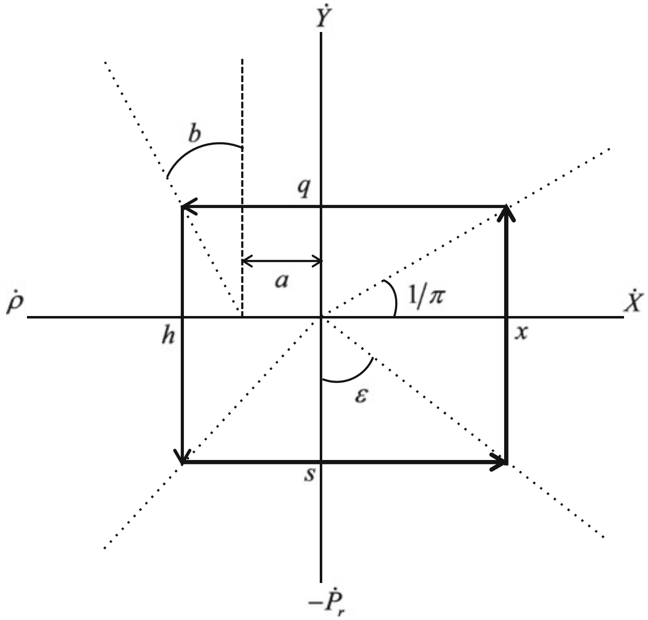


Fig. 4.3 Steady-state regional growth with Keynesian growth model

In order to analyze a disaster situation using this Keynesian growth model, the damages and changes caused by a disaster need to be translated to the parameter values in the model. Since the Keynesian growth model is a demand-side model, no production-side changes, such as increase in the depreciation rate and/or in the saving rate as in the neoclassical models, can be accommodated in the model. Due to a reduced production capacity by the damages and the increased imports for recovery and reconstruction activities, the damaged region can become more dependent on imports, resulting in an increase in the income elasticity of demand for imports. Figure 4.4 illustrates the consequences of such changes. The regional income elasticity of demand for imports becomes π_d, where $\pi_d > \pi$, and this makes the downward shift of the line in the upper right-quadrant, yielding a lower output growth rate of $q_d < q$. While the Verdoorn coefficients, a and b, do not change by the disaster, the smaller output growth rate causes a lower growth rate of labor productivity in the region h_d. Subsequently, the growth rate of exports turns into x_d, which is smaller than the steady-state export growth rate of x. This leads to a cumulative regional decline toward a lower equilibrium growth rate, unless the income elasticity of demand for imports returns to the previous or lower values through an increase in the intraregional inter-industry linkages.

In addition to the above increase in import elasticity, if the damaged region were contaminated by some undesirable sources, such as oil spills on the shoreline, the spread of radioactive materials due to a nuclear accident, and so forth, the demand for the products in the damaged region from the outside would be affected adversely

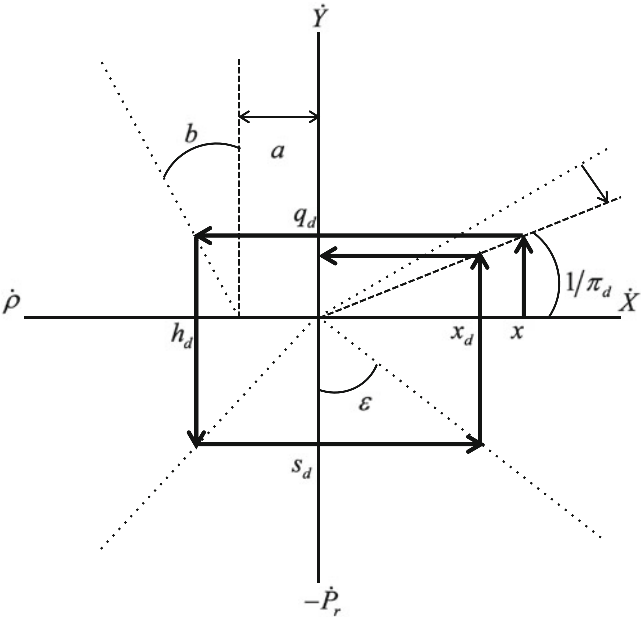


Fig. 4.4 Cumulative regional decline under a disaster situation

based on rumors and asymmetry of information about such contamination, even if the products are tested as safe. This situation can be analyzed with the Keynesian growth model as in Fig. 4.5. The income elasticity of demand for import of the damaged region increases to π_d as in Fig. 4.4, and this leads to a lower growth rate of labor productivity. Since consumers in other regions are afraid to consume the products from the damaged region because of potential but unfound contamination caused by the disaster, this makes the other regions' income elasticity of demand for exports from the damaged region lower, shifting leftwards the line in the lower right-hand quadrant in Fig. 4.5. The gray lines represent the effects of the decreased demand for exports, and it results in a much lower export growth rate at x_{d2}. This results in a further cumulative regional decline, and a set of new equilibrium growth rates becomes even smaller than the above case.

Up to this point, the reconstruction activities are not included in this framework. The intense demand injections of reconstruction activity are certainly a demand-side phenomenon, but cannot be reflected through any of the parameter values in the above Keynesian growth model. Because the parameters signify the economic and production structures in a region, such as changes in export-oriented production or the intensity of intraregional production linkages, temporary increases in production level through reconstruction cannot be handled directly. Meanwhile, if the reconstruction was financed mainly by the national government located outside of the damaged region, the reconstruction demand can be assumed to be a short-run increase in exports because it can be considered as money flowing in from outside

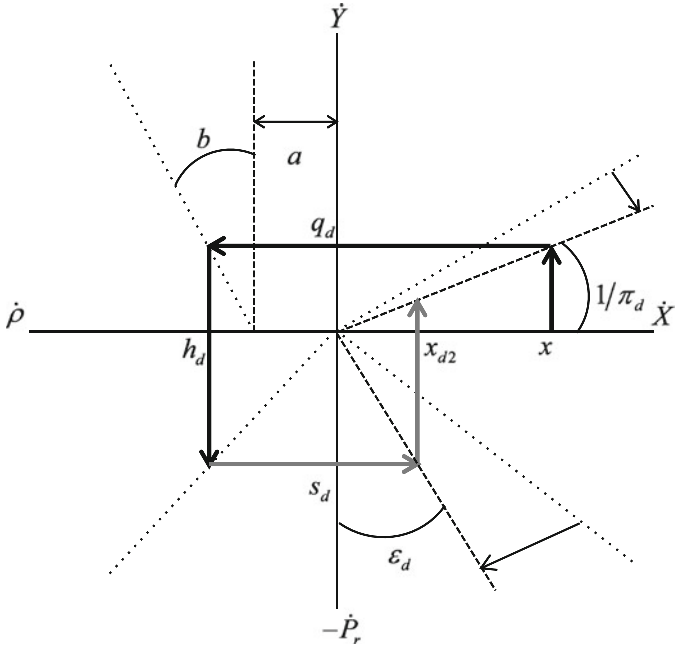


Fig. 4.5 Cumulative regional decline with asymmetry of information

of the region and invested within the region. This could lead to a temporary increase in the income elasticity of demand for exports from the other region, ε, and the upward shift of the line in the lower right-hand quadrant of Fig. 4.4. This will further yield a larger growth rate of exports, then a larger growth rate of output. However, this and the increase in income elasticity of demand for imports could be just a temporary event and will not lead to any long-run structural change of the regional economy. Or, the reconstruction policy could create significant changes in regional economic structure, leading to a permanent deviation of these parameter values from the previous ones. Whether the damaged region exhibits cumulative decline or growth is contingent on how the damaged region is recovered and reconstructed.

The results from the Keynesian growth model for disaster cases look different from the neoclassical counterparts. While neoclassical growth models predict the convergence to a steady state even after a catastrophic disaster, the Keynesian model elucidates a possibility of the cumulative decline (or growth) resulting from the disaster, unless the damaged region overcomes the dependency on imports during the reconstruction period, and/or resolves the asymmetry of information for regaining confidence in regionally produced goods. In terms of technology, as seen in Fig. 4.4, the increase in the income elasticity of demand for imports in the damaged region leads to a lower level of output growth rate, and through Verdoorn's Law, the growth rate of labor productivity becomes lower. This appears contradictory to the notion of technology updates during the reconstruction period discussed in Okuyama (2003). As discussed in Sect. 4.3, the Hallegatte and Dumas (2009) model based on the neoclassical growth model predicts that there will be no technological progress resulting from the reconstruction process, while the production level is boosted by the intense injection of reconstruction demand. At the same time, the neoclassical open economy model, discussed above, showed that if the capital-labor ratio becomes smaller due to the loss of some capital by a disaster, labor in the damaged region will migrate to other regions until the capital-labor ratio reaches a new equilibrium. If this labor migration includes the movement of human capital, and if the labor with higher human capital finds it easier to secure jobs elsewhere, this out-migration from the damaged region will lead to lower technological capacity in the damaged region. These implications of the neoclassical open economy model and of the Keynesian growth model appear consistent with each other, while the models are based on different perspectives.

4.5 Conclusions

The long-run effects of disasters have been empirically studied both from cross-country and cross-section statistical analyses and from more detailed event-specific investigations. While the cross-country and cross-section studies using socio-economic indicators of disaster damage, such as the number of casualties and/or economic damages, have provided conflicting results in terms of the relationship between disasters and economic growth, more recent research employing physical intensity indicators as explanatory variables, like the Richter scale for earthquakes and maximum wind speed for storms, found statistically significant negative relationships. As Skidmore and Toya (2002), Noy (2009), and Albala-Bertrand (2013) argued, the socio-economic indicators appear unreliable for statistical analysis because of their non-standardized definition and the endogeneity problem, which lead to biased estimates of the relationship.

The findings from the studies using physical indicators are well in line with the predictions of neoclassical growth models, in which the decrease in production capital by a natural hazard leads to a lower per capita income, and the subsequent capital accumulations through recovery and reconstruction temporarily bring a higher growth rate toward the original steady state. The analysis in Sect. 4.3 provides the transitional dynamics of recovery and reconstruction, and the changes in saving rate become a determinant of recovery speed. In this context, the saving rate can be seen as a policy instrument during the recovery and reconstruction period. While the neoclassical growth models can simulate the effects of decreased capital and the process of recovery and reconstruction, they also predict that the declined level of per capita production grows with re-accumulation of capital and inevitably converges to the steady-state level, achieving a full recovery in the end. However, some empirical studies reported cumulative negative effects on per capita production after a disaster, such as Hsiang and Jina (2014) with a cross-country analysis, and

Chang (2010), DuPont and Noy (2015), and Okuyama (2016) with the 1995 Kobe earthquake case.

As Okuyama (2014, 2015) revealed with the 1995 Kobe Earthquake case, significant economic structural changes occurred during the reconstruction period and resulted in a prolonged slump of the Kobe economy. This type of structural change can be adapted in the Keynesian growth model through changes in the parameters of income elasticities of demand for imports and of demand for exports from the damaged region, as described in Sect. 4.4. In particular, Okuyama (2015) found that the intraregional inter-industry linkages among manufacturing sectors in the Kobe economy became temporarily strengthened right after the earthquake through providing originally imported intermediate inputs within the damaged region, but were weakened after several years due partly to the underlying hollowing-out process, in which the dependency on and demand for imports increased. This type of change could be reflected by the income elasticity of demand for imports: the increase in intraregional inter-industry linkages translates to a lower income elasticity of import demand, while the following weakened linkages are made through a higher income elasticity for imports. These features make the Keynesian growth model able to simulate cumulative effects of disasters, which should be empirically examined. Hence, the Keynesian growth model can be considered for analysis during the early stage of recovery, because it allows non-equilibrium adjustments, high-level unemployment, and under-utilization of capital. Yet, the neoclassical growth models fit better with the impact analysis of the reconstruction period, when the damaged capital stocks are being re-accumulated. Because the neoclassical models in this chapter are supply-side models and the Keynesian models are on the demand side, it seems intriguing to link between these two perspectives for a more integrative analysis of the disaster process in the long-run.

Most of the empirical studies discussed in Sect. 4.2 investigated the effects of disasters on national economies, typically from the neoclassical perspective. As Felbermayr and Gröschl (2014) claimed, however, these empirical findings sometimes contradict the predictions of the neoclassical growth model, in which losses of capital lead to a higher growth rate afterwards for converging to the steady state. They found a negative impact on per capita GDP but not a higher growth rate in later periods. Cavallo et al. (2013) even argued that the neoclassical growth theory does not have a clear-cut answer to the question of whether or how disasters affect the growth path of an economy, and concluded that it is ultimately an empirical question. In this respect, the empirical studies from the Keynesian perspective could provide new insights to the question at hand. Meanwhile, as Albala-Bertrand (2007) asserted that a disaster causes localized damages and losses on capital and activities but may not affect negatively (or positively) larger economies, such as a national economy, in both short- and longer-runs, more empirical studies about the relationship between disaster and economic growth at the regional level, rather than at the national level, are desired. Such empirical studies at the regional level to date include Noy and Vu (2010) using the sub-national regions in Vietnam, and Tapia and Pinã (2014) based on the sub-national regions in Mexico. Further empirical analyses at a regional level, which can refine the theoretical analysis of disaster effects in the long-run, are also highly anticipated for a better understanding of disaster effects on economic growth.

References

Albala-Bertrand JM (1993a) Natural disaster situations and growth: a macroeconomic model for sudden disaster impacts. World Dev 21(9):1417–1434

Albala-Bertrand JM (1993b) The political economy of large natural disasters: with special reference to developing countries. Clarendon Press, Oxford

Albala-Bertrand JM (2007) Globalization and localization: an economic approach. In: Rodriguez H, Quarantelli EL, Dynes RR (eds) Handbook of disaster research. Springer, New York, pp 147–167

Albala-Bertrand JM (2013) Disasters and the networked economy. Routledge, Oxon

Baade RA, Baumann R, Matheson V (2007) Estimating the economic impact of natural and social disasters, with an application to hurricane Katrina. Urban Stud 44(11):2061–2076

Barro RJ, Sala-i-Martin X (2004) Economic growth: second edition. The MIT Press, Cambridge, MA

Berlemann M, Wendzel D (2016) Long-term growth effects of natural disasters: empirical evidence from droughts. Econ Bull 36(1):464–476

Calzadilla A, Pauli F, Roson R (2007) Climate change and extreme events: an assessment of economic implications. Int J Ecol Econ Stat 7:5–28

Cass D (1965) Optimum growth in an aggregative model of capital accumulation. Rev Econ Stud 32 (3):233–240

Cavallo E, Galiani S, Noy I, Pantano J (2013) Catastrophic natural disasters and economic growth. Rev Econ Stat 95:1549–1561

Chang SE (2010) Urban disaster recovery: a measurement framework and its application to the 1995 Kobe earthquake. Disasters 34(2):303–327

Coffman M, Noy I (2011) Hurricane Iniki: measuring the long-term economic impact of a natural disaster using synthetic control. Environ Dev Econ 17:187–205

Cuaresma JC, Hlouskova J, Obersteiner M (2008) Natural disasters as creative destruction? Evidence from developing countries. Econ Inq 46:214–226

Dacy DC, Kunreuther H (1969) The economics of natural disasters: implications for federal policy. The Free Press, New York

Dell M, Jones BF, Olken BA (2014) What do we learn from the weather?: the new climate-economy literature. J Econ Lit 52(3):740–798

Dixon R, Thirlwall AP (1975) A model of regional growth rate differences on Kaldorian lines. Oxf Econ Pap 27(2):201–214

DuPont W, Noy I (2015) What happened to Kobe?: a reassessment of the impact of the 1995 earthquake. Econ Dev Cult Chang 63(4):777–812

Felbermayr G, Gröschl J (2014) Naturally negative: the growth effects of natural disasters. J Dev Econ 111:92–106

Fomby T, Ikeda Y, Loayza NV (2013) The growth aftermath of natural disasters. J Appl Econ 28 (3):412–434

Fujiki H, Hsiao C (2013) Disentangling the Effects of Multiple Treatments – Measuring the Net Economic Impact of the 1995 Great Hanshin-Awaji Earthquake, IMES Discussion Paper 2013-E-3, Institute for Monetary and Economic Studies, Bank of Japan

Hallegatte S, Dumas P (2009) Can natural disaster positive consequences?: investigating the role of embodied technical change. Ecol Econ 68:777–786

Hallegatte S, Hourcade J, Dumas P (2007) Why economic dynamics matter in assessing climate change damages: illustration on extreme events. Ecol Econ 62:330–340
Harris R (2008) Models of regional growth: past, present and future, SERIC Discussion Paper 2, Spatial Economics Research Centre, UK
Healy A, Malhotra N (2009) Myopic voters and natural disaster policy. Am Polit Sci Rev 103:387–406
Hornbeck R (2009) The enduring impact of the American dust bowl: short and long run adjustments to environmental catastrophe, NBER Working Paper Series: W15605
Hsiang SM, Jina AM (2014) The causal effect of environmental catastrophe on long-run economic growth: evidence fro 6,700 cyclones, NBER Working Papers 20352, National Bureau of Economic Research
Koks EE, Thissen M (2016) A multiregional impact assessment model for disaster analysis. Econ Syst Res 28(4):429–449
Koks EE, Carrera L, Jonkeren O, Aerts JCJH, Husby TG, Thissen M, Standardi G, Mysiak J (2016) Regional disaster impact analysis: comparing input-output and computable general equilibrium models. Nat Hazards Earth Syst Sci 16:1911–1924
Koopmans TC (1965) On the concept of optimal economic growth. In: The econometric approach to development planning. North Holland, Amsterdam
McCann P (2013) Modern urban and regional economics, 2nd edn. Oxford University Press, Oxford
McCombie JSL, Thirlwall AP (1994) Economic growth and the balance-of-payments constraint. Palgrave Macmillan, London
Nijkamp P, Poot J (1998) Spatial perspectives on new theories of economic growth. Ann Reg Sci 32:7–37
Noy I (2009) The macroeconomic consequences of disasters. J Dev Econ 88:221–231
Noy I, Vu TB (2010) The economics of natural disasters in a developing country: the case of Vietnam. J Asian Econ 21:345–354
Odell KA, Weidenmier MD (2002) Real shock, monetary aftershock: The San Francisco earthquake and the panic of 1907, NBER Working Paper Series: W9176
Okuyama Y (2003) Economics of natural disasters: a critical review, Research Paper 2003–12, Regional Research Institute, West Virginia University
Okuyama Y (2014) Disaster and economic structural change: case study on the 1995 Kobe earthquake. Econ Syst Res 26(1):98–117
Okuyama Y (2015) How shaky was the regional economy after the 1995 Kobe earthquake?: a multiplicative decomposition analysis of disaster impact. Ann Reg Sci 55(2):289–312
Okuyama Y (2016) Long-run effect of a disaster: case study on the Kobe earthquake. Singap Econ Rev 16(1):1640009-1-18
Ramsey F (1928) A mathematical theory of saving. Econ J 38(152):543–559
Rose A, Avetisyan M, Rosoff H, Burns WJ, Solvic P, Chan O (2017) The role of behavioral responses in the total economic consequences of terrorist attacks on U.S. air travel targets. Risk Anal 37(7):1403–1418
Skidmore M, Toya H (2002) Do natural disasters promote long-run growth? Econ Inq 40 (4):664–687
Solow RM (1956) A contribution to the theory of economic growth. Q J Econ 70(1):65–94
Solow RM (1962) Technological progress, capital formation, and economic growth. Am Econ Rev 52(2):70–86
Strobl E (2012) The economic growth impact of natural disasters in developing countries: evidence from hurricane strikes in the central American and Caribbean regions. J Dev Econ 97:130–141
Swan TW (1956) Economic growth and capital accumulation. Econ Rec 32(2):334–361
Tapia AG, Pinã CM (2014) The effect of natural disasters on Mexico's regional economic growth: growing disparity or creative destruction? Working Paper Series WP68, Latin American and Caribbean Environmental Economic Program
Thirlwall AP (1980) Regional problems are 'balance-of-payments' problems. Reg Stud 14:419–425

Yasuhide Okuyama is a Professor in the University of Kitakyushu, Japan. He earned his doctoral degree in regional planning from the University of Illinois at Urbana-Champaign in 1999. He also holds master's degrees from the University of Wisconsin-Madison (urban and regional planning, 1994) and from the University of Tsukuba, Japan (environmental science, 1986). His research interests center on economic impacts of disasters, regional science, input–output analysis, and urban and regional planning. He has published a number of articles in various academic journals and book chapters, and edited a book titled *Modeling Spatial and Economic Impacts of Disasters* in 2004 with Professor Stephanie Chang of the University of British Columbia. In addition, he has been contributing to research projects and consultation for organizations such as the World Bank, European Commission, Economic Research Institute for ASEAN and East Asia (ERIA), and Japan Bank for International Cooperation.

Part II
Modeling Variations

Chapter 5
Incorporating Cyber Resilience into Computable General Equilibrium Models

Adam Rose

Abstract Most countries are becoming increasingly dependent on cyber inputs for business, government, and private pursuits. Disruptions of the cyber system can therefore have extensive economic consequences. Resilience is a major way to reduce consequences such as business interruption after the disaster strikes by promoting business continuity and recovery. One approach to analyzing and measuring its effectiveness is to incorporate resilience into economic consequence analysis models of various types, such as Computable General Equilibrium (CGE) models. These models have several attractive properties that make them especially valuable, including being based on behavioral responses of individual producers and consumers, having a role for prices and markets, having the ability to trace economic interdependence, and being based on a non-linear structure that can reflect flexibility of various components. Cyber resilience is a case of economic resilience, pertaining to preventing: (1) supply-side reduction of cyber product and service disruptions to direct and indirect down-stream customers, which also reduces disruptions to the cyber sectors' own direct and indirect up-stream suppliers; and (2) demand-side reduction by customers of their losses from cyber disruptions, which also reduces further upstream and downstream losses. We summarize established and new methodological advances in explicitly incorporating cyber resilience into CGE models. Several types of resilience are inherent, or already naturally included, in CGE models in relation to their core focus (e.g., substitution of inputs in relation to the input scarcity and the allocative mechanism of price signals). Other types of resilience are adaptive in terms of ad hoc reactions after the disaster strikes (e.g., business relocation and lining up new suppliers from within or outside the affected area). Our

A. Rose (✉)
Sol Price School of Public Policy, University of Southern California, Los Angeles, CA, USA
e-mail: adamzros@price.usc.edu

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_5

framework for incorporating various cyber resilience tactics into CGE models is based on economic production theory in relation to decisions regarding inputs and outputs. We explain the methodological refinements needed and provide real world examples of cyber resilience tactics.

5.1 Introduction

Narrowly defined, the cyber sector of the economy includes internet publishing and broadcasting; data processing, hosting, and related services; and telecommunications. More broadly, it includes the equipment directly involved in cyber activity, such as computers, cell phones, and communication satellites, as well as support services. The cyber domain has seen a phenomenal rise in its role in advanced economies and, more recently, even developing ones. Most countries are increasingly dependent on cyber inputs for business, government, and private pursuits. Disruptions of the cyber system can have extensive consequences at all levels.

As with most disruptions in our lives, including major disasters, humans do not respond passively but have a number of existing and improvised coping measures. The term *resilience* embodies these reactions. Unfortunately, the concept of resilience is now over-used, which has contributed to great confusion about this worthy strategy. However, significant advances have been made to define and measure it. Briefly, by way of introduction, *static economic resilience* refers to utilizing remaining resources more efficiently in order to maintain function, while *dynamic economic resilience* refers to investing in repair and reconstruction to accelerate the pace of recovery (Rose 2004, 2017).

Economic resilience is thus a major way to reduce the economic consequences of disasters. One approach to analyzing and measuring its effectiveness is to incorporate resilience into economic consequence analysis (ECA) models. The state-of-the-art in this area includes sophisticated models of several types. In this paper, we focus on Computable General Equilibrium (CGE) models, which are widely used for ECA (e.g., Rose et al. 2007, 2009, 2017; Dixon et al. 2010; Sue Wing et al. 2016). These models have several attractive properties that make them especially valuable for ECA, including being based on behavioral responses of individual producers and consumers, having a role for prices and markets, having the ability to trace economic interdependence, and being based on a non-linear structure that can reflect flexibility of various components (Rose 2015), where flexibility is a key attribute of resilience (Zolli and Healy 2012).

Cyber resilience is a special case of economic resilience. Resilience related to cyber sectors pertains to: (1) their own (supply-side) reduction of product and service disruptions to their direct and indirect down-stream customers, which reduces disruptions to the cyber sectors' own direct and indirect up-stream suppliers; and (2) reduction by their direct customers (demand-side) of their losses from cyber disruptions, which also reduces further upstream and downstream losses. Also, cyber capability itself can also be a *source* of resilience for other sectors, e.g., internet/

telecommunication services facilitate messaging, teleworking, and the relocation of economic activity in the aftermath of a disaster. Cyber resilience is a prime example of interdependent infrastructure in terms of its close relationship with electricity services, though most of the technological considerations (e.g., substitute equipment) differ greatly between the two. Finally, cyber threats, unlike most natural disasters and technological accidents, can have truly national direct repercussions, such as bringing the commercial aviation and banking systems to a halt.

Several methodological advances have been made in explicitly incorporating resilience into CGE models over the past 15 years (see, e.g., Rose and Liao 2005; Rose et al. 2009, 2017; Sue Wing et al. 2016; Rose 2015). At the same time, several types of resilience are inherent, or already naturally included, in CGE models, in relation to their core focus (e.g., the allocative mechanism of price signals) and flexibility (substitution among inputs). In this paper, we will specify methods to incorporate a variety of cyber resilience tactics into CGE models.

To help guide the reader, we delineate the scope of the paper. First, our focus is on the disruption of production stemming from damage to the cyber system or curtailment of electricity supplies. This is in contrast to malware or spyware that often results in theft of data or short duration interruptions in economic activity with specialized fixes. Also, we focus on the cyber system itself in terms of direct impacts, and refer the reader to other work for resilience related to electricity networks (Rose and Lim 2002; Rose et al. 2007). Note that we define resilience in terms of actions taken after the disaster hits, as opposed to those prior to the event. The former is primarily intended to reduce business interruption, or loss of production, as opposed to the latter which comes under the heading of *mitigation* and is primarily intended to reduce property damage and involves a different range of actions. At the same time, we acknowledge that resilience is often a *process*, and resilience capacity can be built up in advance (e.g., back-up equipment or files, broadening the supply chain, emergency management drills), but not actually implemented until after the disaster strikes. Note, however, that the resilience metrics specified below can be translated to analogous mitigation metrics as well.

This paper is divided into six sections. In the following section, we summarize some theoretical foundations of resilience. In Sect. 5.3, we offer rigorous definitions of economic resilience and its many forms. In Sect. 5.4, we present a set of resilience tactics, especially for cyber disruptions, for ordinary businesses, and how they can be incorporated into a CGE model. In Sect. 5.5, we discuss resilience tactics at the meso and macro levels and how they can be incorporated as well. We conclude with a summary and discussion of some limitations of our methodology and how they can be overcome.

5.2 Theoretical Foundations

Economic production theory is a useful starting point for the incorporation of cyber services in economic decisions and operations, and subsequently for considering how these decisions and operations can be resilient to external shocks. In its simplest form, the production function characterizes how businesses convert a number of different inputs to generate various outputs. A number of "functional forms" have been developed to capture and analyze key relationships, such as input substitution, productivity improvements, and economies of scale (see, e.g., Silberberg and Suen 2000). Production functions have been refined over time to include behavioral considerations, which are especially important when considering resilience. These focus primarily on human factors such as perceptions and motivations, which apply both to normal economic activities and to resilience tactics to maintain them (Gigerenzer and Selten 2002).

Of all the economy-wide modeling approaches used to study economic consequences of disasters, CGE is the most powerful, in part because it is able to utilize some of the most sophisticated production functions, such as the constant elasticity of substitution (CES), translog, and generalized Leontief. It can also incorporate more rigid production functions for short-run analyses (say, less than 6 months). Dynamic CGE models can also address considerations relating to the capital stock of equipment in general and investment activities to replace it, key to examining long-term and far-ranging disruptions to economic activity and dynamic resilience to reduce business interruption.

Other microeconomic units of analysis have similar bodies of theory. The theory of consumer choice is the counterpart of production theory in a number of ways. It is typically based on utility functions with similar properties to production functions or various expenditure functions, including those that allow different expenditure elasticities across commodities. More recently, production theory has been extended to consumers with the advent of the household production function approach—households use a combination of inputs, including their own time, to produce household goods and services. For example, households combine raw food, water, energy, and time to produce meals. Application to disasters by Rose and Oladosu (2008) illustrates this in terms of a "boil water" decree, where households use contaminated water, energy, and time to produce potable water. This approach is especially useful in analyzing the value of some "non-market" inputs.

Government operations typically are modeled by two approaches. One is a simple model of providing goods and services—often just shifting their level or mix exogenously. At the other extreme are behavioral theories, which focus on non-economic (often cynical views of the bureaucracy) motivations, such as getting re-elected, rather than operating so as to maximize efficiency of resource utilization or service provision for their constituency. For the purpose at hand, we consider using a government production function analogous to the business production function. This is because cyber resilience is similar in government operations as in business operations. Moreover, it is not unreasonable to expect governments in many countries to be more attentive to their constituencies in a crisis and to be more inclined to optimize utilization of scarce resources, in part because such actions are highly visible and will help them get re-elected. This is also because government agencies are more typically users of cyber services than they are producers of them, i.e., cyber functioning as an input into the provision of government goods and services.

5.3 Defining Economic Resilience

The definitions below are repeated from the recent analysis and formulations in Rose (2009, 2017). Static Resilience in general in the literature refers to the ability of the system to maintain a high level of functioning when shocked (see, e.g., Holling 1973). *Static Economic Resilience* is the efficient use of remaining resources at a given point in time. It refers to the core economic concept of coping with resource scarcity, which is exacerbated under disaster conditions.

In general, Dynamic Resilience refers to the ability and speed of the system to recover (see, e.g., Pimm 1984). *Dynamic Economic Resilience* is the efficient use of resources over time for investment in repair and reconstruction. Investment is a time-related phenomena—the act of setting aside resources that could potentially be used for current consumption in order to re-establish productivity to be used in the future. Static Economic Resilience does not completely restore damaged capacity and is therefore not likely to lead to complete recovery by itself.

Note that the definitions are couched in terms of functionality, typically measured in economics as the *flow* of goods and services, such as Gross Domestic Product (GDP) or broader measures of human well-being, as opposed to property damage. It is not the property (capital *stock*) that directly contributes to economic welfare but rather the flows that emanate from these stocks either for businesses or households. Two things should be kept in mind. First, while property damage takes place at a point in time, the reduced flow, often referred to on the production side as business interruption (BI), just begins at the time of the disaster but continues until the system has recovered or has attained a "new normal." Second, the recovery process, and hence the application of resilience, depends heavily on the behavior of economic decision-makers and on public policy. Of course, recovery is a multi-faceted activity. It is not as simple as, for example, just automatically rebuilding a school destroyed by an earthquake, hurricane, or armed attack.

For both static and dynamic resilience, ability implies a level of attainment will be achieved. Hence, the definitions of economic resilience are contextual—the level of function has to be compared to the level that would have existed had the ability been absent. This means a reference point must be established. In the case of static economic resilience, it refers to the case where resilience is entirely absent. In the case of dynamic resilience, the reference point refers to a recovery path where no special effort is made to accelerate the pace or shorten the duration of the disruption.

Another important distinction is between *inherent* and *adaptive* resilience. The former refers to aspects of resilience already built into the system, such as the availability of inventories, excess capacity, substitutability between inputs, and contingent contractual arrangements accessing suppliers of goods from outside the affected area (imports). Resilience capacity can also be built up through these means ("pre-positioning"), but either way is accessed after the disaster strikes.[1] Adaptive resilience arises out of improvisation under stress, such as Draconian conservation otherwise not thought possible (e.g., working many weeks without heat or air conditioning), changes in the way goods and services are produced, and new contracting arrangements that match customers who have lost their suppliers with suppliers who have lost their customers.

One can analyze resilience pertaining to the economy at three levels:

- Microeconomic (individual business, household, or government)
- Mesoeconomic (individual industry or market)
- Macroeconomic (combination of all economic entities, including their interactions)

Underlying each of the levels of analysis, is an extensive body of economic principles, such as consumer and producer theory, the theory of markets, and macroeconomic theory. Over the years, these have been infused with the complexities of uncertainty, various perspectives on expectations of the future, and bounded rationality that make them even more applicable to resilience to disasters. CGE is an especially attractive modeling approach because it encompasses all three levels of analysis within either regional or national boundaries.

We proceed to discuss resilience at the three levels primarily in general terms and provide more examples relating to cyber in the following section. At the micro level, on the business supplier side, static economic resilience includes redundant systems, improved delivery logistics, and planning exercises. Even more options exist on the business customer side. Broadening the supply chain (see, e.g., Sheffi 2005) by expanding the range of suppliers in place or on a contingency basis is an increasingly popular option. Another is conservation of resources made all the more scarce by the disaster. Conservation is only minimally inherent because economists typically assume that most available efficiencies in resource use are currently being utilized; thus, most resilient conservation options pertain to adaptive applications. All inputs (capital, labor, infrastructure services, and materials) can be conserved, including using fewer cyber inputs per unit of output. The major obstacle is the necessity of the input in the production process, and cyber services are becoming increasingly critical and ubiquitous. Other resilience tactics include primarily input substitution, but also import substitution, back-up equipment, excess capacity, cross-training workers,

[1]Working overtime hours would be an adaptive response if improvised after the disaster strikes, while incorporating overtime work as a disaster response into a business continuity plan would be an example of enhanced inherent resilience capacity.

relocation, and production recapture. Most of the resilience tactics associated with businesses are applicable to government and household operations as well.

At the mesoeconomic level, resilience can bolster an industry or market and include, for instance, industry pooling of resources and information and innovative pricing mechanisms. What is often less appreciated is the inherent resilience of market prices that act as the "invisible hand" to guide resources to their best allocation in the aftermath of a disaster (see, e.g., Horwich 1995). Some pricing mechanisms have been established expressly to deal with such a situation, as in the case of non-interruptible service premia that enable customers to estimate the value of a continuous supply of electricity and to pay in advance for receiving priority service during an outage, an option that is applicable to the cyber domain as well. The price mechanism is a relatively costless guide to redirecting goods and services. Price increases, to the extent that they do not reflect "gouging," serve a useful purpose of reflecting highest value use, even in the broader social setting. Moreover, if the reallocation violates principles of equity (fairness), the outcomes can be adjusted by income or material transfers to the needy. Of course, markets are likely to be damaged by a major disaster in an analogous manner to buildings and humans.

At the macroeconomic level, resilience is very much influenced by interdependencies between sectors. Consequently, macroeconomic resilience is not only a function of resilience measures implemented by single businesses, but it is also determined by the actions taken by all individual companies and markets, including their interaction (see, e.g., Martin and Sunley 2014). Examples of resilience options at the macro level would be primarily inherent, e.g., economic diversity to buffer impacts on individual sectors or geographic proximity to economies not affected by disaster to facilitate access to goods or aid. One strategy would be to segment the cyber system so that it would be impossible to bring an entire national system down. Other tactics, primarily adaptive, include fiscal (e.g., infrastructure spending to boost the affected economy) and monetary policy (e.g., keeping interest rates low to stimulate private sector reinvestment). The macro level overlaps with the popular focus on "community resilience" and represents a more holistic picture (Norris et al. 2008). However, economists have long appreciated the importance of microeconomic foundations of macroeconomic analysis for several reasons. First, the macroeconomy is composed of individual building blocks of producer and consumer behavior as underpinnings for macroeconomic considerations stemming from group interactions. Second, behavioral considerations are best addressed first at the most elemental level because of the prominence of individual motivations for survival and coping mechanisms in anticipation of and in response to disasters.

The previous examples relate primarily to *Static Economic Resilience*. *Dynamic Economic Resilience* is applicable at all three levels, as well as in terms of expediting the recovery process and enhancing its outcome. At the micro level, this can be promoted through rapid processing of insurance claims and arranging financing so as to facilitate repair and reconstruction. At the meso and macro levels, it includes hastening and improving the economic effectiveness of the recovery process by optimizing logistics and coordinating recovery across sectors. Cross-cutting all three levels is adapting to changing conditions by promoting flexibility and translating short-run practices into sustainable ones through a continuous learning process (see, e.g., Chang and Rose 2012; Zolli and Healy 2012; Rose 2015).[2] We acknowledge, however, that the drive to recover more quickly is better evaluated in terms of the bigger picture, especially with regard to reducing vulnerability to future disasters in relation to both static (e.g., temporary relocation) and dynamic resilience (e.g., installing more reliable communications equipment and equipment that is easier to repair).

5.4 Resilience Tactics for Cyber Disruptions and Their Incorporation into CGE Models

In this paper, we focus more on the customer (demand) side—users of cyber equipment and services. It involves many more resilience tactics than the supplier side—producers of cyber equipment and services. Moreover, customer-side tactics are relatively less expensive.

5.4.1 Demand-Side Resilience

Ali and Santos (2012) found that the sectors most impacted by cyber outages were IT sectors themselves, computer and electronic products, administrative and support services, professional and scientific services, and financial sectors. Bisogni and Cavallini (2010) found the sectors most affected in the European community were computer and related activities, finance, real estate and related business activities, transportation, storage, and communications (see also the review of these studies and others by Wei 2015). Also, we note the complementary nature of cyber and electric power. Thus, any attempts to implement resilience in the cyber system would be undercut substantially if electric power is not available. Hence, we need to consider the major sources of resilience for this complementary electricity input, which would include batteries, distributed generation, and access to other power sources in general. Similar considerations pertain to water used for machine cooling at data centers.

Table 5.1 summarizes key features of the analysis of cyber resilience for businesses on the customer side. The table lists major categories of resilience and provides examples of specific tactics within each category applicable to the cyber domain.[3] The resilience categories apply to all production processes, but we have

[2]Resilience is sometimes conflated or confused with related terms such as vulnerability and sustainability. The reader is referred to Rose (2017) for a more detailed discussion.

[3]More detail on specific resilience tactics in the cyber domain, such as satellite phones and Cells on Wheels (COWs), are discussed in Rose and Miller (2019).

Table 5.1 Microeconomic resilience options: business (customer-side)

Category	Possible prior action	Inherent	Adaptive	Applicability	CGE incorporation
Conservation	Minimize use of vulnerable inputs	x	X	K, L, CE, CS, E, M	Increase productivity term (Rose and Liao 2005)
• Reduce non-essential use					
• Recycle cyber equipment					
Input substitution	Enhance flexibility of system	X	X	K, L, CE, CS, E, M	Increase input substitution elasticity (Rose and Liao 2005)
• Back-up systems, wireless, satellites					
• Paper records, traditional couriers					
Import substitution	Broaden supply chain	X	X	k, L, CE, CS, E, M	Increase import substitution elasticity (Sue Wing et al. 2016)
• Mutual aid agreements					
• Re-routing of goods/services					
Inventories (stockpiles)	Enhance; protect	X	x	k, L, CE, E, M	Increase inventories; loosen input constraints (Rose et al. 2016)
• Batteries					
• Pool resources					
Excess capacity	Build and maintain	X	x	K, CE	Increase utilization; loosen input constraints (Rose et al. 2009; Sue Wing et al. 2016)
• System redundancy					
• Maintain in good order					
Input isolation	Reduce dependence on cyber inputs	X	X	K, l, CE, CS, E, M	Loosen input constraints (ATC 1991; Rose et al. 2007)
• Decrease dependence					
• Segment production					
Relocation	Arrange for facilities in advance	x	X	K, L, CE, cs, E, M	Loosen input constraint (Giesecke et al. 2016); shift regions (Sue Wing et al. 2016)
• Back-up data centers					
• Physical move; telecommuting					

(continued)

Table 5.1 (continued)

Category	Possible prior action	Inherent	Adaptive	Applicability	CGE incorporation
Production recapture	Arrange long-term agreements;	x	X	Q	Adjust output levels (Rose and Lim 2002; Rose et al. 2007)
• Supply-chain clearinghouse	Contingency plan and practice for telework				
• Restarting procedures					
Technological change	Increase flexibility	X	X	K, L, CE, CS, e, M, Q	Adjust parameters (Rose 1984)
• Change processes					
• Alter product characteristics					
Management effectiveness	Train; increase versatility; identify	X	X	k, L, CE, CS, e, m	Adjust parameters (Wein and Rose 2011)
• Emergency procedures					
• Succession/continuity					

emphasized the cyber domain with our examples. Resilience tactics unique to cyber include special kinds of back-up systems such as clouds, wireless connectivity, use of batteries and other back-up power sources, and telecommuting. Each row of the table indicates a prior action that can enhance the corresponding resilience category and indicates the degree to which the resilience is inherent and adaptive. Also, the applicability of each resilience category to each factor of production is indicated by the following letter designations: capital (K), labor (L), cyber equipment (CE), cyber services (CS), electricity (E) and materials (M), as well as for the output (Q) that they produce. Upper-case letters representing the inputs or outputs reflect a strong resilience relationship, while lower-case letters represent a weak one. The same convention denotes the strength of inherent and adaptive resilience, but in this case is denoted by the letter X. For example, a firm can readily import all inputs except much of physical capital because of its immobility. That is, factories cannot readily be relocated but equipment can be; thus, this variable is relevant to relocation resilience, but is limited and hence connoted by lower-case letters.

For example, in Table 5.1, a major category of resilience tactics is Input Substitution, which would include the use of back-up systems, wireless or satellite connections, paper records, and traditional couriers. A more subtle category is Conservation, for which examples include reducing non-essential uses and recycling cyber-related equipment. Conservation is only minimally inherent because economists typically assume that most inherent conservation options are currently being maximized. Thus, most conservation options pertain to adaptive applications. All inputs can be conserved. The major obstacle is necessity of the input into the production process. Similar notations are provided for other resilience options for the case of business customers. Note also that the various modifications apply not only to direct effects of cyber disruptions but also to indirect, in this case general equilibrium, effects, though the latter are less dependent on cyber inputs.

The last column of the table indicates how each category of resilience can be incorporated into a CGE model, including a reference to works that have done so. Most resilience tactics can be related to ordinary production function parameters or related to an expanded set of inputs. Some need be applied in an ad hoc manner, such as loosening input constraints or adjusting output. Typically, the inputs into economic activity serve as the independent variables for a formal production function in which the influence of several types of resilience can be linked directly to them or to the production function parameters.

The following is a summary of how various economic resilience tactics can be incorporated into a computable general equilibrium (CGE) model. At the outset, we again note the general effect of the distinction between *inherent* and *adaptive* versions of resilience. CGE models naturally embody several economic relationships that reflect inherent resilience. These emanate from the model being able to represent basic economic relationships in production here (and in consumption and single and multi-market interactions in general). Most adaptive resilience can be incorporated through parametric changes or ad hoc adjustments.

Conservation is a subtle form of resilience. Most economic models assume optimizing behavior, which implies that all inherent substitution possibilities have already been undertaken. Hence, in most applications, conservation would then have to represent the adaptive version. Rose and Liao (2005) have indicated how this form of resilience can be represented by changes in the productivity parameters of pertinent inputs in a CES production function, and have offered an algorithm for making this adjustment with use of empirical data. In standard production function analysis, one enters values of the variables into the production function, and then solves for outputs given these variable values and the production function parameters. To recalibrate a production function parameter in the aftermath of the disaster so as to reflect resilience, one can use the value of the inputs (including any fixed, or constant, levels) and a given level of output to solve for the parameters. In this case, they were able to solve for changes in the productivity term to reflect adaptive conservation by analytical methods. For this tactic and for the next one, the input and output values were obtained from a business interruption survey performed by Tierney (1997).[4]

Most production function relationships in these models allow for *input substitution*, which reflects a base level of this resilience tactic. In the most common form of production function used in CGE modeling, the Constant Elasticity of Substitution (CES) function, the relationship is represented by the elasticity of substitution. Adaptive input substitution refers to enhanced substitution possibilities under stress. The Rose and Liao algorithm also applies to the determination of the increase in CES substitution elasticities to reflect this type of resilience.[5] However, given the complexity of the CES substitution elasticity, changes in this parameter required numerical methods.

Inherent i*mport substitution* is analogously automatically a part of a CGE model through the substitution between production within a geographic area and imports, as represented by Armington elasticities. Analogous to input substitution, adaptive import substitution would be reflected by increasing the elasticity parameter levels along similar lines of the Rose and Liao algorithm. Note that Armington elasticities apply both to interregional and international trade.

Relocation of economic activity can be modeled in a CGE context, though some important distinctions must be made between two possibilities (Giesecke et al. 2015). The first is for a geographic shift in plant and equipment to another location, followed by shifts in labor and materials for the supply of these inputs at the new location. The second is simply shifting production to a new location utilizing existing facilities (e.g., using excess capacity of branch plants), which then likely

[4]Note that many resilience tactics are not constants, but either increase or decrease in their potency over time. For example, Draconian conservation, such as asking employees to work without air-conditioning or heat, are likely to run into opposition after a short time, and inventories will run out. On the other hand, substitution possibilities and technological change capabilities typically increase over time.

[5]We acknowledge the possibility that a disaster may also *reduce* substitution possibilities. This can be accounted for by reducing substitution elasticities using the same algorithm. In addition, there is time dimension to this reduction and to adaptive input substitution resilience. Time allows producers to overcome the stress and to innovate.

diminishes the necessity of geographic movements of labor and materials. If the geographic shift is within the region, this can be modeled by simply reducing the size of the initial shock. If the shift is to another region, then this can be modeled by ordinary interregional substitution of economic activity responding to a shock (constraint) on a productive capacity in the region directly affected by the disaster. The inherent version of relocation is thus reflected in the ordinary workings of the interregional CGE model. Adaptive relocation would be modeled by increasing the capital stock in the region to which the economic activity was shifted, or simply having the "increase" in the capital stock represented by an increase in the utilization of excess capacity.

Inventories are an inherent form of resilience because they refer to resilience capacity already in place. This tactic can be modeled by data on existing input inventory levels in each sector (U.S. Department of Commerce 2016). The percentage of an input held as inventory by each sector would then be used to adjust the percentage of initial disruption of that input in each sector downward (see, e.g., Rose and Wei 2013).

Excess capacity is another form of inherent resilience. Again, the percentage of excess capacity would be used to adjust the initial level of the shock, though, in this case, not with respect to material inputs but with respect to the capital stock of each producing sector. One can also apply the concept of excess capacity to labor by utilizing the unemployment rate in a similar manner to make adjustments, though taking precautions to account for labor skill differentials.

Input Isolation refers to a buffer against disasters when critical inputs are not needed in certain aspects of the production process. The most obvious case is the lack of the need for electricity in growing crops, or of water in many office buildings. For many years, this type of resilience has been referred to as "importance," and adjustment factors have been developed for critical lifeline services such as electricity, natural gas, water, and communications (ATC 1991). We have renamed the concept to make its meaning more apparent.

Production Recapture refers to rescheduling production to a later date to compensate for reduced output during earlier periods of the recovery. This ability is dependent on two key factors. The first is the extent to which capital and other inputs are available (cf., cases where the disruption is simply caused by a power outage with no damage to the factory versus the case of an earthquake, for which both electricity is disrupted and the factory is damaged). Second is the length of the disruption. For short-term cases, customers have inventories and/or will not go to the trouble of lining up other suppliers, but long-term disruptions will likely cause the firm's customers to abandon it. Production recapture is basically an adaptive form of resilience. It can be modeled by applying sectoral recapture factors (HAZUS 2013; Rose and Lim 2002) to gross output or GDP losses. These factors are nearly 100% for manufacturing sectors in the short-term but then are often assumed to decay to zero by year's end for all sectors (Rose and Wei 2013).

Technological change is especially difficult to analyze and to measure in general. One approach that bears special note is that of Rose (1984), which refers to modeling technological change in an I-O context. It basically focuses on many rationales and methods for changing model parameters and is generally applicable to CGE modeling, since so many of such a model's parameters (elasticities being the most notable exception) are based on an I-O table. However, all of the approaches refer to exogenous technological change, as opposed to change endogenously stimulated by explicit economic relationships, which are very difficult to model. The counterpart to exogenous technological change in the context of a disaster would be of the adaptive variety, while the inherent version of this tactic would already be ingrained in the economy. Endogenous technological change would thus not appear to be of much relevance in this context. Adaptive technological change is, of course, limited for short-term disaster recovery periods. Where it is applicable, it would be modeled primarily as fundamental changes in elasticities of substitution or productivity parameters, though likely in a more ad hoc manner than in the cases of input substitution and conservation discussed above. Additional parameters, such as those relating to the timing of the adjustment process of not just technological change, but to input and import substitution as well, would also be helpful.

Management effectiveness refers to organizational changes that can help maintain a firm's functionality, or business continuity (Wein and Rose 2011). It can be modeled by an improvement in the labor input productivity factor (in a manner analogous to the method for incorporating adaptive conservation), or, in cases of more general effectiveness, in terms of a productivity parameter related to all inputs. The best way to approach this is to explicitly incorporate a managerial variable into the production function, so as to distinguish managerial and other (e.g., production line) labor, and to modify the former in terms of productivity enhancement.

Other forms of resilience are applicable in specific contexts. In the case of port disruptions, for example, which are highly vulnerable to cyber disruptions directly or to associated shipping or offshore oil drilling, one form of resilience is *ship-rerouting*, which can offset the disruption of economic activity in the directly impacted region or in the broader economy. For example, *rerouting* of oil tankers to a nearby port would still allow crude oil to be carried by pipeline back to refineries in the directly affected area, thereby muting the initial shock by the applicable percentage. Otherwise, the ship-rerouting simply results in a geographic shift in economic activity, though with a brief delay due to the extra distance traveled. The adjustment for this tactic would be analogous to that made for inventories or excess capacity. Of course, the adjustment would not be applicable if the ships were rerouted beyond the geographic scope of the model being used.

Export diversion refers to shifting goods intended for export to domestic uses. Care must be taken to account for the heterogeneity of goods in a given sector. Sectors comprised of relatively homogeneous goods (e.g., raw materials and primary manufacturing) are more likely to be helped by this form of resilience. The adjustment is just an ad hoc reduction in the sector's initial supply disruption by the amount of the legitimate export diversion. This would be inherent resilience under ordinary circumstances, but adaptive resilience if previous unknown substitutions of differentiated products were made possible (see Rose et al. 2016; Wei et al. 2019).

One neglected aspect of the discussion above is the cost of resilience tactics. Ideally, these would be factored into CGE model simulations as well. However, this is less of a problem for several reasons. First, cost considerations are automatically taken into account for most forms of inherent resilience. Second, economic resilience on the customer side, which is the perspective of the discussion above, is relatively inexpensive, compared with economic resilience on the supplier side (e.g., redundant systems). For example, adaptive conservation more than pays for itself; important input substitution is just the cost differential associated with the supplied good (inherently accounted for in the model, and even for adaptive substitution). This is also the case for import substitution. The cost of inventories is just the carrying cost (already factored in). The cost of using excess capacity is close to nil. The cost of production recapture is just the payment for working overtime or extra shifts, where applicable. The cost relocation of activity to branch plants is relatively low, except perhaps for increases in transportation costs when the move is a long-distance, but this is automatically incorporated in CGE model. For physical shifts of plant equipment, there will, however, be moving costs not automatically included.

The discussion above has focused on resilience tactics that can be used to reduce the losses from disruption of cyber equipment and services. Another perspective is to view the use of these goods and services as sources of resilience for other inputs. The major example would be telework, most often characterized as telecommuting. This can greatly reduce the negative impacts of transportation system or fuel disruptions, as well as disruptions to family life that make it advantageous to stay at home (Cox et al. 2011). Another example would be the use of cyber-related automated systems to make up a loss of manpower. Still another would be the use of cell phones for broader communication purposes. The methodologies to incorporate these into CGE modeling would be similar to those noted in Table 5.1, such as loosening supply constraints on manpower as a result of telecommuting, and substituting cyber inputs for ordinary inputs.

The production theory framework just presented has limitations (e.g., assuming simple optimizing behavior and a select number of factors of production). It can be enhanced by incorporating features of non-optimizing behavior and other aspects of bounded rationality, more production factors, and additional managerial considerations (see, e.g., Gigerenzer and Selten 2002).

5.4.2 Supply-Side Resilience

On the supplier-side, the focus is on the manufacturer of cyber-related equipment and the provision of cyber services. The former relates to ordinary manufacturing, while the latter relates to business and professional services. What differentiates manufacturing of cyber-related equipment from most other manufacturing is the heavy reliance on one input: semi-conductors. And what makes society all the more vulnerable in this case is the fact that these inputs are produced in limited locations. Sheffi (2005) has documented the vulnerability of the cell phone industry, for example, to semi-conductor shortages following disasters affecting factories in Asia, and how Nokia survived by having a flexible supply-chain in contrast to the fate of Ericsson. Accordingly, the major sources of resilience for manufacturers would be inventories of critical inputs and lining up back-up suppliers, or initiating other flexibilities in the supply-chain, such as alternative transportation modes. Linkov et al. (2013) also stress the effects of managerial effectiveness in promoting resilience. The inclusion of these resilience tactics in a CGE model is very similar to the manner in which they are included with respect to the customer-side of the cyber industry.

Cyber service provision includes internet services, telecommunications services, software and tech support. The major distinction here is whether the product is primarily of a technical nature or otherwise. The first two are somewhat akin to electric service provision, and the above examples of supplier-side resilience are applicable here as well; however, one must add system redundancy as another resilience tactic, even though it is typically the most expensive of all possibilities. Completed software is less of a tangible commodity, and if it cannot be transmitted over the Internet, it can be transmitted by other means. Software development and progress can likely readily be shifted to other locations, unless it is so unique and sophisticated that its creators are impaired or immobile. Tech support is similar to software development, though its demand is much accelerated in time.

Table 5.2 presents resilience options on the supplier-side of the cyber domain. Most of the entries are analogous to those for Customer-Side Resilience, though there are several differences. For example, *delivery logistics* refers to how suppliers transport or transmit their products to their customers. Individual tactics include strengthening and/or shoring up wholesale and retail trade relationships and establishing contingency contracts with transportation companies. These actions can be strong for both inherent and adaptive resilience and are mainly applicable to the *output* variable. The major issue in implementing supplier-side resilience is the extent of network connectivity, which is typically damaged by disasters.

As noted before, supply-side resilience options are more limited than demand-side options and are also relatively more expensive, the primary example being redundancy. Note that these resilience options have not yet been simulated in CGE models to any significant extent, so no references to the literature are provided. However, the methodologies for their inclusion are similar to those in Table 5.1, though more of them apply to the output side, which has been further delineated according to general product output (Q), output of cyber equipment (QCE) and output of cyber services (QCS).

5.4.3 Government and Households

Both demand-side and supply-side resilience are applicable to the operation of government analogous to that business (Rose 2017). Additionally, government at various levels plays a broader role in economy-wide recovery. For example, increases in financial or in-kind disaster assistance, acceleration of their delivery, and improvements in the effectiveness of their distribution to the affected parties

Table 5.2 Microeconomic resilience options: business (supplier-side)

Category	Possible prior action	Inherent	Adaptive	Applicability	CGE incorporation
Delivery logistics	Broaden supply chain	X	X	QCE	Increase input substitution elasticities (Rose and Liao 2005); Loosen supply constraints (Wein and Rose 2011)
• Shore-up network of wholesale/retail trade					
• Contingency contracts w/transport companies					
Export substitution	Enhance flexibility	X	X	QCE, QCS	Loosen input constraints (Wei et al. 2019); Increase export elasticities
• Expand markets					
• Re-routing					
Inventories (stockpiles)	Enhance; protect	X	x	QCE, qcs	Loosen input constraints (Rose et al. 2016)
• Strengthen storage facilities					
• Reduce uncertainty					
Excess capacity	Build and maintain	X	x	CE, K	Loosen input constraints (Rose et al. 2009; Sue Wing et al. 2016)
• System redundancy • Maintain in good order • Data center failure					
Relocation	Arrange for facilities in advance;	x	X	K, L, CE, CS, M	Shift regions (Giesecke et al. 2015); loosen input constraints (Sue Wing et al. 2016)
• Move closer to customers • Telecommuting	Practice telework				
Production recapture	Arrange long-term agreements	X	X	QCE, qcs	Adjust output levels (Rose et al. 2007)
• In relation to customer needs					
• Practice restarting					
Technological change	Increase flexibility	X	X	K, L, CE, CS, M, Q	Adjust parameters (Rose 1984)
• Change processes					
• Alter product characteristics					
Management effectiveness	Increase versatility	X	X	QCE, QCS	Adjust parameters (Wein and Rose 2011)
• Project demand change					
• Prioritize goods and services					
Reduce operating impediments	Recovery planning	x	X	K, L, CE, CS, M	Adjust parameters (Wein and Rose 2011)
• Assist worker families					
• Relieve congestion					

promote recovery. Most of these functions are a form of dynamic economic resilience (see, e.g., Xie et al. 2018). However, the provision of aid can have disincentive effects on resilience, just as it does for mitigation when those who suffer from a disaster because they have not undertaken mitigation believe they will always be "bailed out." The government sector is also increasingly dependent on cyber systems. Emergency services and the military are high priority activities for which resilience is especially important. While the technological options presented in Table 5.1, as well as their costs, do not differ much between the application to businesses versus government and households, the benefits from these priority government areas of operation are sizable and extend beyond just the consideration of production activities to life safety and the preservation of the social and political system.

Household resilience on the "customer" side would be analogous to that presented for businesses (Rose 2017). For example, a household can readily import all inputs except infrastructure services and physical capital. Another example is that inherent conservation is primarily already accounted for by maximizing behavior, but we include it as at least weak, because not all households actually maximize their "production" relationships. Still, most conservation options pertain to adaptive applications. All inputs—capital, labor, infrastructure services, and materials—can be conserved, but the moderating factor is the necessity of the input into the household functioning, or, more formally, production process. In addition to customer-side resilience, households have supply-side resilience considerations with respect to providing their own services internally (e.g., using cyber services to prepare their income tax returns) or externally to the economy (e.g., providing labor or capital). The former can be modeled in the context of a household production function (see, e.g., Rose and Oladosu 2008), while the latter is part of the normal factor market workings of the CGE model. The resilience tactics exemplified in Table 5.1 apply to households but to a much more limited extent than to businesses in terms of breadth and scale. Although most household activities are not part of the National Income and Product Accounts, and thus do not typically show up in standard economic indicators such the ones referred to in this paper, they can be measured, as can resilience to maintain these activities, with some non-market valuation techniques.

5.5 Formally Incorporating Resilience at the Meso and Macro Levels

At the meso level, the predominant source of resilience is the role of prices and markets in allocating resources. This is probably the greatest advantage of CGE modeling over all other alternatives, such as I-O and macroeconometric modeling. This is an inherent source of resilience and is embodied in the formulation of CGE models through their supply and demand functions for factors of production, intermediate outputs, and final goods and services. One can measure the source of resilience by simulating the post-disaster situation at pre-disaster prices and comparing the outcome with a flexible-price post-disaster outcome, including changes in variables and parameters. One caveat, however, needs to be issued in the case of extreme disasters. Here, markets may be in disarray, and various imperfections are likely to result in a situation where prices no longer reflect the true value of resources. Several adjustments need to be made for this contingency. Here, CGE does serve a useful purpose of identifying the ideal workings of market, so that policymakers can gauge the extent to which the post-disaster situation deviates from this and then take steps to strengthen markets or administer prices to move toward this ideal outcome.

Resilience at the meso level is also related to supply chains, which have been discussed above. The spatial counterpart to this, and also very relevant to cyber or networks in general, relates to connectivity. One way to model this, albeit a most difficult one, is to overlay the spatial network onto the spatial model of the economy. A prime example is the work of Rose et al. (2011), in which the Los Angeles City economy was divided according to water service areas and how the water system network is overlaid, so that the economic consequences of spatially differentiated loss of water service could be accurately estimated. This provided a stronger basis for the evaluation of static resilience at the micro, meso, and macro levels. An analysis of this type also provides a stronger basis for evaluating dynamic economic resilience that can be used to prioritize repair and reconstruction of pipeline capacity so as to both increase function at any given point in time and to recover more quickly (see also Cagnan et al. 2006). A similar approach is applicable to cyber networks, though with some modification. For example, wireless networks have much different connectivity issues than do "solid" networks. In addition, cyber networks can have much broader coverage, including to the full national level.

The macro level can be thought of in two ways. First, it is the aggregation of individual actions, and the way to model the resilience as discussed above. The second is to note that the macro level is not just the sum of its parts, but involves various synergies or aspects of aggregate behavior or policy. This is much more difficult to model. One major aspect of the macro economy can be readily modeled in a CGE context, that being accessing imports when there are shortages of inputs previously produced domestically, or where export markets provide an alternative to the slump in domestic demand. Here is another CGE strength, where imports and exports are readily modeled through choice functions and so is the inherent resilience associated with them. To adjust for adaptive resilience, one needs to modify import substitution elasticities (and the counterpart transformation elasticities on the export side), but this can be done in an analogous manner to that developed by Rose and Liao (2005) for domestically produced inputs. Some government policy at the macro level can also be modeled. Fiscal policy, as through a stimulus from government spending or tax relief, is a standard application of CGE, without much need for modification. On the other hand, CGE models have typically lacked sophisticated monetary and financial sectors, and hence several aspects of this type of policy (e.g., open market operations) cannot readily be modeled, though important advances are in the works (Nassios and Giesecke 2018). However, adjustments in the interest rate can be modeled in various ways. One is simply ad hoc adjustments, while the superior approach would be to use a dynamic CGE model, where the interest rate represents an intertemporal opportunity cost. Again, the cyber domain differs from most other infrastructure types in being vulnerable to national level disruptions. Moreover, such a broad catastrophe can transmit shock waves throughout the entire globe in financial markets and goods markets. Supply-chain resilience would be epically important in this context.

5.6 Conclusion

Economic vitality and security are becoming increasingly reliant on cyber systems. In fact, of all of the types of disasters we face, cyber threat is one of the few that can have truly national, if not global, implications. Research on the prospects for pre-disaster mitigation of this threat and post-disaster resilience to its disruptions are of paramount importance.

This paper has presented various methods to incorporate resilience into a state-of-the-art approach to economic consequence analysis of disasters—computable general equilibrium analysis. The methods stem from a variety of sources, but are based for the most part on the author's own research on CGE and related I-O modeling. While they have been given explicit attention in relation to the cyber threat, nearly all of them are applicable in a similar manner to analyzing resilience in the face of the wide variety of threats facing most countries and regions today and in the foreseeable future.

We make no pretense that the methods presented are the final word on this topic. More research is needed on the conceptual side and operational side, especially with regard to improving on some ad hoc adjustments. The greatest challenge, as is typical, lies in collecting and refining data that can lead to the empirical implementation of the methodologies.

References

Ali J, Santos J (2012) Framework for evaluating economic impact of IT based disasters on the interdependent sectors of the US economy. In: Systems and information design symposium (SIEDS)

Applied Technology Council (ATC) (1991) Seismic vulnerability and impacts of disruption of lifelines in the coterminous United States. Report ATC-25. Applied Technology Council, Redwood City, CA

Bisogni F, Cavallini S (2010) Assessing the economic loss and social impact of information system breakdowns. In: Critical infrastructure protection IV, IFIP advances in information and communication technology. Springer, Berlin, pp 185–198

Cagnan C, Davidson K, Guikema S (2006) Post-Earthquake Restoration Planning for Los Angeles Electric Power. Earthquake Spectra: 22(3): 589–608

Chang S, Rose A (2012) Economic recovery to disasters. Int J Mass Emerg Disasters 30 (2):171–181

Cox A, Prager F, Rose A (2011) Transportation security and the role of resilience: a foundation for operational metrics. Transp Policy 18:307–317

Dixon P, Rimmer M, Lee B, Rose A et al (2010) Effects on the U.S. of an H1N1 epidemic: analysis with a quarterly CGE model. J Homel Secur Emerg Manag 7(1):Article 7

Federal Emergency Management Agency (FEMA) (2013) Multi-hazard loss estimation methodology (HAZUS®MH MR4). http://www.fema.gov/library/viewRecord.do?id=3726

Giesecke J, Burns W, Rose A, Barrett T, Griffith M (2015) Regional dynamics under adverse physical and behavioral shocks: the economic consequences of a chlorine terrorist attack in the Los Angeles Finance District. In: Nijkamp P, Rose A, Kourtit K (eds) Regional science matters. Springer, Heidelberg

Giesecke JA, Burns WJ, Barrett A, Bayrak E, Rose A, Slovic P, Suher M (2016) Assessment of the regional economic impacts of catastrophic events: CGE analysis of resource loss and behavioral effects of an RDD attack scenario. Risk Anal 32(4):583–600

Gigerenzer G, Selten R (eds) (2002) Bounded rationality: the adaptive toolbox. MIT, Cambridge

Holling C (1973) Resilience and stability of ecological systems. Annu Rev Ecol Syst 4:1–23

Horwich G (1995) Economic lessons of the Kobe earthquake. Econ Dev Cult Chang 48(3):521–542

Linkov I, Eisenberg D, Plourde K, Seager T, Allen J (2013) Resilience metrics for cyber systems. Environ Syst Decis 33(4):471–476

Martin R, Sunley P (2014) On the notion of regional economic resilience: conceptualization and explanation. J Econ Geogr 15(1):1–42

Nassios J, Giesecke J (2018) Informing ex-ante event studies with macro-econometric evidence on the structural policy of terrorism. Risk Anal 38(4):804–825

Norris F, Stevens S, Pfefferbaum V, Whyche K, Pfefferbaum R (2008) Community resilience as a metaphor, theory, set of capacities and strategy for disaster readiness. Am J Community Psychol 41:127–150

Pimm SL (1984) The complexity and stability of ecosystems. Nature 307(26):321–326

Rose A (1984) Technological change and input-output analysis. Socio Econ Plan Sci 18(5): 305–318; Reprinted in Haynes K, et al (eds) Modern classics in regional science. Regional dynamics, vol 2. Edward Elgar, Cheltenham

Rose A (2004) Economic principles, issues, and research priorities in natural hazard loss estimation. In: Okuyama Y, Chang S (eds) Modeling the spatial economic impacts of natural hazards. Springer, Heidelberg, pp 13–36

Rose A (2009) Economic resilience to disasters. CARRI Research Report #8. ORNL

Rose A (2015) Macroeconomic consequences of terrorist attacks: estimation for the analysis of policies and rules. In: Smith VK, Mansfield C (eds) Benefit transfer for the analysis of DHS policies and rules. Edward Elgar, Cheltenham, pp 172–201

Rose A (2017) Defining and measuring economic resilience from a societal. Environmental and security perspective, Springer, Singapore

Rose A, Liao S (2005) Modeling resilience to disasters: computable general equilibrium analysis of a water service disruption. J Reg Sci 45(1):75–112

Rose A, Lim D (2002) Business interruption losses from natural hazards: conceptual and methodology issues in the case of the Northridge earthquake. Environ Hazard 4(1):1–14

Rose A, Miller N (2019) Measurement of cyber resilience from an economic perspective. In: Chatterjee S, Brigantic R, Waterworth A (eds) Applied risk analysis for guiding homeland security policy and decision. Springer, Heidelberg

Rose A, Oladosu G (2008) Regional economic impacts of natural and man-made hazards disrupting utility lifeline services to households. In: Richardson H, Gordon P, Moore J (eds) Economic impacts of Hurricane Katrina. Edward Elgar, Cheltenham

Rose A, Wei D (2013) Estimating the economic consequences of a port shutdown: the special role of resilience. Econ Syst Res 25(2):212–232

Rose A, Oladosu G, Liao S (2007) Business interruption impacts of a terrorist attack on the electric power system of Los Angeles: customer resilience to a total blackout. Risk Anal 27(3):513–531

Rose A, Oladosu G, Lee B, Beeler-Asay G (2009) The economic impacts of the 2001 terrorist attacks on the World Trade Center: a computable general equilibrium analysis. Peace Econ Peace Sci Public Policy 15(2):Article 4

Rose A, Liao S, Bonneau A (2011) Regional economic impacts of a Verdugo earthquake disruption of Los Angeles water supplies: a computable general equilibrium analysis. Earthquake Spectra 27(3):881–906

Rose A, Wing IS, Wei D, Wein A (2016) Economic impacts of a California tsunami. Nat Hazard Rev 17(2):04016002

Rose A, Prager F, Chen Z, Chatterjee S (2017) Economic consequence analysis of disasters (The E-CAT Software Tool). Springer, Singapore

Sheffi Y (2005) The resilient enterprise. MIT, Cambridge, MA

Silberberg E, Suen W (2000) The structure of economics: a mathematical analysis. McGraw-Hill, New York

Sue Wing I, Rose A, Wei D, Wein A (2016) Impacts of the USGS ARkStorm scenario on the California *economy*. Natural Hazards Review 17(4):A4015002-1

Tierney K (1997) Impacts of recent disasters on businesses: the 1993 Midwest floods and the 1994 Northridge earthquake. In: Jones B (ed) Economic consequences of earthquakes: preparing for the unexpected. National Center for Earthquake Engineering Research, Buffalo, NY, pp 189–222

Wei D (2015) Summary of literature on economic impacts of telecommunication or internet disruptions. Draft Report to USGS

Wei D, Chen Z, Rose A (2019) Evaluating the role of resilience in recovering from major port disruptions: a multi-regional analysis. Submitted to Papers in Regional Science

Wein A, Rose A (2011) Economic resilience: lessons from the ShakeOut earthquake scenario. Earthquake Spectra: Special Issue on the ShakeOut Earthquake Scenario 27(2):559–573

Xie W, Rose A, Li S, He J, Li N, Ali T, Wei W (2018) Dynamic economic resilience and economic recovery from disasters: a quantitative assessment. Risk Anal 38(6):1306–1318

Zolli A, Healy AM (2012) Resilience: why things bounce back. Free Press, New York

Adam Rose is a Research Professor in the University of Southern California Sol Price School of Public Policy, and a Research Fellow at USC's Center for Risk and Economic Analysis of Terrorism Events (CREATE). Professor Rose's primary research interest is the economics of natural disasters and terrorism. He has spearheaded the development of CREATE's comprehensive economic consequence analysis framework to include aspects of mitigation, resilience, behavioral responses, and remediation. He has done pioneering theoretical and empirical research on resilience to disasters at the level of the individual business/household, market/industry, and regional/national economy. Professor Rose is the author of several books and 250 professional papers, including most recently *Economic Consequence Analysis of Disasters: The E-CAT Software Tool* (Springer) and *Defining and Measuring Economic Resilience from a Societal, Environmental and Security Perspective* (Springer). He is a Fellow of the Regional Science Association International and President of the International Society for Integrated Disaster Risk Management.

Chapter 6
Rapid Assessments of the Economic Implications of Terrorism Events Using a Regional CGE Model: Creating GRAD-ECAT (*Generalized, Regional and Dynamic Economic Consequence Analysis Tool*)

Peter B. Dixon, Michael Jerie, Maureen T. Rimmer, and Glyn Wittwer

Abstract The Department of Homeland Security (DHS) considers the effects of hypothetical terrorism scenarios distinguished by many dimensions including: perpetrator; target; location; weapon; and delivery method. For each scenario, DHS requires a computationally rapid, in-house (secure) tool for translating impact effects or "driving variables" (e.g. capital destruction, clean-up expenditures, etc.) into economic implication variables (e.g. GDP in the short and long run, regional output in the short and long run, and economic welfare). We use a detailed, dynamic, multi-regional CGE model to generate elasticities E(s,d,v) of 9 implication variables (v) with respect to 14 driving variables (s) occurring as a result of incidents in any of the US's 436 congressional districts (d). Equipped with these elasticities, DHS can apply trivial calculations to estimate the national and regional economic implications of an enormous variety of scenarios. Rose et al. (Economic consequence analysis tool (E-CAT), Springer, Tokyo, 2017) also propose a CGE-based rapid calculation tool for translating terrorism-related driving variables into economic implication variables. They refer to this tool as E-CAT (*E*conomic *C*onsequence

This is an abridged version of a report to the U.S. Department of Homeland Security that we prepared under a sub-award from the Center for Risk and Economic Analysis of Terrorism Events (CREATE) at the University of Southern California. We received excellent administrative support from CREATE and valuable advice throughout the project from Scott Farrow (Coordinator for Economics at CREATE). Tony Cheesebrough from DHS Headquarters was extremely helpful in setting up the project. In working on the project we benefited from enthusiastic encouragement from the project managers Jessica Cox and Scott White. Throughout the project we enjoyed close collaboration with Battelle's Dave Winkel. Adam Rose provided valuable comments on an earlier draft of this chapter. None of the people mentioned here or their organizations is responsible for the contents of the chapter.

P. B. Dixon (✉) · M. Jerie · M. T. Rimmer · G. Wittwer
Centre of Policy Studies, Victoria University, Melbourne, Australia
e-mail: Peter.Dixon@vu.edu.au; Michael.Jerie@vu.edu.au; Maureen.Bleazby@vu.edu.au; Glyn.Wittwer@vu.edu.au

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_6

*A*nalysis *T*ool). Compared with E-CAT, our tool has a more general coverage of economic variables (both driving and implication variables) and introduces regional and dynamic dimensions. In view of the similarities and differences between our approach and E-CAT, we title the tool created here as GRAD-E-CAT (*G*eneralized, *R*egional *A*nd *D*ynamic *E*conomic *C*onsequence *A*nalysis *T*ool).

6.1 Introduction

This chapter describes a multi-regional computable general equilibrium (CGE) tool for use in economic consequence analysis of terrorism events. The tool was designed and constructed for the Terrorism Risk Assessment (TRA) groups in the Department of Homeland Security (DHS). CGE techniques have been applied in disaster consequence analysis for nearly 30 years, see Boisvert (1992), Rose and Guha (2004), Giesecke et al. (2012) and many other studies cited in Dixon et al. (2017a). For reasons explained in Sect. 6.1.1 associated with security and the complexity of CGE computation, the TRA groups have been reluctant to adopt CGE, preferring until recently to use in-house input-output models. This chapter explains how we have overcome the difficulties that the TRA groups had with CGE modeling by creating GRAD-ECAT. Section 6.1.2 explains the acronym.

6.1.1 Converting Scenarios for Driving Factors into Outcomes for Economic Implication Variables

The TRA groups consider the effects of hypothetical terrorism scenarios. These scenarios have many dimensions including: perpetrator; target (e.g. airport); location; agent (e.g. nuclear device, particular type of chemical, disease, etc.); indoor or outdoor; time of day; and delivery method (e.g. infected imported food, car bomb, contaminated water). Further dimensions are added in sensitivity analysis. For example, for a given scenario, a range of outcomes might be generated by considering different prevailing weather conditions. The split between the specification of a scenario and what are considered sensitivity factors depends on what the perpetrators can control. It is easy to see how variations in the scenario and sensitivity factors can lead to millions of hypothetical events.

For each of these events, TRA groups combine historical and engineering data in spreadsheet models to calculate about 160 damage indicators. These describe damage at a high level of detail, for example, loss of shopping expenditures by foreign tourists in the target city, loss of hotel expenditures by foreign tourists in the target city, expenditure on decontamination of outdoor spaces, expenditure on decontamination of indoor spaces, etc. The TRA groups asked us to investigate the feasibility of using CGE modeling to translate these 160 damage indicators into national and regional economic implications.

For use in a CGE model, we suggested to the TRA groups that they aggregate the 160 damage indicators into 14 driving factors on the basis of the channel by which the damage is transmitted to the rest of the economy. The agreed driving factors are as follows:

Driving Factors

(i) capital destruction;
(ii) capital idling[1];
(iii) clean-up expenditures;
(iv) health expenditures;
(v) temporary accommodation and relocation expenses in target city;
(vi) temporary accommodation and relocation expenses outside target city;
(vii) foreign tourism discouragement in target city;
(viii) foreign tourism discouragement outside target city;
(ix) domestic tourism discouragement in target city;
(x) domestic tourism discouragement outside target city;
(xi) interruption of food production in target state;
(xii) interruption of food production outside target state;
(xiii) reduction in national labor supply associated with deaths and injuries;
(xiv) aversion to working in the target region (interpreted in this chapter as the congressional district in which the event takes place).

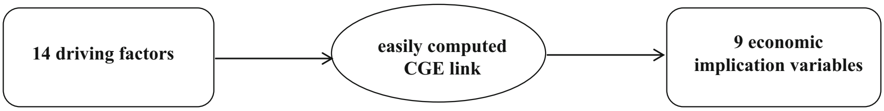
While the aggregation to 14 driving factors sacrifices some micro detail, we judged that there would be little loss of information relevant for working out CGE-implied implications for the 10 main variables of interest to the TRA groups:

Economic Implication Variables

1. national GDP in the event year (year 1)
2. national employment in the event year
3. GRP (gross regional product) in the target region in the event year
4. employment in the target region in the event year
5. national GDP in the long run (year 20)
6. national employment in the long run
7. GRP (gross regional product) in the target region in the long run
8. employment in the target region in the long run
9. present value of loss in economic welfare with a high discount rate (5%)
10. present value of loss in economic welfare with a low discount rate (2%)

To give the TRA groups a CGE capacity we saw our task as being to provide an easily computed CGE link between the 14 driving factors and these 10 economic implication variables:

[1]This refers to capital being taken out of use temporarily during, for example, a decontamination period.



Our approach to this task relies on the estimation of elasticities of the 10 implication variables with respect to the 14 driving factors. The elasticities are estimated from a detailed regional computable general equilibrium (CGE) model of the U.S. Once the elasticities are in place, the effects on each of the 10 implication variables of any given scenario can be computed effortlessly by the TRA groups as a weighted sum of the values of the 14 driving factors for that scenario.

In the past, the TRA groups have relied on input-output (I-O) modeling to provide a link between damage indicators and economic implication variables. In Sect. 6.2 we compare I-O and CGE. In brief, CGE is superior in terms of economic theory and coverage of variables. However, CGE computation is complex and generally requires participation of specialist CGE modelers. These factors raise difficulties in a situation in which rapid calculations are required for a large number of scenarios in a secure environment. This explains the past reluctance of the TRAs to embrace CGE modeling. In Sect. 6.3 we describe how our elasticities approach overcomes both the computational and security challenges. The particular CGE model on which we base the elasticities is USAGE-TERM. This model is described in Sect. 6.4. Section 6.5 sets out the measure of welfare loss that can be computed with our elasticities for each terrorism incident. Welfare is the most important implication variable. As explained in Sect. 6.5, we allow for analysis of the sensitivity of welfare with respect to the discount rate and the value of life. Section 6.6 describes the estimation of the elasticities. Illustrative applications of the elasticities are given in Sect. 6.7. A summary and directions for future research are in Sect. 6.8.

6.1.2 From ECAT to GRAD-ECAT

Ours is not the first attempt to use a CGE model to provide a rapid-computation link between driving factors arising from disruptive events and economic implication variables. Parallel with our work, Rose et al. (2017) and Chen et al. (2017) have created an ECAT (Economic Consequence Analysis Tool). Their approach is to build separate ECAT modules for different types of events, an ECAT module for aviation system disruptions, a module for earthquakes, etc. In many of the modules, they start by specifying a scalar, M, that indicates the severity of an event. For example, in the aviation module, M is the number of national shutdown days (if half the system is shut down for 2 days, then $M = 1$). Rose et al. make a judgment as to the maximum value of M that is likely to be of practical interest, e.g. $M_{max} = 7$. They also specify a lower bound, e.g. $M_{min} = 1$. Then they make judgments about the values of driving factors at the maximum and minimum values of M. In the aviation case, there are 13 driving factors, property damage and output loss in 12 industries. Values of driving factors for intermediate values of M are specified according to:

$$Y_{ij} = \alpha_j + \beta_j * M_i \tag{6.1}$$

where

M_i is an intermediate value of M, e.g. M = 3;
Y_{ij} is the value of the jth driving factor associated with the value M_i for the severity indicator; and
α_j and β_j are parameters deduced by passing a straight line through the (M, Y_j) points for the maximum and minimum values of M.

The next step in the construction of an ECAT module is the choice of 100 values for M in the range [M_{min}, M_{max}]. For each choice, the corresponding vector of driving factors is evaluated from Eq. (6.1). Together with each M choice, Rose et al. make random choices from a limited number of possibilities for dummy variables that introduce intensity levels for resilience and behavioral responses. In the aviation ECAT, for example, resilience refers to the extent (controlled by the resilience dummy) to which saved expenditure from reduced airline travel is switched to spending on alternative travel modes and general consumption. With Y and the related vectors of resilience and behavioral expenses treated as shocks, a CGE solution is obtained showing the effects on GDP and aggregate employment. Finally, the ECAT module is specified as:

$$gdp_h^a = F_{gdp}^a\left(M_h^a, D_{res,h}^a, D_{behav,h}^a\right) \tag{6.2}$$

and

$$emp_h^a = F_{emp}^a\left(M_h^a, D_{res,h}^a, D_{behav,h}^a\right) \tag{6.3}$$

where

gdp_h^a and emp_h^a are the GDP and employment effects of an event of type a (e.g. aviation disruption) and severity M_h^a with the resilience and behavioral response expenditure vectors scaled by dummies $D_{res,h}^a$ and $D_{behav,h}^a$; and
F_{gdp}^a and F_{emp}^a are functions whose coefficients are determined by regressing the 100 GDP and employment results from the CGE solutions against the values for M and the dummies.

By applying Eqs. (6.2) and (6.3), the GDP and employment effects of an event of the appropriate type (e.g. an aviation disruption) can be computed effortlessly after specifying the severity of the event (the M value) and the strength of the resilience and behavioral responses (the D_{res} and D_{behav} values).

The tool that we describe in this chapter, GRAD-ECAT, differs from ECAT in three ways.

First, the nature of the event is treated differently in the two tools. Users of ECAT select the appropriate module (e.g. aviation), specify severity (M) and resilience/behavioral dummies (Ds) and apply reduced-form equations to derive economic consequence results. With GRAD-ECAT, whatever the nature of the event, users must specify values for 14 driving factors. Thus, GRAD-ECAT can be applied to any type of disaster that causes property damage, requires clean-up expenditures, requires health expenditures, etc. We don't try to encapsulate these driving factors in a scalar measure and a limited number of resilience and behavioral dummies. Instead, the driving factors and responses can be in any configuration. This difference reflects the requirements of the TRA groups who need a tool which can handle flexibly any specified vector of shocks. As we see it, a trade-off between the two tools is greater flexibility for GRAD-ECAT but more work for users in presenting their driving factors. In creating the ECAT modules, Chen et al. (2017) and Rose et al. (2017) have undertaken a large volume historical research on the effects of actual events. Users of GRAD-ECAT design the structure of their own shocks (the values of the driving factors), introducing their own interpretation of past events where appropriate.

Second, we use a multi-regional CGE model. The ECAT modules have been created with national models (without regions). Reflecting the requirements of the TRA groups, the tool we have created can generate effects on national and regional variables of terrorism incidents specified by the congressional district in which they were perpetrated.

Third, we use a dynamic CGE model whereas the model underlying the ECATs is single period. By using a dynamic model we create a tool that shows effects in the short run (the year of the incident) and long run (notionally year 20). On a related matter, users of our tool can rank incidents according to their effects on economic welfare. To assess economic welfare we need a time-path of outcomes generated by a dynamic model. For example we need to consider the buildup of foreign debt which may take place in the short run to finance recovery efforts and the repayment of this debt in the long-run. Calculation of GDP and employment effects for a single year, as in ECAT, is not an adequate basis for a welfare calculation.

In view of the pioneering status of ECAT and the similarities and differences between our approach and ECAT, we title the tool created here GRAD-ECAT (Generalized, Regional and Dynamic Economic Consequence Analysis Tool).

6.2 Computable General Equilibrium (CGE) Modeling as an Alternative to Input-Output (I-O) Modeling for Meeting TRA Requirements

Prior to this project, the practice of the TRA groups was to link damage indicators with economic implications via an I-O model. The TRA groups fed a subset of the damage indicators, those concerned with expenditure, into an I-O model and computed outcomes for a limited subset of implication variables, national GDP and employment in year 1. Expenditures were the main focus because I-O models are essentially about working out the effects of expenditure changes, e.g. the effects of public expenditure on clean-up. The results from the I-O model then become part of C(j) in the equation:

$$\mathrm{Risk}(j) = \mathrm{Pr}(j) * \mathrm{C}(j) \tag{6.4}$$

where

Pr(j) is an assessment by the TRA groups of the probability of event j occurring;
C(j) is a measure of the consequences of event j and includes results from the I-O model as well as components, such as fatalities, from the list (i) to (xiv); and
Risk(j) is the expected value of event j.

TRA practice is to rank events by their Risk value. The ranking then becomes a basis for prioritizing preventative policies.

I-O modeling has well known limitations. The most important of these are: (a) difficulties in handling constraints on the availability of resources such as labor, physical capital, government finance and foreign exchange; (b) lack of a time dimension; and (c) a narrow range of result variables that excludes important financial variables such as foreign liabilities.

All of the information in (i) to (xiv) can be fed into a CGE model. CGE models such as USAGE-TERM have detailed representations of resource constraints and produce annual time-series results for a wide range of variables. These cover all of the economic implication variables listed in Sect. 6.1 and many others. Routine outputs from USAGE-TERM include:

- national macro variables such as GDP, employment, wage rates, aggregate private and public consumption, investment, exports, imports, the public sector deficit and foreign liabilities;
- employment in the target region (e.g. CA34, downtown LA), neighboring regions (e.g. rest of LA), rest of state (e.g. rest of California), and rest of U.S.;
- wages rates by region; and
- industry outputs by region.

The dynamic dimension allows capture of both an "immediate" effect in year 1 and summary measures of long-term dynamic effects. Typically we might expect to see the effects of economic stimulation in year 1 associated with immediate unfunded (deficit) public expenditure followed by subdued economic outcomes in later years arising from debt repayment and tight public-sector budgets.

Recognition by the TRA groups of the potential advantages of CGE over I-O explains why they commissioned a study of the feasibility and desirability of replacing I-O with CGE as the link for connecting damage indicators with economic implication variables.

6.3 The Computational and Security Challenges: The Elasticity Solution

Computing solutions for detailed dynamic CGE models such as USAGE-TERM is non-trivial. For example, a 4-region, 23-industry, 20-year simulation with USAGE-TERM takes about 6 min on an advanced desktop computer. This rules out the possibility of undertaking a separate USAGE-TERM simulation for each of the TRAs thousands of hypothetical scenarios.

Another problem is that solving CGE models is not routine. Considerable experience is required to successfully carry out computations, interpret them and to check their validity. Consequently, as a practical matter it is efficient to largely outsource CGE computations to specialists in the field. But this raises a problem of security. Specialist CGE modelers are unlikely to have security clearances that would give them access to the details of the terrorism scenarios that are being considered by the TRA groups.

As set out in this chapter, we solve both problems by using USAGE-TERM to provide estimates of elasticity[2] coefficients of the form E(s,d,v). The s argument refers to the driving factor, one of the 14 in the first list in Sect. 6.1. In economic modeling jargon, s is the shock variable: capital destruction; clean-up expenditure; etc. The d argument refers to the target region. This is the congressional district in which the shock takes place. For this study, we include the 170 congressional districts of interest to the TRA groups, that is districts located in cities of sufficient size to be potential terrorism targets. The v argument refers to an economic implication variable, one of the ten in the second list in Sect. 6.1. Thus, E(s,d,v) is the elasticity of variable v with respect to a shock of type s occurring in region d. For example, E(s,d,v) could be the elasticity of GDP in year 1 (v) with respect to destruction of capital (s) in California congressional district 34 (d).

We provide two sets of elasticities calculated under different assumptions: Keynesian and Neoclassical. Keynesian assumptions are suitable if there are high levels of unemployment and under-utilization of capital in the year of the terrorism event. With normal levels of employment and capital utilization, Neoclassical assumptions are suitable. Our view is that Neoclassical assumptions would be suitable for events happening in 2015 or 16. The difference between the two

[2] An elasticity is the percentage effect on one variable of a 1% change in another variable.

assumptions is that expenditures (e.g. clean-up) undertaken in an underemployed economy are less costly in terms of economic welfare than expenditures undertaken in an economy with normal levels of employment. In an underemployed economy, the opportunity cost of devoting resources to clean-up etc. is lower than in an economy with normal employment. One way of characterizing Keynesian and Neoclassical assumptions is in terms of resilience. As described by Rose (2017b), resilience refers to the ability of the economy to bounce-back from a terrorism event. Within resilience Rose distinguishes inherent and adaptive resilience, that is resilience driven by normal market forces and resilience driven by policy interventions or behavior that would not apply in the absence of the terrorism event. Inherent resilience is greater in Keynesian conditions than in Neoclassical conditions. As described by Rose (2017a), resilience in the face of the 9/11 event was enhanced by the relatively depressed state of the economy in 2001 which allowed businesses to react to capital destruction in down-town New York by taking up excess capacity in other parts of New York city and neighboring regions. Aspects of adaptive resilience are introduced to the CGE model by driving factors such as (iii)–(vi) in Sect. 6.1. More generally, measuring resilience and assessing situations in which resilience will be high or low has been an important part of economic consequence analysis of terrorism events. Both Rose (2017a, b) provide overviews of the resilience literature.

Each of the sets of elasticities E(s,d,v) contains 23,800 components: a three dimensional array with 14 s values (the types of shocks); 170 d values (the congressional districts of interest); and 10 v values (the implication variables). For any given scenario, the TRA groups can calculate the approximate values for the 10 implication variables by picking the appropriate elasticities and carrying out the computation:

$$v_j = \sum_{s \in S} E_A(s, d_j, v) * s_j \quad \text{for all } v \in V \tag{6.5}$$

In this equation A refers to the assumption of Keynesian or Neoclassical conditions and j refers to the scenario under examination. V is the set of implication variables and v_j is the outcome in scenario j for variable v in V, that is the effect on GDP in year 1, etc. S is the set of shock types, that is capital destruction, etc. s_j is the shock applied to driving variable s in scenario j, e.g. 15% capital destruction in the target region. d_j is the congressional district in which the scenario-j event takes place.

Equation (6.5) solves the computational problem. The computation required by the TRA groups to evaluate the effects of any given scenario j is trivial and can be performed in nanoseconds. All of the difficult CGE modeling and computations are pre-performed by the CGE specialists in the estimation of the E's. The TRA groups simply receive the E coefficients.

Equation (6.5) also solves the security problem. The CGE team never needs to know the nature of the terrorism incidents under consideration or the values of the shocks, s_j.

As explained in detail in Sect. 6.6, we estimate the E coefficients by applying shocks in the CGE model and recording the outcomes for the economic implication variables listed in Sect. 6.1. Thus, Eq. (6.5) is a first-order approximation of the true solution from the CGE model. Simplifying the CGE calculation of the effects of any scenario j to a set of 10 linear reduced-form equations (one for each of the 10 implication variables) comes at a cost. In Eq. (6.5) the elasticities E(s,d,v) are treated as parameters, whereas in the CGE model they are variables. We return to this topic in the conclusion where we consider future research directions. This chapter concentrates on the already quite difficult problem of obtaining central values for the E coefficients.

6.4 USAGE-TERM, A Flexible Bottom-Up Regional Model of the U.S.

This section describes USAGE-TERM, the CGE model through which we estimate the elasticity coefficients required for Eq. (6.5). USAGE is an acronym for U.S. Applied General Equilibrium. TERM is an acronym for The Enormous Regional Model. Thus USAGE-TERM is a version of the USAGE model with enhanced regional detail.

6.4.1 The USAGE Model

USAGE is a 400 industry, dynamic, CGE model of the U.S. economy.[3] It has been created over the last 15 years at the Centre of Policy Studies (CoPS), Victoria University, in collaboration with the U.S. International Trade Commission. The model has been used by and on behalf of: the U.S. International Trade Commission; the U.S. Departments of Commerce, Agriculture, Energy, Transportation and Homeland Security; and private sector organizations such as the Cato Institute and the Mitre Corporation. Applications of the model include baseline forecasting and analyses of the effects of: trade policies; environmental regulations; carbon taxes; energy security; illegal immigration; road infrastructure; Next-Gen aviation infrastructure expenditures; the Obama stimulus package; the National Export Initiative; an H1N1 epidemic; and security-related port closures.[4]

USAGE is essentially a national model, although it does have a facility for disaggregating national results in a top-down fashion to the 50 states and the District of Columbia.[5] This facility is effective for working out the regional implications of national policies which are unlikely to have a significantly different effect on costs of production in any given industry in one state compared with other states. A limitation of the top-down facility is that it is unsuitable for projecting the effects of policies and other shocks (including terrorism events) that are initiated at the

[3]The theory underlying USAGE is based on Dixon and Rimmer (2002).

[4]Published USAGE papers on terrorism-related issues include: Dixon et al. (2010, 2011a, b, 2014, Dixon et al. 2017b).

[5]See Dixon et al. (2007).

regional level and affect costs in an industry in one region relative to those in other regions.

6.4.2 USAGE-TERM

To overcome this limitation, the CoPS team with considerable support from Adam Rose and colleagues at the Center for Risk and Economic Analysis of Terrorism Events (CREATE), have developed a series of bottom-up regional versions of USAGE. All of these are in the family of TERM models developed initially by CoPS for Australia.[6]

The first USAGE-TERM model was created in 2011. This version identified the 50 states plus the District of Columbia. It treated these 51 regions as highly integrated economies connected by: trade; factor movements; and a common currency. In this version, policies such as carbon taxes levied at the state level cause changes in production costs in one state relative to those in others, and lead to changes in trade and factor flows. This allows assessments of the costs and benefits to states of state policies.

The initial version of USAGE-TERM was comparative static. In 2012–13 the model was given a dynamic dimension similar to that in the national USAGE model. Thus it became capable of tracing out effects of a shock over a number of years.

In 2013–14 we extended the regional detail from the state to the county level. This work was motivated by wanting to improve the capabilities of USAGE-TERM for modeling terrorism shocks and other disruptive events. These events occur at a localized level, often well below the state level. For analyzing such events, extending the USAGE-TERM capability to the county level is an important enhancement. We also created the version of USAGE-TERM, used in this chapter, in which the identified regions are the 436 congressional districts.

The key data requirements for these regional versions of USAGE are jobs matrices in which the components, J(j,r), are the number of jobs in industry j in region r. Another important data requirement for regional versions of USAGE is interregional trade flows. For each region and each commodity we can estimate net trade flows from data on output and absorption (use of the commodity within the region). Then applying a modified gravity formula, devised by Horridge (2012), we estimate interregional trade flows that are consistent with our estimates of net trade flows. These interregional trade estimates take into account: the tradability of commodities; home bias (the tendency to buy the local variety); and distance between supplying and consuming regions. Descriptions of data sources for the jobs matrices and of the estimation of inter-regional commodity flows are in Wittwer (2017).

[6]See Horridge et al. (2005).

6.4.3 Coping with Huge Dimensions via Flexible Aggregation

The county version of USAGE-TERM has potentially huge dimensions: 400 industries in 3000 counties supplying their products to 400 industries and final users in 3000 counties. The dimensionality problem is reduced for the congressional district version where the regional dimension is 436. Nevertheless, even for the congressional district version, computations at full dimension are impractical, and even if they could be carried out, the interpretation of the results would be unnecessarily time consuming. To address this problem, CoPS has developed a flexible aggregation program that allows model users to specify the regions and industries of interest [see Wittwer (2017)]. The program aggregates the full-dimension master database and creates a version of USAGE-TERM in which only the regions and industries of interest are identified.

6.4.4 Simulations, Baseline Runs and Perturbation Runs

As is the case with USAGE, a *simulation* with the USAGE-TERM model consists of two *runs*: a baseline run and a perturbation run. The baseline run is intended to be a business-as-usual forecast. It incorporates macro forecasts and forecasts for energy variables obtained from the Energy Information Administration's publication titled *Annual Energy Outlook*. We also build in trends in technology and consumer preferences. The perturbation run shows an alternative forecast that includes an additional change in the economic environment. Usually this is a policy change, but here it is a terrorism incident. Consequently, we will sometimes refer to the perturbation run as the terrorism run. Comparison of the terrorism and baseline runs shows the economic effects of the terrorism incident.

6.5 Measuring the Welfare Effects of a Terrorism Incident

Economic implication variables 1–8 listed in Sect. 6.1 refer to GDP and employment for the nation and for the target region in the short- and long-runs. GDP and employment are well understood variables and their measurement is relatively uncontroversial. Perhaps all that needs to be mentioned is that we measure employment in wagebill terms, that is, the loss of a job counts twice as heavily when it occurs in an occupation with wage rate 2 than when it occurs in an occupation with wage rate 1. In our simulations of the effects of terrorism we have found that here is little difference in the movements of the wagebill index for employment and the job-count index.

By contrast, implication variables 9 and 10, the two measures of welfare, need a full explanation.

In all our simulations the terrorism incident under examination takes place in 2015. We call this year 1. The simulations then cover the period out to 2034, year 20.

We measure welfare in terms of present value in 2014, year zero. As discussed below, there are differing views on the discount rate appropriate in calculating present values. We define two welfare measures: one with a discount rate of 5% and the other with a discount rate of 2%.[7]

A terrorism incident perpetrated in year 1 changes the path of the economy through all future years. Depending on the nature of the incident, there will be changes in public expenditures, changes in investment and changes in foreign debt. Typically we would expect a serious incident to cause an initial blow-out in public expenditures followed by contraction as public and foreign debt are reined in. Our problem is to summarize these dynamic effects into a welfare number for each incident. This is necessary if we are to compare and rank incidents.

In popular discussions, GDP effects are often mentioned as if they are indicators of welfare. GDP is a measure of output. A terrorism incident requiring an intensive rebuilding program could increase GDP. But before we draw the conclusion that there is an associated increase in economic welfare, we need to consider the extent to which the rebuilding program draws capital and labor away from the production of goods and services that give people pleasure.

This consideration leads us to focus on private consumption as the central component in measuring welfare. But what aspects of private consumptions should be included and excluded, and what about public consumption?

For assessing the welfare effects of a terrorism incident we decided to exclude private expenditures on health and relocation from our welfare-relevant measure of consumption. Thus, we capture the idea that a terrorism event which imposes additional health and relocation costs on households is, on this account, welfare reducing. It causes households to divert expenditure away from things that give pleasure towards rehabilitation spending. This diversion might be immediate if households finance the expenditures or it might be delayed if the expenditures are subsidized by the government and paid for later by households through tighter macro policy necessitated by debt reduction. However the timing of the diversion doesn't make any difference to the decision to exclude from welfare household rehabilitation expenditures that wouldn't have taken place in the absence of the incident.

In general, there is a case for including public expenditure in measures of welfare. However, here we exclude it. This is clearly appropriate for the target city in which we allow for public rehabilitation expenditures. As with private rehabilitation expenditures these should be excluded from welfare. In regions outside the target city we assume that terrorism events cause the same percentage deviation in public expenditure as in private expenditure. With welfare measured in percentage deviation terms, the exclusion of public consumption makes almost no difference to our calculation of welfare rankings.

Remaining issues are distribution, timing (dynamics) and loss of life. On distribution, we have adopted a utilitarian approach. We don't distinguish between a

[7]These are real discount rates, that is they are applied after correcting values of future variables for changes in the price level.

dollar of lost consumption for a rich household and a poor household. This is more a necessity than a carefully chosen assumption: our present model treats households in each region as a single entity.

On timing, the issue comes down to the discount rate and the terminal conditions. On the discount rate, there are arguments in the literature suggesting rates anywhere between 1 and 15%.[8] The U.S. Office of Management and Budget favors the use of U.S. bond rates as discount rates[9]. Given the uncertainty surrounding the appropriate choice, we decided to produce results for two rates: 5% which we consider high and 2% which we consider low. A discount rate of 5% means that the loss of $1 of consumption next year is equivalent to the loss of $0.95 this year while a discount rate of 2% means that the loss of $1 of consumption next year is equivalent to the loss of $0.98 this year.[10] Terminal conditions are necessary because computations must be finite. As mentioned earlier, we end the computations at year 20, 2034. At the end of year 20, we must take account of how the terrorism incident in year 1 has affected the stock of U.S. wealth. If this stock is lower at the end of year 20 in the terrorism run than in the baseline run, then this is a welfare loss additional to that associated with reductions in consumption in years 1 to 20. We measure the stock of U.S. wealth by the value of physical assets in the U.S. (buildings, machines, houses, infrastructure) less U.S. net foreign liabilities. For inclusion in our welfare measure, the stock of wealth is adjusted for inflation (that is we consider real wealth) and we also apply a time-preference discount rate of either 5% or 2% a year, giving a discount factor for real wealth held at the end of year 20 of 0.341 or 0.651 (= 0.95^21 or 0.98^21, which discounts from the end of year 20 to the start of year 0).

The final factor in our welfare measure is an allowance for death. Our modeling already takes account of lost output associated with reduced labor supply. What we have in mind here is pain and suffering for surviving family members. We have assumed $9.6 million per death. This is the number recommended by the Chief Regulatory Economist at DHS.[11] As discussed below, it is relatively simple to check the sensitivity of welfare results to the assumed value for death. Re-computation of USAGE-TERM solutions is not required.

In mathematical terms we measure the welfare effect of a terrorism incident occurring in 2015 according to the formula

---

[8]See for example, Harrison (2010) and Garnaut (2016, Sect. 3.1).

[9]See https://www.federalregister.gov/documents/2011/02/11/2011-3044/discount-rates-for-cost-effectiveness-analysis-of-federal-programs

[10]We assume zero inflation or equivalently that next year's dollar is adjusted for inflation.

[11]DHS is following the Department of Transportation, see https://www.transportation.gov/sites/dot.gov/files/docs/VSL%20Guidance%202016.pdf. For earlier estimates of the value of life see Partnoy (2012).

$$
\begin{aligned}
PV_{2014}dWELFARE = & \sum_{t=2015}^{2034} (1-DR)^{t-2014} * \left(\frac{C(t)/POP(t)}{CB(t)/POPB(t)} - 1 \right) \\
& + (1-DR)^{2035-2014} * KCRatio * \left(\frac{K(2035)/POP(2035)}{KB(2035)/POPB(2035)} - 1 \right) \\
& - (1-DR)^{2035-2014} * GDPCRatio * \left(\frac{NFLGDP(2035)/POP(2035)}{NFLGDPB(2035)/POPB(2035)} - 1 \right) \\
& - \frac{(1-DR)}{CB(2014)} * VLIFE * [POPB(2015) - POP(2015)]
\end{aligned}
\tag{6.6}
$$

In this formula, the LHS is the present value in 2014 of welfare changes caused by the terrorism incident. The first term on the RHS is the present value of the deviations in private consumption per capita from 2015 to 2034 caused by the incident in 2015. This is calculated by comparing for each year t the consumption level per capita in the terrorism run, C(t)/POP(t), with the consumption level per capita in the baseline run, CB(t)/POPB(t). C(t) and CB(t) are index numbers for real private consumption, excluding rehabilitation expenditures. POP(t) and POPB(t) are population numbers. The per capita consumption deviations are discounted back to 2014 (year 0). DR is the discount rate, set at either 0.05 or 0.02.

The second term on the RHS allows for the terminal deviation in the capital stock per capita. The deviation is calculated by comparing the quantity of U.S. capital per capita in 2035 in the terrorism run, K(2035)/POP(2035), with the quantity per capita in the baseline, KB(2035)/POPB(2035). This is turned into units that are comparable with consumption by multiplying by the ratio of the value of capital stock to consumption in 2014, KCRatio. Finally we discount back to 2014 by applying the factor (1-DR)^21.

The third term on the RHS allows for the terminal deviation in net foreign liabilities per capita. The variable we use is net foreign liabilities per capita expressed as a ratio of GDP. We compare this ratio in 2035 in the terrorism run, NFLGDP (2035)/POP(2035), with the ratio in the baseline run, NFLGDPB(2035)/POPB (2035). To convert to consumption units we multiply by the ratio of GDP to consumption in 2014, GDPCRatio. Again we discount back to 2014 by applying the factor (1-DR)^21.

The last term on the RHS of Eq. (6.6) allows for deaths. We assume that these take place in 2015 and are measured by POPB(2015) minus POP(2015). The number of deaths is multiplied by the value of life, VLIFE. This product is expressed as a fraction of consumption in 2014 and discounted back one year to 2014.

As mentioned earlier, we set VLIFE at $9.6 million. The effect on welfare results of varying this number can be worked out without reference to USAGE-TERM. For example, if we wanted to set VLIFE at \$7.7 m[12] with DR = 0.05, then we would modify welfare results based on VLIFE = \$9.6 m and DR = 0.05 according to:

$$\begin{aligned} \text{Welfare}(\text{DR} = 0.05, \text{VLIFE} = 7.7) = {} & \text{Welfare}(\text{DR} = 0.05, \text{VLIFE} = 9.6) \\ & + (1 - 0.05) * \frac{(9.6 - 7.7) * 10^6}{9663046 * 10^6} \\ & * [\text{POPB}(2015) - \text{POP}(2015)] \end{aligned} \tag{6.7}$$

In Eq. (6.7), 9,663,046 × 10^6 is the value of CB(2014).

Given the form of Eq. (6.6), what interpretation should be attached to a simulation that produces the result:

$$\text{PV}_{2014}\text{dWELFARE} = -0.01? \tag{6.8}$$

We should think of this as implying that the economic damage caused by the terrorism incident being examined is equivalent to a loss of 1% of welfare-generating consumption in 2014. Looked at like this, we can see that Eq. (6.6) is a similar approach to measuring welfare as Compensating Variation (CV) and Equivalent Variation (EV). These measures summarize the welfare effect of a change in the economic environment by calculating what would be a comparable loss of money or income that could otherwise have been devoted to pleasure-generating consumption (utility). For example, we would need a 1% boost in the present value of income to allow us to increase consumption and wealth sufficiently to compensate for the damage encapsulated in Eq. (6.8).

6.6 Estimating of the Elasticity Coefficients, E_A(s,d,v), Using USAGE-TERM

From a conceptual point of view, the most obvious method for estimating the E coefficients is to set up a 436-region version of USAGE-TERM and then perform 14 by 170 by 2 simulations: 14 shocks applied to 170 regions of interest by 2 sets of assumptions (Keynesian or Neoclassical). Results from these simulations could be recorded for our 10 economic implication variables. Elasticities would then be formed by dividing results by shocks. For this project we have chosen to work at a 23-industry level with the solution covering 20 years. Even with this quite high level of industry aggregation and with time truncated to 20 years, computation with a 436-region model is infeasible. Consequently to estimate the elasticities for Eq. (6.5), we must find a different way of handling the regional dimension.

[12]This is an average of the numbers used by the Environmental Protection Agency, the Food and Drug Administration and the Department of Transformation in 2012, see Partnoy (2012).

The next method we considered was to create 170 4-region models, each identifying one of the 170 congressional districts of interest as a target region together with 3 other regions that we refer to as Rest of city, Rest of state and Rest of U.S. Then, with each of the 170 models we could conduct 28 simulations (14 under each of 2 assumptions) to determine elasticities of the 10 economic implication variables with respect to the shocks. Computations with the first model would reveal $E_A(s,1,v)$ for both As and all s and v. Computations with the second model would reveal $E_A(s,2,v)$, and so on. In this way, we could build up estimates of $E_A(s,d,v)$ for each of the 170 values of d. Computations with a 23-industry, 4-region, 20-year model are relatively straightforward. However, we judged that it would be unmanageable to build 170 models each with 4 regions, 23 industries and 20 years and then process the outputs from 28 simulations with each model. This approach would involve about 190,000[13] annual solutions which, inevitably, would need to be repeated many times in the process of ironing out bugs and moving to a usable set of elasticities.

This brought us to a third method, and the one that we implemented. Instead of creating 170 4-region models, we created only 4 such models. As explained in the next subsection, we use results from these 4 models to generate elasticity estimates for terrorism incidents in all 170 congressional districts of interest.

The target congressional districts in our 4 USAGE-TERM models are FL24 in Miami, AZ07 in Phoenix, NY14 in New York and WA09 in Seattle. We judged that this selection gives a reasonable coverage of U.S. city types: medium to large; east coast, west coast and central.

In each of our 4 models we used a distance algorithm to determine the congressional districts that make up "Rest of city", "Rest of State" and "Rest of U.S." We did not interpret these names literally. Rest of city consists of those congressional districts, excluding the target region, whose geographic centre is no more than 25 miles from that of the target region. Together the target region and the Rest of city form the Target city. In most cases, Rest of state consists of those congressional districts whose geographic center is between 25 and 150 miles from that of the target region. All other congressional districts form Rest of U.S. We made an exception to the rule for Rest of state in the densely populated North east of the U.S. There, Rest of state is the set of congressional districts whose geographic centre is between 25 and 75 miles from that of the target region. Application of these rules generates some cases in which there is no Rest of city: the target region and the Target city are the same. For these cases our 4-region model would have only 3 regions.

[13]This is calculated as 170 models times 20 years times 14 shocks times 2 runs (baseline and perturbation) times 2 sets of assumptions (Keynesian and Neoclassical).

6.6.1 Turning 8 Matrices into 340 Matrices: The Theory of the Relevant Variable Approach

We used our 4 models to compute 8 matrices: E_A(•,FL24,•), E_A(•,AZ07,•), E_A(•,NY14,v) and E_A(•,WA09,•) for both assumptions A (Keynesian and Neoclassical).[14] This was a large but manageable computational task requiring 4480 annual solutions (4 models times 20 years times 14 shocks times 2 runs times 2 assumptions), repeated several times to incorporate refinements following analysis of preliminary results. How should we use these 8 matrices to develop Keynesian and Neoclassical matrices for all 170 congressional districts?

One idea that can be quickly dismissed is that we should use the same Keynesian and Neoclassical matrices for each congressional district, some sort of average of matrices obtained from the USAGE-TERM simulations for the 4 models. However it is clear that the matrices should vary across congressional districts. For example, the effect on GDP of destruction of *x%* of the capital in a congressional district depends on the quantity of capital in that congressional district: the effect will be greater for districts that have a lot of capital than for districts that have only a small amount of capital. We would expect destruction of *x%* of the capital in a congressional district with \$150 billion worth of capital to reduce the nation's GDP by about twice as much as the destruction of *x%* of the capital in a congressional district with \$75 billion worth of capital. This leads us to the idea of relevant variables.

For each s, v and A, can we find an observable variable RV(s,d,v) for which there exists a coefficient, C_A(s,v), independent of d, such that:

$$E_A(s,d,v) = C_A(s,v) * RV(s,d,v) \qquad \text{for all d?} \tag{6.9}$$

We refer to RV as a relevant variable. The idea of the relevant variable is to capture data differences across regions that explain elasticity differences across regions. Notice that we assume that the same relevant variable will be adequate under either assumption A. This is not theoretically necessary but proved to be a non-damaging simplification. If a relevant variable exists for s and v, and we know the value for a particular d of the elasticity, E_A(s,d,v), then we can deduce the value of the coefficient C_A(s,v). From there we can compute E_A(s,d,v) for all d.

To clarify, we consider the example of s equals capital destruction and v equals GDP. As we have already suggested it is reasonable to suppose that the elasticity of the nation's GDP in year 1 with respect to capital destruction in any congressional district is proportional to the amount of capital in that district, that is, there exists a factor of proportionality, which we can denote by C, such that

[14] E_A(•,d,•) is the 14 by 10 matrix with components E_A(s,d,v).

$$\begin{aligned} E_A(\text{K-destruct}, d, \text{GDP}) = {} & C_A(\text{K-destruct}, \text{GDP}) \\ & * RV(\text{K-destruct}, d, \text{GDP}) \quad \text{for all } d \end{aligned} \tag{6.10}$$

where

E_A(K-destruct,d, GDP) is the elasticity of GDP in year 1 with respect to capital destruction in region d under assumption A;
RV(K-destruct,d,GDP) is the quantity of capital in region d, or more conveniently the share of the nation's capital that is located in region d; and
C_A(K-destruct, GDP) is the factor of proportionality under assumption A.

If we have evaluated E_A for a particular d, say FL24, and we know the values of the RV's, then we can evaluate C_A(K-destruct, GDP) as

$$C_A(\text{K-destruct}, \text{GDP}) = \frac{E_A(\text{K-destruct}, \text{FL24}, \text{GDP})}{RV(\text{K-destruct}, \text{FL24}, \text{GDP})} \tag{6.11}$$

allowing us to estimate E_A(K-destruct,d, GDP) for all d via Eq. (6.10).

How can we find relevant variables and how can we know that they are legitimate, that is have the proportionality property described in Eq. (6.9)?

From our knowledge of the theory and data of USAGE-TERM we make guesses of relevant variables. For example, we have guessed that

$$RV(\text{K-destruct}, d, \text{GDP}) = \frac{\text{VAL\_K}(d)}{\text{VAL\_K\_NAT}} \tag{6.12}$$

is a legitimate relevant variable for s equals capital destruction and v equals GDP where

VAL_K(d) is the value of capital in region d; and
VAL_K_NAT is the value of capital in the nation.

To check the validity of the guesses for the relevant variable for any s,v pair we can calculate

$$C_A^{\text{FL24}}(s, v) = \frac{E_A^{\text{FL24}}(s, \text{FL24}, v)}{RV^{\text{guess}}(s, \text{FL24}, v)} \tag{6.13}$$

$$C_A^{\text{AZ07}}(s, v) = \frac{E_A^{\text{AZ07}}(s, \text{AZ07}, v)}{RV^{\text{guess}}(s, \text{AZ07}, v)} \tag{6.14}$$

$$C_A^{\text{NY14}}(s, v) = \frac{E_A^{\text{NY14}}(s, \text{NY14}, v)}{RV^{\text{guess}}(s, \text{NY14}, v)} \tag{6.15}$$

$$C_A^{WA09}(s,v) = \frac{E_A^{WA09}(s, WA09, v)}{RV^{guess}(s, WA09, v)} \tag{6.16}$$

where

$E_A^{FL24}(s, FL24, v)$, $E_A^{AZ07}(s, AZ07, v)$, etc., are elasticities calculated from our 4 models, which we take as the true elasticities;

RV^{guess} refers to our guess for the relevant variable, e.g. capital share; and

$RV^{guess}(s, FL24, v)$, $RV^{guess}(s, AZ07, v)$, etc. are the observed values of this variable for FL24, AZ07 etc.

We say that RV^{guess} is a legitimate relevant variable for the s,v pair if there is little variation across the 4 values $C_A^{FL24}(s,v)$, $C_A^{AZ07}(s,v)$, $C_A^{NY14}(s,v)$ and $C_A^{WA09}(s,v)$ for each A.

If for a given A the 4 values are not close, then we must think more deeply about the theory and data of the model to come up with a refined guess of the relevant variable. As well as meeting the immediate requirement of obtaining proportionality factors (C coefficients) that are consistent across our 4 models, the process of finding legitimate relevant variables is a valuable way of understanding key features of USAGE-TERM and of checking for unrealistic specifications and errors. Once we were satisfied that the C coefficients were as uniform as possible across the 4 models, we averaged them and calculated the elasticities for all 170 congressional districts of interest to the TRA groups according to:

$$E_A^{TRA}(s,d,v) = C_A^{ave}(s,v) * RV(s,d,v) \tag{6.17}$$

where

$C_A^{ave}(s,v)$ is the average value across the four models of the s,v-coefficients under assumption A; and

RV(s,d,v) is the value for region d of the relevant variable for shock s and implication variable v.

The results from the four models for the coefficients, C_A(s,v), and the definitions of the relevant variables, RV(s,d,v), are set out and discussed in our working paper (see Dixon et al. 2017a). In brief, we found satisfactory RV variables for all shocks s when v is a national implication variable (GDP, national employment and welfare). However for some s's and some regional implication variables the RV variables left considerable variation across the four C_A coefficients calculated in Eqs. (6.13) to (6.16). This means that we can be less confident about regional results derived from the elasticities Eq. (6.5) than about national results.

6.6.2 Sample Elasticity Matrices

On the basis of Eq. (6.17) we supplied the TRA groups with 170x2 matrices of elasticities (170 target regions times 2 assumptions). Each matrix has 14 rows (shock variables) and 10 columns (implication variables). Sample elasticity matrices are given in Tables 6.1, 6.2, 6.3, and 6.4.

6.6.2.1 Understanding the Nature of the Underlying Shocks and the Resulting Elasticities

Focusing on Table 6.1, we see that the first entry is −0.0013. This means under Keynesian assumptions that the destruction of 1% of the capital in FL24 would reduce the nation's GDP in year 1 (2015) by 0.0013%. Moving along the first row we see that destruction of 1% of capital in FL24 would reduce national employment in year 1 by 0.0009%. The percentage effects in FL24 would be much greater. This can be seen in the 3rd and 4th entries in the first row which imply reductions in FL24's output (GRP) and employment of 0.7828% and 0.6304%. Continuing along the first row, we see that the long run (year 20) effects on national output and employment of capital destruction in FL24 are negligible. Even in FL24, the long-run effects are small (−0.0145% and 0.0078%). Although the economy would recover from capital destruction in FL24, the event would have a noticeable negative effect on national economic welfare. This is shown in the last two columns of row 1. Under a 5% discount rate, replacement of destroyed capital (requiring extra savings and loss of consumption) would reduce national welfare accumulated over years 1 to 20 by an amount equivalent to the loss of 0.0076% of a single year's consumption. When future losses of consumption are discounted at a lower rate (2% rather than 5%) the national welfare loss from destruction of 1% of FL24's capital becomes 0.0101%.

Row 2 of Table 6.1 shows under Keynesian assumptions the percentage effects on the 10 implication variables of a reactivation of 1% of FL24's capital taking place at the beginning of year 2. Elasticities in this row can be used in conjunction with those in row 1 to handle scenarios in which there is both capital destruction and temporary capital contamination. For example, for a scenario in which 10% of capital in FL24 is taken out of use in year 1, with 7% being destroyed and 3% being contaminated, we would conduct a simulation in which 10% is "destroyed" in year 1 and 3% is reactivated at the beginning of year 2. The effects of the 10% capital destruction would be captured via elasticities from row 1 while the effects of capital reactivation would be captured via elasticities from row 2. In this way, we would ascertain the effects of losing 7% of FL24's capital permanently but losing the use of 3% only temporarily (for 1 year). Reactivation of capital at the beginning of year 2 has zero effect on variables in year 1 and negligible effects in year 20. The welfare effects are approximately the same as those for capital destruction but with opposite sign.

Table 6.1 Elasticities for incident in FL24 with Keynesian assumptions: % effects on implication variables of 1% shocks to driving variables

	Implication variables									
Driving variables	National GDP Year 1	National employment Year 1	Target region GRP Year 1	Target region employment Year 1	National GDP Year 20	National employment Year 20	Target region GRP Year 20	Target region employment Year 20	National welfare Accumulated years 1 to 20, discount rate 0.05	National welfare Accumulated years 1 to 20, discount rate 0.02
1. Value of capital taken out of use in target region	−0.0013	−0.0009	−0.7828	−0.6304	0.0000	0.0000	−0.0145	0.0078	−0.0076	−0.0101
2. Value of capital returned to use after 1 year in target region	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	0.0324	−0.0011	0.0073	0.0101
3. Public expenditure in target city, clean-up	0.0017	0.0016	0.0866	0.0917	0.0000	0.0000	−0.0012	−0.0002	−0.0001	−0.0005
4. Public health expenditures in target city	0.0001	0.0001	0.0073	0.0088	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5. Accommodation expenses in target city	0.0002	0.0002	0.0073	0.0080	0.0000	0.0000	0.0002	0.0001	−0.0001	−0.0001
6. Accommodation expenses outside target city	0.0303	0.0280	0.0132	0.0108	0.0002	0.0001	0.0000	0.0000	−0.0138	−0.0229
7. Loss of foreign visitor expenditure in target city	−0.0012	−0.0010	−0.0448	−0.0402	0.0000	0.0000	0.0000	0.0000	−0.0008	−0.0008
8. Loss of foreign visitor expenditure outside target city	−0.0126	−0.0104	−0.0114	−0.0096	0.0000	0.0000	0.0000	0.0000	−0.0086	−0.0090
9. Loss of domestic traveler expenditure in target city	0.0000	0.0000	−0.0804	−0.0708	0.0000	0.0000	−0.0003	−0.0003	0.0000	0.0000
10. Loss of domestic traveler expenditure outside target city	−0.0360	−0.0284	−0.0237	−0.0191	0.0000	−0.0001	0.0000	−0.0001	−0.0263	−0.0238
11. Loss of food production in target state	−0.0012	−0.0009	−0.0335	−0.0261	0.0000	0.0000	0.0001	0.0001	−0.0009	−0.0010
12. Total loss of food production in U.S. including target state	−0.1421	−0.1012	−0.1310	−0.1179	−0.0004	−0.0005	−0.0013	−0.0004	−0.0999	−0.1020
13. Deaths and serious injuries, permanent removal from work (people)	−0.5470	−0.6131	−51.3175	−56.4681	−0.9546	−0.9873	−0.0130	−0.0096	−298.6371	−307.3186
14. Aversion, per cent reduction in labor supply to target region	0.0000	0.0000	−0.4354	−0.4796	0.0000	0.0000	−0.8123	−0.8927	0.0000	0.0000

Table 6.2 Elasticities for incident in FL24 with Neoclassical assumptions: % effects on implication variables of 1% shocks to driving variables

	Implication variables									
Driving variables	National GDP Year 1	National employment Year 1	Target region GRP Year 1	Target region employment Year 1	National GDP Year 20	National employment Year 20	Target region GRP Year 20	Target region employment Year 20	National welfare Accumulated years 1 to 20, discount rate 0.05	National welfare Accumulated years 1 to 20, discount rate 0.02
1. Value of capital taken out of use in target region	−0.0013	−0.0009	−0.7828	−0.6304	0.0000	0.0000	−0.0145	0.0078	−0.0076	−0.0101
2. Value of capital returned to use after 1 year in target region	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	0.0324	−0.0011	0.0073	0.0101
3. Public expenditure in target city, clean-up	0.0007	0.0013	0.0211	0.0430	0.0000	0.0000	−0.0009	−0.0003	−0.0006	−0.0009
4. Public health expenditures in target city	0.0000	0.0001	0.0023	0.0044	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001
5. Accommodation expenses in target city	0.0001	0.0001	0.0035	0.0053	0.0000	0.0000	0.0003	0.0002	−0.0001	−0.0002
6. Accommodation expenses outside target city	0.0085	0.0129	0.0018	0.0041	0.0000	0.0000	−0.0001	0.0000	−0.0231	−0.0324
7. Loss of foreign visitor expenditure in target city	−0.0002	−0.0003	−0.0089	−0.0115	0.0000	0.0000	−0.0002	−0.0001	−0.0004	−0.0005
8. Loss of foreign visitor expenditure outside target city	−0.0020	−0.0029	−0.0020	−0.0039	0.0000	0.0000	0.0001	0.0000	−0.0040	−0.0045
9. Loss of domestic traveler expenditure in target city	0.0000	0.0000	−0.0182	−0.0218	0.0000	0.0000	−0.0002	0.0000	0.0000	0.0000
10. Loss of domestic traveler expenditure outside target city	−0.0044	−0.0064	−0.0019	−0.0054	0.0002	0.0000	0.0002	0.0000	−0.0125	−0.0102
11. Loss of food production in target state	−0.0013	−0.0011	−0.0133	−0.0101	0.0000	0.0000	0.0000	0.0000	−0.0002	−0.0002
12. Total loss of food production in U.S. including target state	−0.0539	−0.0373	−0.0208	−0.0479	0.0003	0.0000	0.0012	−0.0001	−0.0631	−0.0655
13. Deaths and serious injuries, permanent removal from work (people)	−0.2086	−0.3564	−19.8407	−33.3864	−0.9552	−0.9910	−0.0145	−0.0099	−298.6014	−307.2679
14. Aversion, per cent reduction in labor supply to target region	0.0000	0.0000	−0.1478	−0.2488	0.0000	0.0000	−0.8142	−0.8930	0.0000	0.0000

Table 6.3 Elasticities for incident in CA34 with Keynesian assumptions: % effects on implication variables of 1% shocks to driving variables

Driving variables	Implication variables									
	National GDP Year 1	National employment Year 1	Target region GRP Year 1	Target region employment Year 1	National GDP Year 20	National employment Year 20	Target region GRP Year 20	Target region employment Year 20	National welfare Accumulated years 1 to 20, discount rate 0.05	National welfare Accumulated years 1 to 20, discount rate 0.02
1. Value of capital taken out of use in target region	−0.0019	−0.0012	−0.8668	−0.6980	0.0000	0.0000	−0.0160	0.0087	−0.0109	−0.0146
2. Value of capital returned to use after 1yr in target region	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	0.0359	−0.0013	0.0104	0.0145
3. Public expenditure in target city, clean-up	0.0069	0.0063	0.0579	0.0613	0.0000	0.0000	−0.0008	−0.0001	−0.0002	−0.0021
4. Public health expenditures in target city	0.0005	0.0005	0.0050	0.0061	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0002
5. Accommodation expenses in target city	0.0011	0.0010	0.0134	0.0147	0.0000	0.0000	0.0003	0.0002	−0.0005	−0.0008
6. Accommodation expenses outside target city	0.0294	0.0271	0.0151	0.0124	0.0001	0.0001	0.0000	0.0001	−0.0133	−0.0222
7. Loss of foreign visitor expenditure in target city	−0.0010	−0.0008	−0.0088	−0.0079	0.0000	0.0000	0.0000	0.0000	−0.0007	−0.0007
8. Loss of foreign visitor expenditure outside target city	−0.0129	−0.0106	−0.0116	−0.0098	0.0000	0.0000	0.0000	0.0000	−0.0088	−0.0092
9. Loss of domestic traveler expenditure in target city	0.0000	0.0000	−0.0172	−0.0151	0.0000	0.0000	−0.0001	−0.0001	0.0000	0.0000
10. Loss of domestic traveler expenditure outside target city	−0.0360	−0.0284	−0.0282	−0.0228	0.0000	−0.0001	0.0000	−0.0001	−0.0263	−0.0238
11. Loss of food production in target state	−0.0048	−0.0034	−0.0634	−0.0495	−0.0001	−0.0001	0.0002	0.0001	−0.0038	−0.0041
12. Total loss of food production in U.S. including target state	−0.1421	−0.1012	−0.2754	−0.2479	−0.0004	−0.0005	−0.0027	−0.0009	−0.0999	−0.1020
13. Deaths and serious injuries, permanent removal from work (people)	−0.5470	−0.6131	−8.5104	−9.3645	−0.9546	−0.9873	−0.0270	−0.0198	−298.6371	−307.3186
14. Aversion, per cent reduction in labor supply to target region	0.0000	0.0000	−0.4425	−0.4874	0.0000	0.0000	−0.8256	−0.9073	0.0000	0.0000

Table 6.4 Elasticities for incident in CA34 with Neoclassical assumptions: % effects on implication variables of 1% shocks to driving variables

	Implication variables									
Driving variables	National GDP Year 1	National employment Year 1	Target region GRP Year 1	Target region employment Year 1	National GDP Year 20	National employment Year 20	Target region GRP Year 20	Target region employment Year 20	National welfare Accumulated years 1 to 20, discount rate 0.05	National welfare Accumulated years 1 to 20, discount rate 0.02
1. Value of capital taken out of use in target region	−0.0019	−0.0012	−0.8668	−0.6980	0.0000	0.0000	−0.0160	0.0087	−0.0109	−0.0146
2. Value of capital returned to use after 1 year in target region	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	0.0359	−0.0013	0.0104	0.0145
3. Public expenditure in target city, clean-up	0.0027	0.0052	0.0141	0.0287	0.0000	0.0000	−0.0006	−0.0002	−0.0022	−0.0038
4. Public health expenditures in target city	0.0001	0.0003	0.0016	0.0031	0.0000	0.0000	0.0000	0.0000	−0.0002	−0.0002
5. Accommodation expenses in target city	0.0003	0.0005	0.0063	0.0096	0.0000	0.0000	0.0006	0.0003	−0.0008	−0.0012
6. Accommodation expenses outside target city	0.0082	0.0125	0.0021	0.0047	0.0000	0.0000	−0.0001	0.0000	−0.0224	−0.0314
7. Loss of foreign visitor expenditure in target city	−0.0002	−0.0002	−0.0017	−0.0023	0.0000	0.0000	0.0000	0.0000	−0.0003	−0.0004
8. Loss of foreign visitor expenditure outside target city	−0.0021	−0.0030	−0.0020	−0.0039	0.0000	0.0000	0.0001	0.0000	−0.0041	−0.0046
9. Loss of domestic traveler expenditure in target city	0.0000	0.0000	−0.0039	−0.0047	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10. Loss of domestic traveler expenditure outside target city	−0.0044	−0.0064	−0.0023	−0.0064	0.0002	0.0000	0.0002	0.0000	−0.0125	−0.0102
11. Loss of food production in target state	−0.0051	−0.0045	−0.0252	−0.0191	0.0000	0.0000	−0.0001	0.0000	−0.0008	−0.0009
12. Total loss of food production in U.S. including target state	−0.0539	−0.0373	−0.0438	−0.1008	0.0003	0.0000	0.0026	−0.0003	−0.0631	−0.0655
13. Deaths and serious injuries, permanent removal from work (people)	−0.2086	−0.3564	−3.2903	−5.5367	−0.9552	−0.9910	−0.0300	−0.0205	−298.6014	−307.2679
14. Aversion, per cent reduction in labor supply to target region	0.0000	0.0000	−0.1502	−0.2529	0.0000	0.0000	−0.8275	−0.9075	0.0000	0.0000

Row 3 of Table 6.1 shows under Keynesian assumptions the percentage effects on the 10 implication variables of a temporary[15] 1% boost in public expenditure throughout FL24's city. These elasticities are used in calculating the effects of clean-up expenditures. Notice that unlike capital destruction, we assume that clean-up expenditures take place throughout the Target city (FL24 plus nearby congressional districts). It is reasonable to suppose that clean-up would be conducted by the use of capital and labor located in the Target city, not just the target congressional district, FL24. Under Keynesian assumptions, a 1% increase in public expenditure in FL24's city stimulates the nation's output and employment in year 1 by 0.0017 and 0.0016%, and FL24's output and employment by 0.0866 and 0.0917%. By year 20, the output and employment effects have faded away at the national level and are tiny negatives at the FL24 level (−0.0012 and −0.0002). Despite stimulation of the economy in year 1, the national welfare effects of the 1% boost in public expenditure in FL24's city are negative (−0.0001 and −0.0005 with 5% and 2% discount rates). Extra public expenditure in year 1 leads to higher public debt. This induces tighter fiscal policy which reduces consumption (and therefore welfare) after year 1.

Row 4 of Table 6.1 shows under Keynesian assumptions the percentage effects of a temporary (1 year) 1% boost in public health expenditure throughout FL24's city. These elasticities are much smaller than those in Row 3 because public health expenditure is small relative to total public expenditure. The long-run effects of a 1% boost in public health expenditure in FL24's city are too small to register at 4 decimal places.

The TRA scenarios contain separate items for accommodation expenditure in the Target city and outside the Target city for displaced people. Rows 5 and 6 of Table 6.1 show, under Keynesian assumptions, elasticities with respect to accommodation expenditure in FL24's city and outside FL24's city. At the national level, a 1% increase in accommodation expenditure in FL24's city has only small effects (output and employment effects of 0.0002% in year 1and zero in year 20). A 1% increase in accommodation expenditure outside FL24's city is a much larger shock. Consequently, the year-1 national elasticities in row 6 (0.0303 and 0.0280) are much larger than the corresponding elasticities in row 5. Even for FL24, the year-1 elasticities are greater for accommodation expenditure outside FL24's city than for accommodation expenditure in FL24's city.

Despite the year-1 boosts in the output and employment from increased accommodation expenditure, the welfare effects in rows 5 and 6 of Table 6.1 are negative.

Similarly, the TRA scenarios contain separate items for loss of foreign visitor expenditure in the target city and outside the target city. Rows 7 and 8 of Table 6.1 show, under Keynesian assumptions, elasticities with respect to a temporary loss of foreign visitor expenditure in FL24's city and outside FL24's city. As with rows 5 and 6, the year-1 national elasticities in row 8 for the shock outside FL24's city are

[15] After 1 year, public expenditure returns to its baseline path. We adopt this approach for all of the expenditure shocks (rows 3 to 6).

much larger in absolute size than those in row 7 for the shock in FL24's city. Again, this reflects the much larger magnitude of the shocked variable for outside FL24's city than for in FL24's city. By contrast with rows 5 and 6, the elasticities for year-1 output and employment in FL24 are larger in absolute size for the own city shock than for the outside city shock (−0.0448 and −0.0402 in row 7 compared with −0.0114 and −0.0096 in row 8). This reflects the high level of importance of foreign tourism to FL24's city (Miami).

The next pair of rows in Table 6.1 (rows 9 and 10) show, under Keynesian assumptions, elasticities with respect to temporary loss of domestic visitor expenditure in FL24's city and outside FL24's city. The pattern of results for this pair of rows is qualitatively similar to that in the previous pair of rows: non-negligible year-1 national elasticities only for the outside shock (−0.0360 and −0.0284); relatively large year-1 FL24 elasticities for the shock to FL24's city (−0.0804 and −0.0708); and significant negative welfare elasticities only for the outside shock (−0.0263 and −0.0238).

The setup of the next pair of rows, 11 and 12, is slightly different from that of the previous pairs. Row 11 gives Keynesian elasticities with respect to loss of food production[16] in FL24's state, namely Florida,[17] holding constant total U.S. food output, and row 12 gives elasticities with respect to loss of food production in the U.S. holding constant food production in Florida. The difference between the set up in rows 11 and 12 and the earlier pairs is the "holding constant" condition. Even though U.S. food output is held constant in row 11, (implying the reduction in Florida is offset by an increase in the rest of the U.S.) the year-1 national output and employment elasticities are negative (−0.0012 and −0.0009). This is because the replacement of lost food from Florida requires diversion of resources towards food production in the rest of the U.S. and away from other productive activities. Even though Florida food output is held constant in row 12, the year-1 FL24 output and employment elasticities are negative (−0.1310 and −0.1179). This is because FL24 is damaged by its connection through trade with the Rest of the U.S. As in the earlier rows, the year-20 elasticities in rows 11 and 12 for output and employment at the national and regional levels are small. This reflects long-run recovery of the economy from the shock (in this case temporary loss of food production) imposed in year 1. Also consistent with the earlier rows, the negative shocks in year 1 produce negative accumulated welfare effects.

Row 13 shows effects of a loss of 1% of the population through deaths. These elasticities look very large relative to the other elasticities in Table 6.1. The row-13 elasticities are large because the shock is large, about 3.2 million deaths. With a life valued at $9.6 million (see Sect. 6.5), 3.2 million deaths translates into $30.72 trillion, about 3 times the value of a year's consumption. This is the reason that the welfare entries in the last two columns of row 13 are about −300%. There are

[16]Includes outputs of all agricultural and processed food products.

[17]FL24's "state" doesn't cover the whole of Florida. Nevertheless, for convenience we will refer to it as Florida.

also large entries for the year-1 FL24 output and employment elasticities (−51.3175 and −56.4681). In computing these elasticities, we assume that half the people who die are in the labor force and that in year 1, only half the deceased workers in FL24's city are replaced by incoming workers. Thus, there is a net loss of 800,000 workers in FL24's city. This translates into large percentage loses in employment and output in each of the city's 3 congressional districts, including FL24. Compared with earlier rows, row 13 shows relatively large negative year-20 national output and employment elasticities (−0.9546 and −0.9873). The loss of workers is permanent.

Row 14 shows aversion elasticities. These are elasticities of implication variables with respect to a permanent 1% reduction in labor supply to FL24. By this we mean a permanent shift in the supply curve so that at any given real wage, 1% less labor is supplied to FL24. Reflecting the permanent nature of the shock, there are significantly negative year-20 elasticities for FL24's output and employment (−0.8123 and −0.8927). By contrast, the national effects in both the short and long-runs are zero. Aversion merely changes the regional allocation of economic activity without affecting its total level.

6.6.2.2 Neoclassical Elasticities Versus Keynesian Elasticities

Table 6.2 gives the elasticity matrix calculated under Neoclassical assumptions for an event in FL24. Comparison of Tables 6.1 and 6.2 shows the effects of moving from Keynesian assumptions (high levels of unemployment and underutilization of capital in year 1) to Neoclassical assumptions (normal levels of unemployment and capital utilization in year 1).

The first two rows of Table 6.2 are the same as those in Table 6.1. We assume that capital destruction and reactivation have the same effects under the two assumptions. This makes sense if we assume that the particular capital which is destroyed or reactivated was fully used even in the Keynesian situation.

Rows 3 to 6 in Table 6.2 give Neoclassical elasticities for the 10 implication variables with respect to public expenditure, public health expenditure and accommodation expenditure. All of the year-1 elasticities in these rows have smaller positives values than the corresponding elasticities in Table 6.1. For example, in row 3 of Table 6.2 the Neoclassical elasticity of national GDP in year 1 with respect to public expenditure in FL24 is 0.0007 whereas the corresponding Keynesian elasticity in Table 6.1 is 0.0017. Under Neoclassical assumptions there is less scope for increased expenditures to cause short-run stimulation of the economy. With less favorable short-run impacts of expenditures, Table 6.2 shows less favorable accumulated welfare elasticities. For example, in row 6 of Table 6.2, the Neoclassical elasticity of welfare (5% discount) with respect to accommodation expenditures outside the target city is −0.0231. Table 6.1 shows the corresponding Keynesian elasticity as −0.0138.

Neoclassical elasticities for the effects of reductions in foreign and domestic visitor expenditures are in rows 7 to 10 of Table 6.2. The year-1 elasticities in these rows are negative but smaller in absolute terms than the corresponding

Keynesian elasticities in Table 6.1. In an economy experiencing normal levels of employment (Neoclassical assumptions), loss of tourism expenditures has a less depressing effect than is the case in an underemployed economy (Keynesian assumptions). Reflecting this, the accumulated welfare effects in rows 7 to 10 of Table 6.2 are less strongly negative than those in Table 6.1.

For loss of food output at the national level (row 12), the relationship between the Neoclassical elasticities in Table 6.2 and the Keynesian elasticities in Table 6.1 follows the same pattern as the elasticities in rows 7 to 10: the year-1 elasticities and welfare effects in Table 6.2 are negative but smaller in magnitude than those in Table 6.1. Loss of food output at the state level holding constant national output (row 11) has negligible national effects under either Keynesian or Neoclassical assumptions. At the regional level the year-1 Neoclassical elasticities are smaller in absolute size than the corresponding Keynesian elasticities. Again, the reason is that negative shocks do more damage in an under-employed economy than in an economy with normal levels of employment.

Comparison of row 13 (deaths) in Table 6.2 with that in Table 6.1 follows the usual pattern: negative year-1 elasticities and welfare elasticies that are smaller in absolute size in Table 6.2 than in Table 6.1. The row-13 welfare elasticities are only slightly smaller in absolute size in Table 6.2 than in Table 6.1 because the values of these elasticities are overwhelmingly determined by the direct contribution from loss of life which is the same in both tables.

Permanent aversion to working in FL24 has similar long-run national, regional and welfare effects under Neoclassical assumptions (row 14, Table 6.2) as under Keynesian assumptions (row 14, Table 6.1). The year-1 effects of aversion are less severe for FL24's economy under Neoclassical conditions than under Keynesian conditions (elasticities of -0.1478 and −0.2488 in Table 6.2 compared with −0.4354 and −0.4796 in Table 6.1).

6.6.2.3 Elasticities for Events in One Region Compared with Those for Another Region

Tables 6.3 and 6.4 give Keynesian and Neoclassical elasticities for shocks occurring in CA34. Qualitatively, the elasticities in these tables are similar to those in Tables 6.1 and 6.2. They all have the same signs and moving from Table 6.3 to Table 6.4, that is going from Keynesian to Neoclassical assumptions in CA34, shows similar effects to those we saw in comparing Tables 6.1 and 6.2 for FL24. In all cases, the differences between the elasticities in Tables 6.3 and 6.4 have the same signs as the differences between those in Tables 6.1 and 6.2.

While Tables 6.3 and 6.4 are qualitatively similar to Tables 6.1 and 6.2, the comparison shows at a quantitative level that the region in which an event takes place is potentially important. The differences in the elasticities as we move from one region to another reflect differences in the size and structure of the regional economies. To illustrate this, we consider a few examples starting with the elasticities in rows 1 and 2. The entries in these rows in Tables 6.3 and 6.4 are larger in absolute size than the corresponding entries in Tables 6.1 and 6.2. This reflects features of the USAGE-TERM database which shows a greater value for capital in CA34 than in FL24 and a larger capital share in the income of CA34 than in the income of FL24. For row 3, the greater absolute values for the year-1 national elasticities and welfare elasticities in Tables 6.3 and 6.4 than in Tables 6.1 and 6.2 are explained by CA34's city having larger total public expenditure than FL24's city. By contrast the year-1 regional elasticities in row 3 of Tables 6.3 and 6.4 are smaller in absolute size than the corresponding elasticities in Tables 6.1 and 6.2. This is because public expenditure in CA34's city is less important to the economy of CA34 than is the case for public expenditure in FL24's city to the economy of FL24. As a final example, consider row 7. Foreign visitors spend approximately the same amount of money in CA34's city as in FL24's city. Consequently the year-1 national elasticities and welfare elasticities are similar in row 7 of Tables 6.3 and 6.4 to those in row 7 of Tables 6.1 and 6.2. On the other hand, the year-1 regional elasticities are much smaller in absolute size in row 7 of Tables 6.3 and 6.4 than the corresponding elasticities in row 7 of Tables 6.1 and 6.2. This is because foreign visitor expenditure in CA34's city is not important to CA34 whereas foreign visitor expenditure in FL24's city is a major driver of activity in FL24.

6.7 Computing the Economic Implications of Three Illustrative Scenarios

This section illustrates how GRAD-ECAT converts shocks (s) into outcomes (v). Table 6.5 sets out shocks for 3 scenarios. Initially we will assume that the target region is FL24. Then we will look briefly at some results with the target region being CA34 rather than FL24.

The three scenarios are hypothetical and have no significance other than illustrating the workings of GRAD-ECAT. However, it is useful to give them labels. We refer to the first scenario as S1: Epidemic. This scenario has a large number of deaths (38,181, shown in the "absolute" column for S1), considerable public health expenditures ($3068.06 m), and large losses in foreign-visitor expenditure ($8836.55 m and $46,098.62 m). In the second scenario the standout item is an enormous clean-up bill ($62,691.14 m, shown in the "absolute" column for S2). This is combined with a significant death toll (1645). We refer to the second scenario as S2: Dirty bomb. The third scenario involves losses in agriculture/food production in the target state. There is no loss outside the target state. We refer to this scenario as S3: Food contamination.

Before we can apply GRAD-ECAT, the shocks must be converted into percentages. Assuming that the target region is FL24, this requires 2014 data available in USAGE-TERM for: the value of capital in FL24; the value of public expenditures in FL24's city (which consists of FL24, FL23 and FL27); the value of public health expenditure in FL24's city; the values of accommodation expenses in FL24's city and outside the city; the values of foreign and domestic visitor expenditure in FL24's

Table 6.5 Three example scenarios: absolute values and % shocks when target regions are FL24 and CA34

Driving factors	S1: Epidemic			S2: Dirty bomb			S3: Food contamination		
	absolute[a]	%, FL24	%, CA34	absolute[a]	%, FL24	%, CA34	absolute[a]	%, FL24	%, CA34
1. Value of capital taken out of use in target region	0	0	0	2621.59	2.8338	2.1222	0	0	0
2. Value of capital returned to use after 1 year in target region	0	0	0	2621.59	2.8338	2.1222	0	0	0
3. Public expenditure in target city, clean-up	393.30	2.4951	0.6185	62,691.14	397.7188	98.5943	48.61	0.3084	0.0764
4. Public sector health expenditures	3068.06	244.4013	60.5861	128.43	10.2307	2.5362	65.30	5.2018	1.2895
5. Accommodation expenses in target city	0	0	0	215.27	7.8594	1.3123	0	0	0
6. Accommodation expenses outside target city	0	0	0	215.27	0.0487	0.0502	0	0	0
7. Loss of foreign visitor expenditure in target city	8836.55	50.7424	62.8414	5847.72	33.5796	41.5862	3569.97	20.5000	25.3879
8. Loss of foreign visitor expenditure outside target city	46,098.62	25.3712	24.9115	22,180.09	12.2072	11.9860	18,623.84	10.2500	10.0643
9. Loss of domestic traveler expenditure in target city	14.57	0.0773	0.0849	1652.55	8.7624	9.6319	6.38	0.0338	0.0372
10. Loss of domestic traveler expenditure outside target city	0	0	0	0	0	0	0	0	0
11. Loss of food production in target state	0	0	0	0	0	0	210.00	1.3976	0.3205
12. Total loss of food production in U.S. including target state	0	0	0	0	0	0	210.00	0.0195	0.0195
13. Deaths & serious injuries, permanent removal from work	38,181	0.0119	0.0119	1645	0.0005	0.0005	493	0.0002	0.0002
14. Aversion, per cent reduction in labor supply to target region	NA	0	0	NA	10.0	10.0	0	0	0

[a]Absolute values are $m (2014 prices) except in row 13 where the unit is people and in row 14 when there are no absolute values

city and outside the city; the values of agriculture and food production in FL24's state (city *plus* FL07-09, FL14-22, FL25-26) and in the U.S.; and the U.S. population. The three scenarios from the "absolute" columns of Table 6.5 are converted to percentage change form in the columns marked "%, FL24" when the target region is FL24, and in the columns marked "%, CA34" when the target region is CA34. For a given scenario, the differences between the "%, FL24" and the "%, CA34" columns are due to differences in the 2014 data for FL24 and CA34. For example, Cleanup (row 3) in each of the three scenarios has a percentage shock that is 4.034 times larger in the "%, FL24" column than in the "%, CA34" column. This is because public expenditure in FL24's city is1/4.034 times that in CA34's city.

Tables 6.6 and 6.7 set out the GRAD-ECAT calculations of the effects of the Epidemic scenario occurring in FL24 under Keynesian and Neoclassical assumptions. The top panel in Table 6.6 is the Keynesian FL24 elasticity matrix, reproduced from Table 6.1. The bold emphasised column at the top right of Table 6.6 shows the percentage shocks for the Epidemic scenario, reproduced from Table 6.5. The lower panel is calculated by multiplying the elasticities by the shocks. Each component of the lower panel shows the contribution of the shock identified in the row to the outcome for the implication variable identified in the column. For example the contribution to national GDP in year 1 of the 2.4951% increase in public expenditures in FL24's city (row 3, Clean-up) under Keynesian assumptions is 0.00429% ($= 2.4951 \times 0.0017$). The total percentage effect of all the shocks on implication variables is the column sum of the contributions, shown in the last row. Table 6.7 sets out the calculations using Neoclassical elasticities from Table 6.2.

Comparing Tables 6.6 and 6.7, we see that the year-1 total effects for national variables are more negative under Keynesian assumptions than under Neoclassical assumptions. GDP and national employment decline by 0.35435 and 0.28808% under Keynesian assumptions (last row, first two columns of Table 6.6) whereas under Neoclassical assumptions they decline by only 0.05340 and 0.07339% (Table 6.7). This can be explained by looking at the contribution matrices. Under Keynesian assumptions the declines in visitor expenditures caused by the Epidemic make much larger negative contributions than under Neoclassical assumptions. For example, in row 8 column 1 of the contribution matrices we see a negative contribution to year-1 GDP from lost foreign-visitor expenditure of 0.32036 under Keynesian assumptions whereas the corresponding Neoclassical contribution is a negative of only 0.05143. This illustrates the point that losing visitor expenditures in an under-employed economy where new jobs are hard to obtain is much more economically damaging than in a normal-employment economy. Positive public expenditure shocks make larger positive year-1 contributions under Keynesian assumptions than under Neoclassical assumptions. For example, the Clean-up contribution to year-1 GDP under Keynesian assumptions is 0.00429, whereas under Neoclassical assumptions it is 0.00165. However, in the Epidemic scenario the stimulatory effects of extra public expenditures are only a minor offset to the depressing effects of lost foreign-visitor expenditures under either assumption.

Detailed study of the contribution matrices allows us to unravel seemingly mysterious results. For example, why does the Epidemic simulation show a negative

Table 6.6 Converting shocks into outcomes: epidemic scenario, FL24, Keynesian

	Elasticities FL24 Keynesian										Shocks
	GDPy1	EMPy1	GRPy1	RegEMPy1	GDPy20	EMPy20	GRPy20	RegEMPy20	Welf05	Welf02	
1KDestruct	−0.0013	−0.0009	−0.7828	−0.6304	0.0000	0.0000	−0.0145	0.0078	−0.0076	−0.0101	**0.0000**
2KReturn	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	0.0324	−0.0011	0.0073	0.0101	**0.0000**
3CleanUp	0.0017	0.0016	0.0866	0.0917	0.0000	0.0000	−0.0012	−0.0002	−0.0001	−0.0005	**2.4951**
4PubHealth	0.0001	0.0001	0.0073	0.0088	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**244.4013**
5AccomTarCity	0.0002	0.0002	0.0073	0.0080	0.0000	0.0000	0.0002	0.0001	−0.0001	−0.0001	**0.0000**
6AccOutsideTC	0.0303	0.0280	0.0132	0.0108	0.0002	0.0001	0.0000	0.0000	−0.0138	−0.0229	**0.0000**
7LostFgnVisTC	−0.0012	−0.0010	−0.0448	−0.0402	0.0000	0.0000	0.0000	0.0000	−0.0008	−0.0008	**50.7424**
8LostFgnVisOuTC	−0.0126	−0.0104	−0.0114	−0.0096	0.0000	0.0000	0.0000	0.0000	−0.0086	−0.0090	**25.3712**
9LostDomVisTC	0.0000	0.0000	−0.0804	−0.0708	0.0000	0.0000	−0.0003	−0.0003	0.0000	0.0000	**0.0773**
10LostDomVisOutTC	−0.0360	−0.0284	−0.0237	−0.0191	0.0000	−0.0001	0.0000	−0.0001	−0.0263	−0.0238	**0.0000**
11LostFoodTarStaste	−0.0012	−0.0009	−0.0335	−0.0261	0.0000	0.0000	0.0001	0.0001	−0.0009	−0.0010	**0.0000**
12LostFoodNation	−0.1421	−0.1012	−0.1310	−0.1179	−0.0004	−0.0005	−0.0013	−0.0004	−0.0999	−0.1020	**0.0000**
13LostNationLab	−0.5470	−0.6131	−51.3175	−56.4681	−0.9546	−0.9873	−0.0130	−0.0096	−298.6371	−307.3186	**0.0119**
14AversionToTarReg	0.0000	0.0000	−0.4354	−0.4796	0.0000	0.0000	−0.8123	−0.8927	0.0000	0.0000	**0.0000**
	Contributions of shocks										
1KDestruct	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
2KReturn	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
3CleanUp	0.00429	0.00392	0.21607	0.22880	−0.00002	0.00001	−0.00311	−0.00044	−0.00015	−0.00128	
4PubHealth	0.03031	0.03055	1.78266	2.15220	0.00024	0.00000	−0.00269	−0.00929	−0.00269	−0.00929	
5AccomTarCity	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
6AccOutsideTC	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
7LostFgnVisTC	−0.06206	−0.05120	−2.27407	−2.03736	0.00071	0.00056	−0.00051	−0.00107	−0.04130	−0.04237	
8LostFgnVisOuTC	−0.32036	−0.26404	−0.29004	−0.24427	−0.00033	−0.00107	0.00030	−0.00074	−0.21895	−0.22885	
9LostDomVisTC	0.00000	0.00000	−0.00621	−0.00547	0.00000	0.00000	−0.00002	−0.00002	0.00000	0.00000	
10LostDomVisOutTC	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
11LostFoodTarStaste	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
12LostFoodNation	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
13LostNationLab	−0.00653	−0.00732	−0.61232	−0.67378	−0.01139	−0.01178	−0.00016	−0.00011	−3.56334	−3.66693	
14AversionToTarReg	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
Total effects	−0.35435	−0.28808	−1.18391	−0.57989	−0.01078	−0.01227	−0.00617	−0.01167	−3.82643	−3.94871	

Table 6.7 Converting shocks into outcomes: epidemic scenario, FL24, Neoclassical

	Elasticities FL24 Neoclassical										Shocks
	GDPy1	EMPy1	GRPy1	RegEMPy1	GDPy20	EMPy20	GRPy20	RegEMPy20	Welf05	Welf02	
1KDestruct	−0.0013	−0.0009	−0.7828	−0.6304	0.0000	0.0000	−0.0145	0.0078	−0.0076	−0.0101	**0.0000**
2KReturn	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	0.0324	−0.0011	0.0073	0.0101	**0.0000**
3CleanUp	0.0007	0.0013	0.0211	0.0430	0.0000	0.0000	−0.0009	−0.0003	−0.0006	−0.0009	**2.4951**
4PubHealth	0.0000	0.0001	0.0023	0.0044	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0001	**244.4013**
5AccomTarCity	0.0001	0.0001	0.0035	0.0053	0.0000	0.0000	0.0003	0.0002	−0.0001	−0.0002	**0.0000**
6AccOutsideTC	0.0085	0.0129	0.0018	0.0041	0.0000	0.0000	−0.0001	0.0000	−0.0231	−0.0324	**0.0000**
7LostFgnVisTC	−0.0002	−0.0003	−0.0089	−0.0115	0.0000	0.0000	−0.0002	−0.0001	−0.0004	−0.0005	**50.7424**
8LostFgnVisOuTC	−0.0020	−0.0029	−0.0020	−0.0039	0.0000	0.0000	0.0001	0.0000	−0.0040	−0.0045	**25.3712**
9LostDomVisTC	0.0000	0.0000	−0.0182	−0.0218	0.0000	0.0000	−0.0002	0.0000	0.0000	0.0000	**0.0773**
10LostDomVisOutTC	−0.0044	−0.0064	−0.0019	−0.0054	0.0002	0.0000	0.0002	0.0000	−0.0125	−0.0102	**0.0000**
11LostFoodTarStaste	−0.0013	−0.0011	−0.0133	−0.0101	0.0000	0.0000	0.0000	0.0000	−0.0002	−0.0002	**0.0000**
12LostFoodNation	−0.0539	−0.0373	−0.0208	−0.0479	0.0003	0.0000	0.0012	−0.0001	−0.0631	−0.0655	**0.0000**
13LostNationLab	−0.2086	−0.3564	−19.8407	−33.3864	−0.9552	−0.9910	−0.0145	−0.0099	−298.6014	−307.2679	**0.0119**
14AversionToTarReg	0.0000	0.0000	−0.1478	−0.2488	0.0000	0.0000	−0.8142	−0.8930	0.0000	0.0000	**0.0000**
	Contributions of shocks										
1KDestruct	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
2KReturn	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
3CleanUp	0.00165	0.00324	0.05269	0.10726	−0.00003	0.00001	−0.00227	−0.00063	−0.00138	−0.00234	
4PubHealth	0.00855	0.01564	0.57361	1.08661	0.00000	0.00000	0.00660	−0.00855	−0.00953	−0.01466	
5AccomTarCity	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
6AccOutsideTC	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
7LostFgnVisTC	−0.00969	−0.01385	−0.45049	−0.58455	0.00030	0.00036	−0.00827	−0.00335	−0.01984	−0.02299	
8LostFgnVisOuTC	−0.05143	−0.07416	−0.05056	−0.09798	0.00104	0.00015	0.00198	0.00030	−0.10128	−0.11371	
9LostDomVisTC	0.00000	0.00000	−0.00140	−0.00169	0.00000	0.00000	−0.00001	0.00000	0.00000	0.00000	
10LostDomVisOutTC	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
11LostFoodTarStaste	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
12LostFoodNation	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
13LostNationLab	−0.00249	−0.00425	−0.23674	−0.39837	−0.01140	−0.01182	−0.00017	−0.00012	−3.56291	−3.66632	
14AversionToTarReg	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
Total effects	−0.05340	−0.07339	−0.11290	0.11128	−0.01008	−0.01130	−0.00215	−0.01235	−3.69495	−3.82002	

year-1 employment result for the target region, FL24, under Keynesian assumptions (−0.57989) but a positive result under Neoclassical assumptions (0.11128)? Under both sets of assumptions the increases in public expenditure rows 3 and 4 are stimulatory for FL24's employment while the cuts in foreign visitor expenditures in rows 7 and 8 are contractionary. Keynesian assumptions magnify both stimulatory and contractionary effects relative to Neoclassical assumptions. However, the magnification effect is weaker for labor intensive activities, such as public expenditures on clean-up and health, than for more capital intensive activities, such as providing hotel accommodation for foreign visitors. This can be seen by looking at the Public health and Lost foreign visitor contributions in rows 3 and 7 to year-1 regional employment. In Table 6.7 the Public health contribution is 1.08661 compared with 2.15220 in Table 6.6, a magnification effect as we go from Neoclassical to Keynes of about 2. The Foreign visitor contribution is −0.58455 in Table 6.7 compared with −2.03736 in Table 6.6, a magnification of about 3.5. By magnifying the bad news by more than the good news, the adoption of Keynesian assumptions turns the year-1 employment effect for FL24 from positive to negative.

The Epidemic scenario has very little effect on economic activity in the long run under either Keynesian or Neoclassical assumptions. For year 20, Tables 6.6 and 6.7 show total effects for national and regional output and employment that are smaller in absolute size than 0.01235%. The only sustained negative effect in the long run flows from the reduction in population. This contributes nearly all of the year-20 effects on GDP and national employment, row 13 in the contribution matrices. Recall that the epidemic kills 38,181 people which is about 0.012% of the population.

The 38,181 deaths make the overwhelmingly dominant contribution to the welfare effect of the Epidemic scenario. With a discount rate of 0.05 and Keynesian assumptions, this contribution is −3.56334% of a year's consumption which is 93.1% of the total welfare effect (=100 × 3.56334/3.82643). With a discount rate of 0.02 and Keynesian assumptions, deaths contribute 92.9% of the total welfare effect (=100 × 3.66693/3.94871). These contribution shares are even higher under Neoclassical assumptions, 96.4% when the discount rate is 0.05 and 96.0% when the discount rate is 0.02.

A notable aspect of the contributions to welfare in the Epidemic scenario under both Keynesian and Neoclassical assumptions and both discount rates is that they are negative for all the non-zero shocks. This is true even for Clean-up and Public health (rows 3 and 4) which show positive year-1 effects for output and employment. As explained in Sect. 6.5, following a serious terrorism or other disruptive shock, there is an initial blow-out in public expenditures (clean-up and health in the Epidemic scenario). This is followed by contraction as public and foreign debt are reined in. With the initial expenditures being of a non-welfare-creating nature, the required subsequent contraction in consumption causes the accumulated welfare effect to be negative.

Table 6.8 shows welfare effects for all three scenarios with the target regions being FL24 and CA34. The FL24 results were calculated with the elasticity matrices from Tables 6.1 and 6.2 and the percentage shocks from the "%, FL24" columns in

Table 6.8 Three example scenarios: welfare effects measured as percentage loss in a year's consumption

Target region and macro assumption	S1: Epidemic		S2: Dirty bomb		S3: Food contamination	
Discount rate	0.05	0.02	0.05	0.02	0.05	0.02
FL24 (Miami)						
Keynesian	−3.8263	−3.9485	−0.3120	−0.5021	−0.1545	−0.1607
Neoclassical	−3.6947	−3.8198	−0.4396	−0.6041	−0.0968	−0.1048
CA34 (Los Angeles)						
Keynesian	−3.8263	−3.9485	−0.3121	−0.5021	−0.1544	−0.1606
Neoclassical	−3.6947	−3.8198	−0.4397	−0.6041	−0.0968	−0.1047

Table 6.5. The CA34 results were calculated with the elasticity matrices from Tables 6.3 and 6.4 and the percentage shocks from the "%,CA34" columns in Table 6.5.

There are four outstanding features of Table 6.8. First, the target region makes almost no difference to the results. What this means is that the $ amount of the shocks and the number of deaths is just about all that counts in national welfare. Where the shocks are delivered is unimportant from a national welfare point of view.

Second, the Epidemic scenario is easily the worst. Analysis of contribution results quickly shows that the welfare effect of the 38,181 deaths in the Epidemic scenario in the dominant factor.

Third, the state of the economy (Keynes versus Neoclassical) at the time of the event can make a noticeable difference to the eventual welfare result. For the Epidemic scenario we saw that the year-1 effects were relatively negative under Keynesian assumptions. This was explained by a larger magnification factor, as we go from Neoclassical to Keynes, for the negative visitor effects than for the positive public expenditure effects. Reflecting the contributions to welfare of the year-1 effects, the Epidemic scenario shows larger negative welfare outcomes under Keynesian than under Neoclassical assumptions. The main shocks in the Dirty bomb scenario are public expenditures. The magnification of the positive effect of these expenditures is sufficient to make the year-1 effects more favorable under Keynes than under Neoclassical. Thus, the welfare effects for the Dirty bomb scenario are less negative under Keynes than under Neoclassical. The Food contamination scenario is similar to the Epidemic scenario in having large Lost-visitor-expenditure shocks relative to Public-expenditure shocks. This explains why the eventual welfare effects for the Food contamination scenario are more negative under Keynes than under Neoclassical.

Fourth, a lower discount rate means a bigger computed welfare loss. This is because a low discount rate gives a relatively high weight to consumption that is foregone in the future to pay for Clean-up, Health and other Public expenditures that are unfinanced in the year of the terrorism event.

6.8 Summary and Directions for Future Research

The aim of the project described in this chapter was to develop a method for and test the practicality of using a detailed CGE model as the link between driving factors in TRA scenarios and economic implication variables.

The theoretical advantages of CGE relative to I-O (the previous linking tool) are well known: short-run and long-run perspective; increased variable coverage; and better recognition of resource constraints, price effects, and debt accumulation. But the practicality of using CGE had not been established. To do this we needed to overcome two related problems: (1) computation; and (2) security.

Through our elasticity approach, implemented in GRAD-ECAT, we have provided a solution to both problems. We have shown that CGE can be adapted to the needs of the TRAs and deliver insights well beyond those available from I-O. The main insights arising from the GRAD-ECAT analysis of the sample scenarios presented in Sect. 6.7 are as follows:

(a) In ranking terrorism events in terms of economic damage, the use of welfare as a metric rather than GDP is likely to lead to quite different conclusions.
(b) With life valued at $9.6 million, scenarios with a significant loss of life are likely to generate much bigger welfare losses than those in which the main costs are property losses, visitor discouragement and clean-up expenses.
(c) For scenarios with the same array of $ shocks and deaths, the target region is unimportant in determining outcomes for national variables.
(d) By contrast, short-run regional outcomes depend crucially on the target region.
(e) The only shock with significant long-run implications for GDP and national employment is loss of life.
(f) The only shock with long-run implications at the regional level that are significantly different from those at the national level is aversion.
(g) Long-run regional implications for employment can differ sharply from short-run implications.
(h) The state of the economy (recessed or non-recessed) can have a significant bearing on the short-run implications for GDP and employment of a given scenario at both the national and regional levels.
(i) By contrast, the state of the economy in the year of the incident has almost no bearing on the long-run implications for GDP and employment but it does have noticeable implications for welfare.
(j) Varying the discount rate for welfare within the range that is usually recommended for cost-benefit analyses is unlikely to have a major impact on the damage ranking of terrorism events.

The CGE model underlying GRAD-ECAT is USAGE-TERM. This is a new variant of USAGE, with a greatly enhanced regional dimension. The estimation of elasticities, E(s,d,v), for GRAD-ECAT was the first major application of USAGE-TERM. In the course of applying USAGE-TERM for this project we learnt several technical lessons about the model. These led to improvements in: (1) computation through a better treatment of zero data points; (2) estimation of interregional trade flows through more realistic gravity formulas; and (3) delineation of regions. With regard to this last point, our initial plan was to set up 4-region versions of USAGE-TERM in which the regions were: Target congressional district; Rest of city; Rest of state; and Rest of USA. This did not prove adequate for coping with joint cities such as New York and Newark or for cities on state borders such as Kansas City. Although we retained the original nomenclature, we defined the regions in the 4-region versions of USAGE-TERM by reference to distances from the centre of the target congressional district.

There are many ways in which GRAD-ECAT can be improved and developed further. Here we discuss five.

First, we could improve the estimation of the elasticities, E_A(s,d,v). Detailed examination of tables in our working paper (Dixon et al. 2017a) containing the proportionality coefficients, C(s,v), reveals that for some of the driving factors, s, and some of the implication variables v, especially regional variables, there is considerable variation across our estimates. This means that the relevant variables, RV(s,d,v), do not fully encapsulate all of the factors in USAGE-TERM that explain differences across target regions d in the reaction of implication variable v to shocks of type s. Further research on the RV(s,d,v)s would allow us to improve the estimation of elasticities by bringing the estimates of the proportionality coefficients C(s,v) more closely into line. There are also possibilities for improving the consistency of the estimates of the C(s,v)s by making improvements in the specification of USAGE-TERM.

Second, we could reduce doubt about the legitimacy of the E_A(s,d,v) estimates by basing them on more than four models. Initially we made estimates of the E_A(s,d,v)s based on three 4-region models. In these models the target regions were FL24, AZ07 and WA09. Subsequently we added a fourth model with the target region being NY14. The addition of the fourth model lead to noticeable modifications in some of the elasticity estimates. On this basis it seems worthwhile to make further increases in the number of 4-region models underlying the elasticity estimation.

Third, we could improve the equations for estimating the effects of scenarios on implication variables. In the present version of GRAD-ECAT these equations have the linear form:

$$\mathrm{v_j} = \sum_{\mathrm{s}\in \mathrm{S}} \mathrm{E_A}\left(\mathrm{s}, \mathrm{d_j}, \mathrm{v}\right) * \mathrm{s_j} \qquad \mathrm{v} = 1, \ \ldots, \ 10, \tag{6.18}$$

where the notation was explained with reference to Eq. (6.5). Through Eq. (6.18), GRAD-ECAT provides a linear approximation to the USAGE-TERM relationships between driving factors and implication variables. In future research we should test the adequacy of these linear equations by comparing their outcomes for implication variables with those obtained from simulations with USAGE-TERM. Starting from these comparisons it is likely that we could find non-linear versions of Eq. (6.18) that would more accurately approximate the USAGE-TERM relationships between driving and implication variables.

Fourth, we could continue to work closely with the TRA groups to improve our understanding of the precise nature of the driving factors in the TRA scenarios. This would lead to improved representation in USAGE-TERM of these driving factors. We could also change the industrial/commodity classifications in USAGE-TERM to be more suited to TRA requirements. For example, it would be possible to provide more disaggregation of food and agriculture than in the versions of USAGE-TERM used for this project.

Finally, the present project suggests that the specification of the welfare function is an important part of GRAD-ECAT. Further research together with consultation with economists specializing in welfare economics could be expected to generate improvements in the specification of the welfare function, including the discount rate, the value of life, and the treatment of public-sector expenditures. As described in Sect. 6.5, we have allowed users of GRAD-ECAT to conduct sensitivity analysis with respect to both the discount rate and the value of life.

References

Boisvert R (1992) Indirect losses from a catastrophic earthquake and the local, regional, and national interest. In: Indirect economic consequences of a catastrophic earthquake. FEMA, Washington, DC, pp. 204–266

Chen Z, Rose A, Prager F, Chatterjee S (2017) Economic consequences of aviation systems disruptions: a reduced-form computable general equilibrium analysis. Transp Res A Policy Pract 95:207–226

Dixon PB, Rimmer MT (2002) Dynamic general equilibrium modelling for forecasting and policy: a practical guide and documentation of MONASH. Contributions to economic analysis 256, North-Holland Publishing Company, Amsterdam, pp xiv+338

Dixon PB, Rimmer MT, Tsigas ME (2007) Regionalizing results from a detailed CGE model: macro, industry and state effects in the U.S. of removing major tariffs and quotas. Pap Reg Sci 86(1):31–55

Dixon PB, Lee B, Muehlenbeck T, Rimmer MT, Rose AZ, Verikios G (2010) Effects on the U.S. of an H1N1 epidemic: analysis with a quarterly CGE model. J Homel Secur Emerg Manag 7(1): Article 75

Dixon PB, Johnson M, Rimmer MT (2011a) Economy-wide effects of reducing illegal immigrants in U.S. employment. Contemp Econ Policy 29(1):14–30

Dixon PB, Giesecke JA, Rimmer MT, Rose A (2011b) The economic costs to the U.S. of closing its borders: a computable general equilibrium analysis. Def Peace Econ 22(1):85–97

Dixon PB, Rimmer MT, Roberts BW (2014) Restricting employment of low-paid immigrants: a general equilibrium assessment of the social welfare implications for legal U.S. wage-earners. Contemp Econ Policy 32(3):639–652

Dixon PB, Jerie M, Rimmer MT, Wittwer G (2017a) Using a regional CGE model for rapid assessments of the economic implications of terrorism events: creating GRAD-ECAT (Generalized, regional and dynamic economic consequence analysis tool). CoPS/IMPACT Working Paper G280, April, p 77. https://www.copsmodels.com/ftp/workpapr/g-280.pdf

Dixon PB, Rimmer MT, Wittwer G, Rose AZ, Heatwole N (2017b) Economic consequences of terrorism and natural disasters: the Computable General equilibrium approach, Chapter 8. In: Abbas A, von Winterfeldt D, Tambe M (eds) Improving homeland security decisions. Cambridge University Press, Cambridge, pp 158–192

Garnaut R (2016) Economic analysis versus business rent seeking: the eclipse of analysis in Australia, Chapter 3. In: Hill H, Menon J (eds) Managing globalization in the Asian century. ISEAS Yusof Ishak Institute, Singapore

Giesecke JA, Burns W, Barret A, Bayrak E, Rose A, Slovic P, Suher M (2012) Assessment of the regional economic impacts of catastrophic events: CGE analysis of resource loss and behavioral effects of an RDD attack scenario. Risk Anal 32(4):583–600

Harrison M (2010) Valuing the future: the social discount rate in cost-benefit analysis. Productivity Commission, Australian Government, Canberra, pp IX + 175. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1599963

Horridge M (2012) The TERM model and its database, Chapter 2. In: Wittwer G (ed) Economic modeling of water: the Australian CGE experience. Springer, Dordrecht, pp 13–35

Horridge JM, Madden JR, Wittwer G (2005) Impact of the 2002-03 drought on Australia. J Policy Model 27(3):285–308

Partnoy F (2012) The cost of a human life, statistically speaking. http://www.theglobalist.com/the-cost-of-a-human-life-statistically-speaking/

Rose A (2017a) Benefit-cost analysis of economic resilience actions. In: Cutter S (ed) Oxford research encyclopedia of natural hazard science. Oxford, New York

Rose A (2017b) Economic resilience to terrorism and natural hazards, Chapter 9. In: Abbas A, von Winterfeldt D, Tambe M (eds) Improving homeland security decisions. Cambridge University Press, Cambridge, pp 193–219

Rose A, Guha G (2004) Computable general equilibrium modeling of electric utility lifeline losses from earthquakes. In: Okuyama Y, Chang S (eds) Modeling spatial economic impacts of natural hazards. Springer, Heidelberg, pp 119–142

Rose A, Prager F, Chen Z, Chatterjee S (2017) Economic consequence analysis tool (E-CAT). Springer, Tokyo

Wittwer G (ed) (2017) Multi-regional dynamic general equilibrium modeling of the U.S. economy: USAGE-TERM development and applications. Springer, Switzerland

Peter Dixon is professor in the Centre of Policy Studies at Victoria University, Melbourne, Australia. His primary research interests are the development and application of computable general equilibrium models. He previously held positions at the IMF, the Reserve Bank of Australia, the IMPACT Project in the Australian Government, La Trobe University, University of Melbourne and Monash University. Dixon received his doctorate from Harvard University in 1972. He is a Fellow of the Academy of the Social Sciences in Australia, a Member of the GTAP Hall of Fame, a Distinguished Fellow of the Economic Society of Australia, and an Officer in the Order of Australia.

Michael Jerie is senior research fellow in the Centre of Policy Studies at Victoria University, Melbourne, Australia. His principal research interests and responsibilities are in the development and maintenance of GEMPACK software for creating, analysing and solving large scale CGE models. GEMPACK is used under licence at about 600 sites throughout the world. Previously Jerie held programing, teaching and research positions at La Trobe University and Monash University. He received his doctorate in mathematics from La Trobe University in 2005. In 2018 he was awarded a fellowship in the Global Trade Analysis Project.

Maureen Rimmer is professor in the Centre of Policy Studies at Victoria University, Melbourne, Australia. Her primary research interests are the development and application of computable general equilibrium models. She previously held positions at the IMPACT Project in the Australian Government, La Trobe University and Monash University. Rimmer received her doctorate in mathematics from La Trobe University in 1978 and a Masters degree in economics from the University of Melbourne in 1990. In 2015 she was awarded a fellowship in the Global Trade Analysis Project.

Glyn Wittwer is professor in the Centre of Policy Studies at Victoria University, Melbourne, Australia. His primary research interests are the development and application of computable general equilibrium models. In this field he specializes in agricultural, regional, environmental and data issues. He previously held positions at the University of Adelaide, Monash University, and in various research arms of the Australian government. In 2017 he was awarded a fellowship in the Global Trade Analysis Project.

Chapter 7
The Challenge of Estimating the Impact of Disasters: Many Approaches, Many Limitations and a Compromise

Andre F. T. Avelino and Geoffrey J. D. Hewings

Abstract The recent upward trend in the direct costs of natural disasters is a reflection of both an increase in asset densities and the concentration of economic activities in hazard-prone areas. Although losses in physical infrastructure and lifelines are usually spatially concentrated in a few areas, their effects tend to spread geographically and temporally due to the more spatially disperse nature of production chains and the timing and length of disruptions. Since the 1980s, several techniques have been proposed to model higher-order economic impacts of disruptive events, most of which are based on the input-output framework. However, their contributions are fragmented in different models, and, still missing, is a more comprehensive accounting of production scheduling, seasonality in industrial linkages and demographics dynamics post-event. In this chapter, the Generalized Dynamic Input-Output (GDIO) framework is presented and its theoretical basis derived. It integrates previous contributions in terms of intertemporal dynamics, explicit intratemporal modeling of production and market clearing, inventory depletion/formation and expectation's adjustment. Moreover, we add to the literature by introducing induced effects via a demo-economic extension to study the impact of displacement and unemployment post-disaster, the impact of disruption timing via seasonal input-output tables, and production chronology via the sequential interindustry model.

A. F. T. Avelino (✉)
Regional Economics Applications Laboratory, Department of Agricultural and Consumer Economics, University of Illinois, Urbana, IL, USA
e-mail: fernan17@illinois.edu

G. J. D. Hewings
Regional Economics Applications Laboratory, University of Illinois, Urbana, IL, USA
e-mail: hewings@illinois.edu

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_7

7.1 Introduction

Disasters have unique features and effects that pose challenges to traditional economic modeling techniques. Most of them derive from a time compression phenomenon (Olshansky et al. 2012) in which, instead of a gradual transition phase after the steady-state is disrupted, an accelerated adjustment process (due to recovery efforts) brings the economy to a new steady-state.[1] Even though some activities compress better than others (e.g., money flows in relation to construction), it creates an intense transient economic shock (non-marginal) that is spatially heterogeneous and simultaneous depending on the intensity of damages, the local economic structure and the nature and strength of interregional linkages. As a result of the speed of disaster recovery, there is significant uncertainty, simultaneous supply constraints with specific forward and backward linkages effects due to production chronology and schedules, and behavioral changes that affect both the composition and volume of demand (Okuyama 2009). Timing is, therefore, fundamental in determining the extent of impacts since capacity constraints, inventories and production cycles vary throughout the year (see Avelino 2017).

In terms of economic modeling, the aforementioned features translate into a series of effects for which the net outcome (positive/negative) is unknown as it depends on the idiosyncrasies of the region. In the aftermath of a disaster, the previous steady-state of the economy is disrupted by changes in both supply and demand. Household displacement, income loss, structural changes in expenditure patterns, diminished government expending and reconstruction efforts imply positive and negative effects to final demand. Industrial response to the latter, in terms of output scheduling, affects intermediate demand. Conversely, supply may be locally constrained due to physical damage to capital and loss of inventory, or externally constrained by limited input availability for production (due to accessibility issues or disruptions in the production chain). Whether the net effect on the region is positive or negative will depend on the characteristics of the disaster, the resilience of local industries, the volume of reconstruction funds made available and the size of interregional linkages. Spillover effects spread through supply chains' disruptions and resource allocations for reconstruction in different regions at different times.

Hence, modeling efforts are essential to understand the role of different constraints in the recovery path post-disaster and to better inform mitigation planning. Regional industrial linkages topologies have a key role in spreading or containing disruptions, as well as sectoral robustness in terms of inventories, excess capacity, and trade flexibility (Rose and Wei 2013). Supply chain disruptions can have significant impacts on the financial health of firms by constraining sales, diminishing operating income and increasing share price volatility (Hendricks and Singhal 2005). Nonetheless, most firms do not properly quantify these risks, with few developing backup plans for production shutdowns due to physical damage or alternative

[1]E.g., a large amount of damaged assets is intensely replaced during recovery, moving the dynamics of capital depreciation and replacement to a new steady-state in the region or across regions.

suppliers in case of disruptions (University of Tennessee 2014). Assessing the dynamics of dissemination and identifying crucial industrial nodes can lead to more resilient economic systems.

As highlighted by Oosterhaven and Bouwmeester (2016), ideally, the assessment of regional impacts should be based on an interregional computable general equilibrium (CGE) framework. However, as a set of such models is required to account for both short-run (when substitution elasticities are minimal) and long-run impacts, the cost-time effectiveness of this approach is usually problematic (Rose 2004; Richardson et al. 2015). The widely used alternative has been input-output (IO) models due to their rapid implementation, easy tractability and integration flexibility with external models that are essential in the estimation of impacts post-disaster. The tradeoff between its CGE counterpart is more rigid assumptions on substitutability of goods, price changes and functional forms, which make IO more appropriate for short-term analysis. A variety of IO models have been proposed to deal with disruptive situations, most of them built upon the traditional demand-driven Leontief model (Okuyama 2007; Okuyama and Santos 2014). Nevertheless, these contributions are fragmented in different models, many of which either fail to incorporate the aforementioned constraints or do so in an indirect way that may be inconsistent with the assumptions of the IO framework (Oosterhaven and Bouwmeester 2016; Oosterhaven 2017).

In this chapter, we offer a compromise that encompasses the virtues of *intertemporal* dynamic IO models with the explicit *intratemporal* modeling of production and market clearing, thus allowing supply and demand constraints to be simultaneously analyzed. The Generalized Dynamic Input-Output (GDIO) framework is presented and its theoretical basis derived. The GDIO synthetizes many of the early contributions in the disaster literature, especially those contained in the Inventory Adaptive Regional IO Model (Hallegatte 2014), complementing them with the Sequential Interindustry Model, a demo-economic extension and seasonality effects. We integrate in a single model inventory dynamics, expectations' adjustment, timing of the event, impacts of displacement, unemployment and reconstruction. The GDIO provides insights into the role of pivotal production chain bottlenecks, population dynamics and interindustrial flow patterns that can guide the formulation of better recovery strategies and mitigation planning.

In the next section, a concise literature review of models focused on disruptive events using the IO framework is presented. Section 7.3 describes the intuition, mathematical formulation and solution of the GDIO model. Section 7.4 presents a simple 3-sector example to show the basic feedbacks in the model, and compares these results with the recovery paths of other models in the literature. Conclusions follow.

7.2 Literature Review

The input-output literature on natural disasters is vast, and although a comprehensive review is outside the scope of this chapter, it is available in Okuyama (2007), Przyluski and Hallegatte (2011) and Okuyama and Santos (2014). In this section, we briefly highlight the main contributions and some of the pitfalls from the current literature.

In explicitly considering supply, demand and trade constraints, and their sources inside the framework, optimizing rebalancing algorithms were introduced by Cochrane (1997), Oosterhaven and Bouwmeester (2016) for squared IO tables, and extended by Koks and Thissen (2016) and Oosterhaven and Többen (2017) to supply and use tables (SUT). Alternatively, Rose and Wei (2013) use both supply- and demand-driven models to capture backward and forward spillovers from shortfalls in intermediate inputs. These approaches, however, rely on an implicit assumption of perfect information to rebalance the economy and calculate total multiplier effects. A way to incorporate the increase in uncertainty in the aftermath of a disaster—arising from information asymmetries (Okuyama and Santos 2014)—is to incorporate these constraints in the IO framework by explicitly modeling the market clearing process (in a Marshallian sense). In the Adaptive Regional IO Model (ARIO) model (Hallegatte 2008), sectors produce according to an expected demand level that might differ from the actual demand resulting in over- or under-supply (a reflection of highly uncertain environments).

For *ex-ante* analyses, it is also essential to consider the interaction between local demand-production conditions and the evolution of these constraints instead of imposing an exogenous recovery trajectory. An alternative is provided by Lian and Haimes (2006) in the Dynamic Inoperability Input-Output Model.[2] They transform the Leontief Dynamic growth model into a recovery model that determines the speed with which the production gap post-disaster closes in each period according to supply-demand unbalances.

In terms of dynamics, a few studies have proposed formulations focused on industrial chronologies and production sequencing in order to capture intertemporal disruption leakages. The time-lagged model proposed by Cole (1988, 1989)[3] and the Sequential Interindustry Model (SIM) by Romanoff and Levine (1981) relax the assumption of production simultaneity, instead accounting for production timing. This is essential, as production delays can have ripple effects in different industrial chains, and perpetuate in the economy for several periods, influencing output

[2]The DIIM is the dynamic version of the Inoperability Input-Output Model (IIM) (Santos 2003; Santos and Haimes 2004). Despite IIM's wide application in the literature, it offers no methodological advances in relation to the traditional IO model. In fact, as shown in Dietzenbacher and Miller (2015) and Oosterhaven (2017), it is just a normalization of the Leontief model.

[3]The time-lagged model has been criticized in a series of papers by Jackson et al. (1997), Jackson and Madden (1999) and Oosterhaven (2000), due to Cole's assumption of a fully endogenized system which is theoretical inconsistent and non-solvable. No other disaster applications are available.

intertemporally (Okuyama et al. 2002, 2004). However, still unaccounted for in the available dynamic models is the role of seasonality in the economic structure. Although some sectors have more stable production structures over the course of a year, the bias of using annual multipliers in seasonal sectors such as agriculture can be significant (Avelino 2017). Hence, fluctuations in production capacity and interindustrial linkages *intra-year* have a significant impact on the magnitude, spread and duration of unexpected disruptive events, which affects sectoral adaptive responses.

The important role of inventories in mitigating short-term effects of disruptions has also been incorporated in the dynamic literature: the Inventory-SIM (Romanoff and Levine 1990; Okuyama and Lim 2002), the Inventory-DIIM (Barker and Santos 2010) and the Inventory-ARIO (Hallegatte 2014). However, there is still limited consideration of different types of inventories (materials and supplies, work-in-progress, finished goods) and their formation in the same framework. Besides inventories, Rose and Wei (2013) also consider other mitigation strategies such as using goods destined for export in the local economy, input conservation and production recapture. Further, Koks and Thissen (2016)'s MRIA model allows increasing local production of by-products to reduce inoperability.

Natural disasters also tend to change expenditure patterns both in the affected region (due to layoffs, reduced production, governmental assistance programs) and outside of it (relief aid). These have been incorporated in Okuyama et al. (1999) and Li et al. (2013), but the main issue is to properly identify and quantify such behavioral changes. Another important challenge is the application of a systems approach to disaster modeling, i.e., the integration of regional macro models with physical networks (transportation, utilities, etc.) that operate at different scales and frequencies. There are temporal mismatches between low frequency economic models (monthly, quarterly, yearly basis) and high frequency physical networks (daily, hourly intervals), as well as spatial mismatches in terms of systems boundaries and granularity (economic models usually defined over administrative boundaries at macro level versus micro level larger/smaller networks). Efforts in integrating physical networks include the Southern California Planning Model (Richardson et al. 2015), the National Interstate Economic Model (Richardson et al. 2014) combining a MRIO with transportation networks, and the work of Rose and Benavides (1998) who focused on electricity supply.

In sum, several alternatives have been proposed but their contributions are fragmented in several models, without a common synthesis framework. The Inventory-ARIO model introduces many of the aforementioned contributions, such as modeling supply-demand in a dynamic context to explicitly incorporate constraints, consideration of inventory formation (materials and supplies only), and some adaptation behavior from agents, but such model is still incomplete. Missing are a more comprehensive accounting of production scheduling, seasonality in the production structure, and demographic dynamics post-event. The next section introduces a new model that departs from the Inventory-ARIO model and integrates these points in a consistent and theoretically sound way.

7.3 Methodology

When dynamics are introduced in the IO framework, the economic system becomes a combination of *intratemporal* flows and *intertemporal* stocks. The latter are key to exploiting these dynamics and essential to fulfill both reproducibility (conditions for production in the next period) and equilibrium conditions (market clearing) across time periods. Inventories assure irreversibility of production (i.e., inputs need to be available before output is produced) and the feasibility of free disposal in a consistent accounting sense (by absorbing unused inputs/outputs) (Debreu 1959). Therefore, as echoed by Aulin-Ahmavaara (1990), a careful definition of flows and stocks is paramount to avoid theoretical inconsistencies in the model.

Following the past literature (Leontief 1970; Romanoff and Levine 1977; ten Raa 1986), time is discretized into intervals $t \in \mathrm{T}$, $\mathrm{T} \supset \mathbb{Z}$, of length h. The discretization of a continuous process (production), requires that any flow $\mathbf{Z}_{ij}$ occurring during the length h be time-compressed, as $\nexists \mathbf{Z}_{ij}(t^{*})$, $\forall\, t^{*} \mid t < t^{*} < t + 1$. Moreover, since the production process per se is not explicitly modeled, production begins and ends simultaneously and synchronously within h for all industries, and output is sold at the end of the period to final demand or inventories (stocks).[4]

Flows and stocks need to be organized in a certain way in order to comply with time-relevant neoclassical assumptions on production sets. If production is to occur in period t, *irreversibility* mandates that all required inputs be available in advance and, therefore, input purchases occur in $t - 1$. Note that the discretization displaces all interindustrial flows that would occur within h to a single purchase event in the previous period, i.e., industries cannot purchase inputs during production. In addition, *free disposal* requires the existence of inventories, so that unused materials and finished goods can be consistently accounted for and transferred intertemporally.

Based on these assumptions, the length h can be divided into a sequence of events that starts with the formation of supply from production and ends with demand being realized, markets cleared and goods allocated, thus creating the necessary conditions for production in the next period.[5] We assume intratemporal asymmetric information between producers and consumers; hence, production schedules cannot be changed in response to demand shifts within h, but they can and will be adjusted between periods.

An overview of the model is presented in Fig. 7.1. The intuition behind it is straightforward: producers determine the feasibility of their production schedules for the period, given the current availability of industrial inputs, capital and labor. Assuming non-substitutability between finished goods for intermediate and final consumptions, if the total schedule is not feasible, producers use a rationing rule to set how much to offer in each market in excess of any inventories from the previous period (Sect. 7.3.1). Therefore, final demand, influenced by reconstruction efforts,

[4] This includes both finished and work-in-progress goods.

[5] It follows from ten Raa (1986): all outputs for the period are assumed to form together at the end of h.

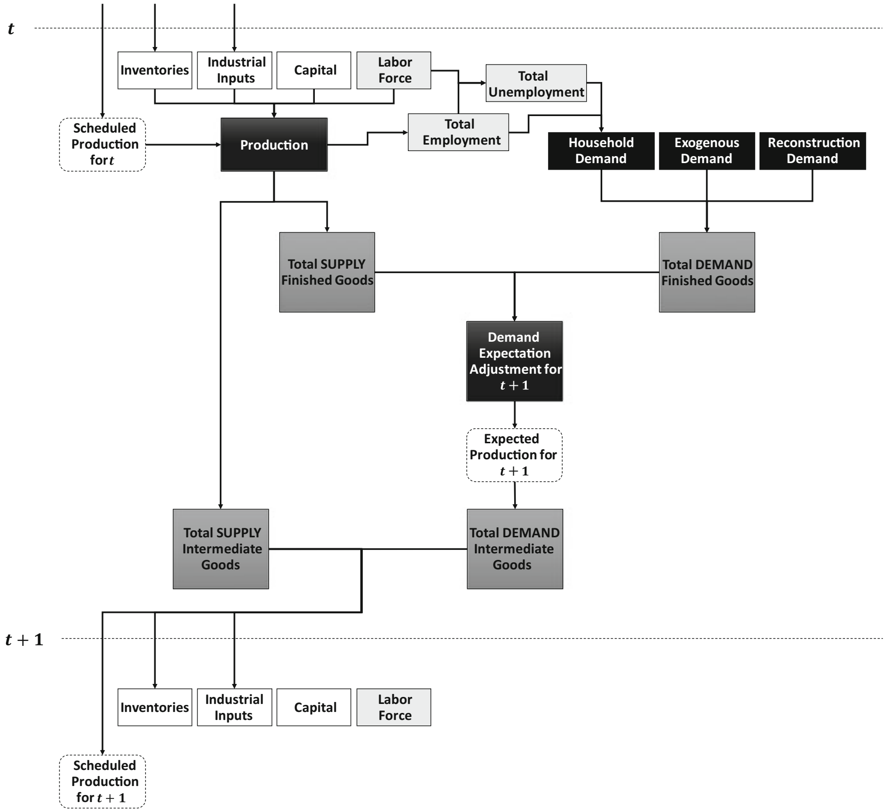


Fig. 7.1 Generalized dynamic input-output model (GDIO) scheme

displacement, labor conditions and income, might be under- or over-supplied. Industries react to this supply-demand unbalance by adjusting their expectations for the next production cycle, and by attempting to purchase the necessary level of inputs (Sect. 7.3.2). Because this interindustrial demand may also be under- or over-supplied, after markets clear, each sector determines a feasible production schedule for the upcoming period (Sect. 7.3.3). The stock losses of a disaster occur between periods, diminishing inputs, capital and displacing population, thus affecting production feasibility and demand level/composition for the next period.

The generic formulation of the GDIO model is detailed in Fig. 7.2,[6] so no specific functional forms are presented where there is flexibility (although examples are

[6]The standard IO notation is used in this chapter. Moreover, matrices are named in bold capital letters, vectors in bold lower case letters (except inventories denoted by **I**) and scalars in italic lower case letters. The Greek letter $\boldsymbol{\iota}$ (*iota*) denotes a unitary row vector of appropriate dimension. Finally, a hat sign over a vector indicates diagonalization, a prime sign transposition, $\times$ standard multiplication, and $\bigotimes$, $\oslash$ indicate element-wise multiplication and division respectively.

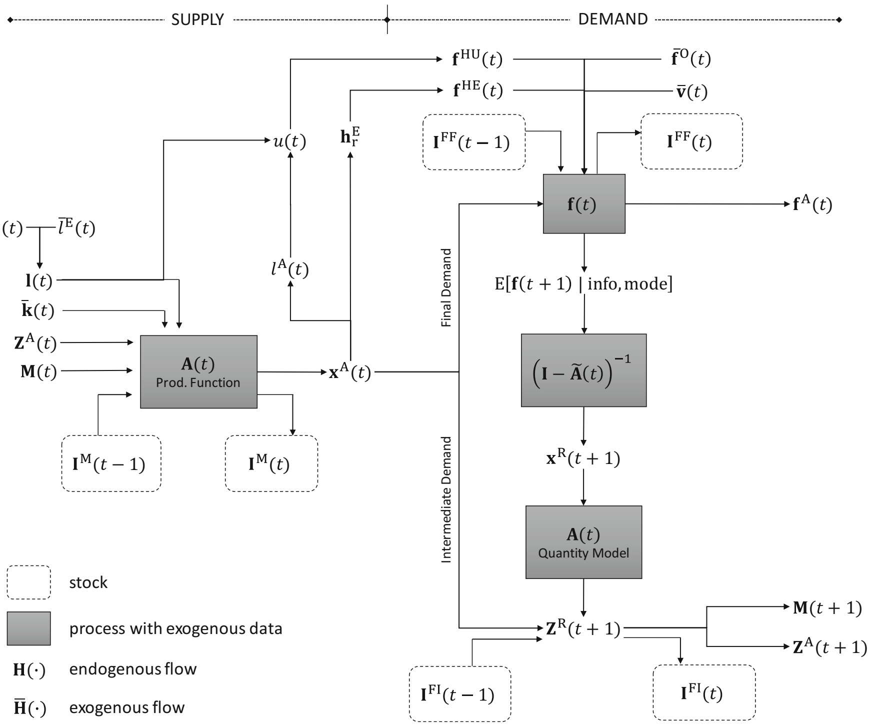


Fig. 7.2 Generalized dynamic input-output model (GDIO) overview

provided). Assume an economy with n industries and T production periods of length h. An industry $\mu \in 1, \ldots, n$ and time period $t \in 1, \ldots, T$ are taken as reference points for expositional purposes.

7.3.1 Supply Side

It is imperative to distinguish between a local direct input requirement matrix ($\tilde{\mathbf{A}}$) and a proper technical coefficient matrix ($\mathbf{A}$), as the terminology has often been indiscriminately used in the literature. The former is derived from locally purchased inputs only, while the latter arises from *all* inputs required for production, both local and imported, thus reflecting the structure of a Leontief production function. Local direct input requirement matrices change when regional purchase coefficients (RPC) vary since $\tilde{\mathbf{A}}(t) = \mathbf{RPC}(t) \otimes \mathbf{A}$, i.e., when there is a change in the share of domestic/external suppliers. This is quite frequently the case in disaster situations as local supply plunges. Conversely, technical coefficient tables are stable and may only change due to seasonality—if *intra-year tables* are used (Avelino 2017)—or due to the adoption of alternative production technologies, the choice of which might depend on the availability of local supply.[7]

In contrast to traditional IO specifications, the Leontief production function is extended to include primary inputs (**l**) and assets/capital (**k**), besides industrial inputs (**Z**). This modification introduces supply constraints due to limited input availability, physical damage to capital or displacement of the workforce. Hence, production capacity in industry μ is given by available industrial inputs, and by the coefficients $\mathbf{a}_{\mu}^{\mathrm{L}}(t)$ and $\mathbf{a}_{\mu}^{\mathrm{K}}(t)$, which reflect primary inputs and assets requirements per unit of output respectively.[8]

Total available industrial inputs from industry i for production of industry μ at time t is the sum of locally purchased inputs ($\mathbf{Z}^{\mathrm{A}}$), imports ($\mathbf{M}^{\mathrm{I}}$) and *materials and supplies inventories* ($\mathbf{I}^{\mathrm{M}}$) from the previous period[9]:

$$\mathbf{Z}_{i\mu}^{\mathrm{T}}(t) = \mathbf{Z}_{i\mu}^{\mathrm{A}}(t) + \mathbf{M}_{i\mu}^{\mathrm{I}}(t) + \mathbf{I}_{i\mu}^{M}(t-1) \quad \forall i \tag{7.1}$$

Total labor supply $l^{T}(t)$ is determined endogenously as a fixed share τ of the current resident population $p(t)$, which in itself depends on total net migration ($\bar{n}(t)$) for the period, plus any external commuting labor $\bar{l}^{\mathrm{E}}(t)$.[10]

$$p(t) = p(t-1) - \bar{n}(t) \tag{7.2}$$

$$l^{\mathrm{T}}(t) = \tau \times p(t) + \bar{l}^{\mathrm{E}}(t) \tag{7.3}$$

The labor supply can have different degrees of substitutability between industries, depending on available information on skills, age, and/or education (Kim et al. 2014;

---

[7]Technology choice with constraints could be modeled using Duchin and Levine's (2011) framework.

[8]E.g., suppose an industry μ relies on a 10,000 sqft factory to produce \$ten million of output. Given the traditional linearity assumption, $\mathbf{a}_{\mu}^{\mathrm{K}}(t) = 10^3$ sqft/million \$. These coefficients change with the economic structure, i.e., due to seasonality, labor and capital requirements might change to accommodate different production functions.

[9]The inventory strategy in the GDIO is quite different from the Inv-ARIO model. The latter is based on the premise that all industries seek to maintain a target level of M&S inventories similar to "order-point systems" used in managing inventories prior to the 1970s (Ptak and Smith 2011). The issue with such approach is that modern inventory management relies on "material requirement planning" systems that consider the full supply chain conditions when a firm re-orders inputs, not only its own inventory position (Ptak and Smith 2011). In the GDIO, priority is given to attend demand in the post-disaster period, instead of rebuilding inventories.

[10]In a multiregional specification, external labor availability would be bounded by unemployed individuals in other regions. Also, if housing data is available, net migration can be endogenous: the amount of in- (out-)migration as a proportion φ of added (lost) residential squared footage in the previous period ($n(t) = \varphi * \Delta sqft^{\mathrm{RES}}(t-1)$).

Kim and Hewings 2019). In the simplest case, it can be assumed perfectly substitutable so that $\mathbf{l}(t) = l^{\mathrm{T}}(t) \times \mathbf{l}(0) \times (\boldsymbol{\iota} \times \mathbf{l}(0))^{-1}$.

Given available industrial inputs ($\mathbf{Z}^{\mathrm{T}}(t)$), primary inputs ($\mathbf{l}(t)$) and capital ($\mathbf{k}(t)$), industries produce in the current period following a Leontief production function, up to a total potential output $\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t)$:

$$\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t) = f\left(\mathbf{Z}^{\mathrm{T}}, \mathbf{l}, \mathbf{k}\right) = \min\left\{\frac{\mathbf{Z}_{1\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{1\mu}(t)}, \ldots, \frac{\mathbf{Z}_{\mu\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{\mu\mu}(t)}, \ldots, \frac{\mathbf{Z}_{n\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{n\mu}(t)}, \frac{\mathbf{l}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{L}}(t)}, \frac{\mathbf{k}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{K}}(t)}\right\} \quad (7.4)$$

As aforementioned, the only reason for $\mathbf{A}_{ij}(t-1) \neq \mathbf{A}_{ij}(t)$ is a change in production technology as noted earlier. If regional purchase coefficients change from $t-1$ to t, they may not affect $\mathbf{A}_{ij}(t)$.

The actual total output $\mathbf{x}_{\mu}^{\mathrm{A}}(t)$ depends on the scheduled total output for the period $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$ (to be discussed in Sect. 7.3.3) and any available *inventory of finished goods for intermediate demand* $\mathbf{I}_{\mu}^{\mathrm{FI}}$ from the last period (inventories of finished goods for final demand $\mathbf{I}_{\mu}^{\mathrm{FF}}$ were already embedded in $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$):

$$\mathbf{x}_{\mu}^{\mathrm{A}}(t) = \min\left\{\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t), \quad \mathbf{x}_{\mu}^{\mathrm{S}}(t) - \mathbf{I}_{\mu}^{\mathrm{FI}}(t-1)\right\} \quad (7.5)$$

After production is completed, unused inputs enter the stock of *materials and supplies inventories* ($\mathbf{I}^{\mathrm{M}}$) at period t. We assume that imported inputs are used first in the production process and then local inputs are consumed.[11] In addition, note that $\mathbf{I}_{i\mu}^{\mathrm{M}}(t) \geq 0$, although $\Delta\mathbf{I}_{i\mu}^{\mathrm{M}}(t)$ can be either positive or negative:

$$\mathbf{I}_{i\mu}^{\mathrm{M}}(t) = \left[\mathbf{Z}_{i\mu}^{\mathrm{T}}(t)\right] - \left[\mathbf{A}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{A}}(t)\right] \quad \forall i \quad (7.6)$$

7.3.2 Demand Side

On the demand side, a semi-exogenous final demand vector ($\mathbf{f}_{\mu}(t)$) and endogenous intermediate demands ($\mathbf{Z}_{\mu j}^{\mathrm{R}}(t)$) are locally supplied by $\mathbf{x}_{\mu}^{\mathrm{A}}(t)$ and any available *finished goods inventory*. It is assumed that there is non-substitutability between finished goods for final demand and finished goods for intermediate demand (analogous to the use of the Armington assumption for local versus imported goods in most CGE models), although there is perfect substitution of the latter among industries.[12] The amount of $\mathbf{x}_{\mu}^{\mathrm{A}}(t)$ destined for each type of demand is determined

[11] In this way, there is no change in inventory for external industries.

[12] Thus the existence of two types of finished goods inventories: $\mathbf{I}_{\mu}^{\mathrm{FF}}(t)$ and $\mathbf{I}_{\mu}^{\mathrm{FI}}(t)$ respectively.

by the scheduled total output $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$ and scheduled demands $\mathbf{Z}_{\mu i}^{\mathrm{S}}(t)\forall i, \mathbf{f}_{\mu}^{\mathrm{S}}(t)$ that were set when purchasing inputs in $t-1$. In the case when $\mathbf{x}_{\mu}^{\mathrm{S}}(t) \neq \mathbf{x}_{\mu}^{\mathrm{A}}(t)$, a rationing scheme $\mathbf{r}(t) \mid \sum_i \mathbf{r}_i(t) = 1$ must be applied (Bénassy 2002). It can reflect a uniform or proportional rationing, or an industrial prioritization, for example considering the production chronology in the sequential interindustry model and prioritizing supply to those flows closer to final demand (Li et al. 2013; Hallegatte 2014). Notice that it is still possible to model such imbalance between supply and demand in an IO framework as long as t is not too large, since prices may not be able to adjust rapidly. The rationing rule is constrained by:

$$\mathbf{x}_{\mu}^{\mathrm{A}}(t) = \sum_{i} \mathbf{Z}_{\mu i}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) \tag{7.7}$$

The composition and mix of final demand ($\mathbf{f}_{\mu}(t)$) are usually affected during the recovery period due to displacement of households, changes in income distribution, financial aid, government reconstruction expenditures and investment in capital formation. Most studies model final demand change exogenously with a recovery function that gradually returns it to the pre-disaster conditions (Okuyama et al. 1999; Li et al. 2013), and a few attempt to endogenize it in the core modeling framework by closing the system regarding households (Bočkarjova 2007).

However, the simple endogenization of households to estimate induced effects implies strong assumptions. It assumes a linear homogeneous consumption function, i.e., there is a constant proportional transmission of changes in income to/from changes in consumption, that all employed individuals have the same wage and consumption pattern (consumption of unemployed individuals is exogenous) and it ignores the source of new workers (Batey and Weeks 1989; Batey et al. 2001). Of particular interest for disaster analysis is the fact that Type II multipliers artificially inflate induced effects by excluding the expenditure of workers who are unemployed in the region. As highlighted in Batey (2018), when the consumption of unemployed individuals is ignored, any change in labor requirements results in a significant change in the level of final demand as new hires suddenly "enter" the local economy. Thus, in negative growth scenarios this technique overstates the impact of the regional decline. Further, there is the additional problem, noted by Okuyama et al. (1999) that households may delay purchases of durable goods in the aftermath of an unexpected event, confining expenditures to immediate needs (necessity goods).

A way to mitigate these issues is to build upon the demo-economic framework that has been developed in the last 30 years. These integrated (demographic) models attempt to relax some of the previous assumptions by explicitly considering indigenous and in-migrant wages and consumption responses, as well as unemployment, social security benefits and contractual heterogeneity (van Dijk and Oosterhaven 1986; Madden 1993).

The demo-economic framework will be used to capture part of the change in level/mix post-disaster and its implication in terms of induced effects. We focus on the impact of displacement, unemployment and shifts in income distribution and expenditure patterns between households within the final demand. The other components of final demand are still considered to be exogenous ($\bar{\mathbf{f}}^{\mathrm{O}}$) and reconstruction demand is treated as an external shock ($\bar{\mathbf{v}}$).[13] We build upon a simplified version of Model IV proposed in Batey and Weeks (1989), by aggregating the intensive and extensive margins (see Appendix 7.1).[14]

Therefore, once the actual total output of industry ($\mathbf{x}^{\mathrm{A}}$) is determined, total employment for the period ($l^{A}(t)$) is estimated by Eq. (7.8), and total final demand from employed *residents* ($\mathbf{f}^{\mathrm{HE}}(t)$) by Eq. (7.9). Total unemployment determines the amount of final demand for these households ($\mathbf{f}^{\mathrm{HU}}(t)$) according to Eq. (7.10).

$$l^{\mathrm{A}}(t) = \mathbf{a}^{\mathrm{L}} \times \hat{\boldsymbol{\rho}} \times \mathbf{x}^{\mathrm{A}}(t) \tag{7.8}$$

$$\mathbf{f}^{\mathrm{HE}}(t) = \mathbf{h}_{\mathrm{c}}^{\mathrm{E}} \times \left(\mathbf{h}_{\mathrm{r}}^{\mathrm{E}} \times \hat{\boldsymbol{\rho}} \times \mathbf{x}^{\mathrm{A}}(t) + f_{\mathrm{H}}(t)\right) \tag{7.9}$$

$$\mathbf{f}^{\mathrm{HU}}(t) = s \times \mathbf{h}_{\mathrm{r}}^{\mathrm{U}} \times \left(l^{\mathrm{T}}(t) - l^{\mathrm{A}}(t)\right) \tag{7.10}$$

Total final demand for the period ($\mathbf{f}(t)$) is estimated by combining *resident* households' expenditures, other final demand components (exogenous) and reconstruction stimulus (exogenous).

$$\mathbf{f}(t) = \mathbf{f}^{\mathrm{HE}}(t) + \mathbf{f}^{\mathrm{HU}}(t) + \bar{\mathbf{f}}^{\mathrm{O}}(t) + \bar{\mathbf{v}}(t) \tag{7.11}$$

Given this semi-exogenous final demand, the actual demand supplied locally ($\mathbf{f}_{\mu}^{\mathrm{A}}(t)$) depends on finished goods produced in the period and any inventory from the previous period:

$$\mathbf{f}_{\mu}^{\mathrm{A}}(t) = \min\left(\mathbf{f}_{\mu}(t), \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t-1)\right) \tag{7.12}$$

In the case where local supply is insufficient for final demand, imports ($\mathbf{m}^{\mathrm{FD}}$) are required. The amount of available imports can be exogenously imposed in a single region setting, or it can be endogenized in a multiregional setting, where firms produce to satisfy both local and external final demand. In the latter case, spatio-temporal disruption spillover effects can be assessed. Availability can also be linked

[13] In many Regional Econometric IO models, state and local government expenditures are assumed to be endogenous with the revenues coming from a variety of direct and indirect taxes. After an unexpected event, this relationship might be uncoupled as disaster relief, funded by the federal government, pours into the region. Further, the allocation of these funds is likely to be different from the "average" portfolio of state and local government expenditures.

[14] We use this simplified version for expositional purposes only. Empirical applications should include a further demographic disaggregation, considering the number of individuals displaced and the expenditure pattern change of those rebuilding.

to *accessibility* through an additional transportation model (Sohn et al. 2004).[15] In our single region exposition, we assume an external import constraint $\mathbf{T}_{\mu}^{\mathrm{FD}}(t)$ that determines how much trade flexibility there is in terms of finished goods for final demand consumption in the external industry μ.[16]

$$\mathbf{m}_{\mu}^{\mathrm{FD}}(t) = \min\left(\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t), \mathbf{T}_{\mu}^{\mathrm{FD}}(t)\right) \tag{7.13}$$

Sectors that can hold finished goods' inventories[17] update their stocks:

$$\mathbf{I}_{\mu}^{\mathrm{FF}}(t) = \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t-1) - \mathbf{f}_{\mu}^{\mathrm{A}}(t) \tag{7.14}$$

Next, industries form expectations regarding final demand in the following period in order to purchase the required inputs at t. Industries do so by means of an expectation function $\mathrm{E}[\mathbf{f}_{\mu}(t+1)|\ \mathrm{info}]$, whose form is to be defined by the modeler, and may include an inventory strategy that varies according to the uncertainty in the system.[18] At this point, the GDIO intersects with the SIM, allowing sectors to behave as anticipatory, responsive or just-in-time (JIT). Anticipatory industries forecast final demand and, thus, their expectation function may or may not match the actual final demand in the next period. Just-in-time industries are a particular case in which $\mathrm{E}[\mathbf{f}_{\mu}(t+1) \mid \mathrm{info, JIT}] = \mathbf{f}_{\mu}(t+1)$, because they produce according to actual demand next period. Finally, responsive industries react to orders placed in previous periods (for a discussion on this terminology see Romanoff and Levine 1981).[19]

The required output for $t+1$ ($\mathbf{x}^{\mathrm{R}}(t+1)$) is determined by its expected final demand via the Leontief model [Eq. (7.15)]. After accounting for any labor or capital

[15]Such extension is not included in the model's exposition. Moreover, accessibility could also consider commuting to/from the region, constraining available labor force.

[16]In case there is an upper bound to imports, final demand not supplied in some sectors can be accumulated to next period (e.g., construction demand), reflecting a backlog in orders: $\bar{\mathbf{f}}^{\mathrm{O}}(t+1) = \bar{\mathbf{f}}^{\mathrm{O}}(t+1) + \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t) - \mathbf{m}_{\mu}^{\mathrm{FD}}(t)\right]$.

[17]See Sect. 7.3.6 for notes on inventories.

[18]Such strategy could be included either as a deterministic (see Hallegatte 2014) or a stochastic component.

[19]An example of a SIM formulation with a simple inventory formation mechanism sensitive to the uncertainty in the system is:

$$\mathrm{E}\left[\mathbf{f}_{\mu}(t+1)|\ \mathrm{info, mode}\right] = \begin{cases} \mathbf{f}_{\mu}(t) + \sigma \times \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t)\right], \text{if anticipatory} \\ \mathbf{f}_{\mu}(t+1) + \sigma \times \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t)\right], \text{if just in time} \\ \mathbf{f}_{\mu}(t-1) + \sigma \times \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t)\right], \text{if responsive} \end{cases}$$

where the adjustment parameter σ reflects the reaction of the sectors to such uncertainty. Therefore, we relax the assumption of perfect knowledge for production scheduling, a critique raised by Mules (1983) on the original SIM.

constraints [Eq. (7.16)], and any available materials and supplies inventory, industries determine the total intermediate input requirements in the period $\mathbf{Z}_{i\mu}^{\mathrm{R}}(t)$ (that includes both local and imported goods) [Eq. (7.17)].[20]

$$\mathbf{x}^{\mathrm{R}}(t+1) = \left(\mathbf{I} - \tilde{\mathbf{A}}(t)\right)^{-1}\left[\mathrm{E}[\mathbf{f}(t+1) \mid \text{info}, \text{mode}] - \mathbf{I}^{\mathrm{FF}}(t)\right] \tag{7.15}$$

$$\mathbf{x}_{\mu}^{\mathrm{R}}(t+1) = \min\left(\mathbf{x}_{\mu}^{\mathrm{R}}(t+1), \mathbf{l}_{\mu}(t)/\mathbf{a}_{\mu}^{\mathrm{L}}(t+1), \mathbf{k}_{\mu}(t)/\mathbf{a}_{\mu}^{\mathrm{K}}(t+1)\right) \tag{7.16}$$

$$\Rightarrow \quad \mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1) = \mathbf{A}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{R}}(t+1) - \mathbf{I}_{i\mu}^{\mathrm{M}}(t) \quad \forall i \tag{7.17}$$

Each industry then attempts to purchase its required inputs from other industries in the economy. Input supply of industry i to industry μ depends on the scheduled production, on any imposed rationing scheme, and on inventory of finished goods for intermediate demand of i. Since there is perfect substitutability of finished goods for intermediate demand among sectors, an inventory distribution scheme $\mathbf{d}(t)$ is required to allocate any available inventories between industries that are undersupplied. In its simplest form, it can distribute equally within those demands that exceed current supply, or it can prioritize certain industries. The actual amount of inputs purchased locally is given by:

$$\mathbf{Z}_{i\mu}^{\mathrm{A}}(t+1) = \min\left(\mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1), \mathbf{Z}_{i\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{i}(t) + \mathbf{I}_{i}^{\mathrm{FI}}(t-1) \times \mathbf{d}_{i}(t)\right) \quad \forall i \tag{7.18}$$

In case local supply is insufficient for intermediate demand, imports are required. Besides possible trade constraints, for consistency the production modes of external industries need to be accommodated. In this single region exposition, the lag in production for anticipatory industries and foreign inventories is embedded in the constraint $\mathbf{T}_{i\mu}^{\mathrm{I}}(t)$ that provides import flexibility.[21] In a multiregional framework, external adjustments are explicitly modeled in the other region.

[20]If an industry is just-in-time, for the model to be consistent with perfect foresight under discretization, technical coefficients and local purchase coefficients in Eqs. (7.15–7.17) would be indexed $t + 1$.

[21]This constraint can be endogenized. A simple example would be a logistic function $\mathbf{T}_{i\mu}^{\mathrm{I}}(t) = f(\alpha, k) = \left(\alpha_i \times \mathbf{M}_{i\mu}^{\mathrm{I}}(0)\right)/\left(1 + e_i^{-k_i t}\right)$, where α_i indicates the amount of underutilized external capacity and k_i an industry specific speed of production increase. $\mathbf{T}_{i\mu}^{\mathrm{I}}(t)$ can also be a constant number that represents external inventories.

$$\mathbf{m}^{\mathrm{I}}_{i\mu}(t+1) = \min\Big(\mathbf{Z}^{\mathrm{R}}_{i\mu}(t+1) - \mathbf{Z}^{\mathrm{A}}_{i\mu}(t+1), \mathbf{T}^{\mathrm{I}}_{i\mu}(t)\Big) \quad \forall i \tag{7.19}$$

Inventories of finished goods for intermediate demand are updated, allowing free disposal for industries that cannot hold inventories:

$$\mathbf{I}^{\mathrm{FI}}_{\mu}(t) = \begin{cases} \sum_j \mathbf{Z}^{\mathrm{S}}_{\mu j}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}^{\mathrm{FI}}_{\mu}(t-1) - \sum_j \mathbf{Z}^{\mathrm{A}}_{\mu j}(t+1), & \text{if } \mu \text{ can hold inventories} \\ 0, & \text{o.w.} \end{cases} \tag{7.20}$$

7.3.3 Production Scheduling for the Next Period

Finally, given the amount of inputs effectively purchased, industries determine the production schedule for the next period[22]:

$$\mathbf{x}^{\mathrm{S}}_{\mu}(t+1) = \min\left\{\frac{\mathbf{Z}^{\mathrm{T}}_{1\mu}(t+1)}{\mathbf{A}_{1\mu}(t)}, \ldots, \frac{\mathbf{Z}^{\mathrm{T}}_{\mu\mu}(t+1)}{\mathbf{A}_{\mu\mu}(t)}, \ldots, \frac{\mathbf{Z}^{\mathrm{T}}_{n\mu}(t+1)}{\mathbf{A}_{n\mu}(t)}, \frac{\mathbf{l}_{\mu}(t)}{\mathbf{a}^{\mathrm{L}}_{\mu}(t)}, \frac{\mathbf{k}_{\mu}(t)}{\mathbf{a}^{\mathrm{K}}_{\mu}(t)}\right\} \tag{7.21}$$

$$\mathbf{Z}^{\mathrm{S}}_{i\mu}(t+1) = \tilde{\mathbf{A}}_{i\mu}(t) \times \mathbf{x}^{\mathrm{S}}_{\mu}(t+1) \quad \forall i \tag{7.22}$$

$$\bar{\mathbf{f}}^{\mathrm{S}}_{\mu}(t+1) = \min\left(\mathrm{E}[\mathbf{f}(t+1) \mid \text{info}, \text{mode}], \mathbf{x}^{\mathrm{S}}_{\mu}(t+1) - \sum_j \mathbf{Z}^{\mathrm{S}}_{\mu j}(t+1) + \mathbf{I}^{\mathrm{FF}}_{\mu}(t)\right) \tag{7.23}$$

These create the necessary conditions for production in the next period. Note that the disaster significantly impacts anticipatory industries, since they base decisions about the level of future production on previous final demands. Inventories, thus, have an essential role in smoothing production mismatches due to asymmetric information.

Regional purchase coefficients for the period are, therefore, implicitly determined as a function of local supply capacity (see Sect. 7.3.5). The assumption of price stability is adequate in disruptions arising from unexpected events, as prices are slower to adjust. Also, if the analysis is performed in a small region, the assumption of price taking can be effective.

[22]See footnote 20 regarding the time indexes for JIT industries.

7.3.4 Solution Procedure

Recall that the SIM assumes that, in any period, JIT and responsive industries have perfect information on current and future final demands. If we assumed complete exogeneity of the latter, this requirement is easily satisfied and the model could be solved sequentially. With the demo-economic extension, however, households' final demand is endogenous and an iterative correcting approach is necessary. The SIM assumption is satisfied by reiterating periods in which the expected final demand and the actual final demand differ for responsive and JIT industries. For instance, at the first iteration of period t, expected final demand for these industries is set to a *prior* (the pre-disaster household's final demand) in Eq. (7.15) and the model is solved until $\mathbf{f}(t+1)$ is calculated via Eq. (7.11). If there is a mismatch between $\mathrm{E}[\mathbf{f}_\mu(t+1) \mid \text{info, JIT or Responsive}]$ and $\mathbf{f}_\mu(t+1)$ for $\forall \mu \mid$ JIT or Responsive, the *prior* is updated according to the convex adjustment function:

$$
\begin{aligned}
&\mathrm{E}\left[\mathbf{f}_\mu(t+1) \mid \text{info, J or R}\right] \\
&= \begin{cases} (1 + (\Delta(t+1) \times 100)^{\varepsilon}/100) * \mathrm{E}\left[\mathbf{f}_\mu(t+1) \mid \text{info, J or R}\right] & \text{if } \Delta(t+1) > 0 \\ (1 - (-\Delta(t+1) \times 100)^{\varepsilon}/100) * \mathrm{E}\left[\mathbf{f}_\mu(t+1) \mid \text{info, J or R}\right] & \text{if } \Delta(t+1) < 0 \end{cases}
\end{aligned} \tag{7.24}
$$

where $\Delta(t+1) = (\mathbf{f}(t+1)/\mathrm{E}[\mathbf{f}_\mu(t+1) \mid \text{info, J or R}]) - 1$ and $\varepsilon = 0.9$ is the adjustment elasticity.[23] The current process halts and period t is reiterated with the adjusted *prior*. Period $t+1$ is finally allowed to proceed when $\mathrm{E}[\mathbf{f}_\mu(t+1) \mid \text{info, JIT or Resposive}] = \mathbf{f}_\mu(t+1)$.[24]

7.3.5 Recovering the Input-Output Table for the Period

An IO table reflecting actual flows can be extracted for each period according to Fig. 7.3. Most of the vectors are determined directly from the previous equations. Interindustrial flows are determined by $\mathbf{Z}(t) = (\mathbf{A}(t) \times \hat{\mathbf{x}}^{\mathrm{A}}(t)) - \mathbf{M}^{\mathrm{I}}(t)$, as imported inputs are consumed first. Hence, total change in inventories is derived as:

$$
\begin{aligned}
\Delta\mathbf{I}(t) = &\left\{\left[\mathbf{Z}(t+1) + \mathbf{I}^{\mathrm{M}}(t)\right] \times \boldsymbol{\imath} + \mathbf{I}^{\mathrm{FI}}(t) + \mathbf{I}^{\mathrm{FF}}(t)\right\} \\
&- \left\{\left[\mathbf{Z}(t) + \mathbf{I}^{\mathrm{M}}(t-1)\right] \times \boldsymbol{\imath} + \mathbf{I}^{\mathrm{FI}}(t-1) + \mathbf{I}^{\mathrm{FF}}(t-1)\right\}
\end{aligned} \tag{7.25}
$$

[23] By letting $\varepsilon < 1$, the adjustment portrayed in Eq. (7.24) becomes non-linear, implying a smoother convergence correction so that each iteration allows some error room for adjustment in the next round.

[24] In case of responsive industries with forward lags >1, the algorithm requires reiterating previous periods when the forward lag is reached.

	Interindustrial Flows	**Final Demand**	**Δ in Inv.**	**Output**
Interindustrial Flows	$\left(\mathbf{A} \times \hat{\mathbf{x}}^{\mathrm{A}}(t)\right) - \mathbf{M}^{\mathrm{I}}(t)$	$\mathbf{f}^{\mathrm{A}}(t)$	$\left(\Delta\mathbf{Z}^{\mathrm{A}} + \Delta\mathbf{I}^{\mathrm{M}}\right) \times \boldsymbol{\iota} + \Delta\mathbf{I}^{\mathrm{FI}} + \Delta\mathbf{I}^{\mathrm{FF}}$	$\mathbf{x}^{\mathrm{A}}(t)$
Imports	$\boldsymbol{\iota} \times \mathbf{M}^{\mathrm{I}}(t)$	$\boldsymbol{\iota} \times \mathbf{m}^{\mathrm{FD}}(t)$		
Value Added	$\mathbf{x}^{\mathrm{A}}(t)' - \boldsymbol{\iota} \times \left(\mathbf{A} \times \hat{\mathbf{x}}^{\mathrm{A}}(t)\right)$			
Output	$\mathbf{x}^{\mathrm{A}}(t)'$			

Fig. 7.3 Extracted input-output table for period *t*

7.3.6 A Note on Inventories

First, recall that we assumed that besides relative prices, nominal prices do not change intertemporally. If they did, it would be necessary to account for holding gains/losses in inventories from period to period. Second, service sectors are assumed not to hold any finished goods inventory. It could be argued that they hold work-in-progress inventories (in case of consulting, entertainment, etc.), but it is assumed that these can be compartmentalized and produced in each time period. Unless h is very short (say, a day), one would expect finished services to be delivered in each time period.

Finally, the concept of partitioning transactions adopted in the System of National Accounts, which directly translates to the definition of distribution sectors (retail, wholesale and transportation) in the IO framework, needs to be accounted for when defining inventories. Transactions of retailers, wholesalers and transportation are recorded as their respective margins and, thus, represent services provided and not goods sold per se (United Nations 2009). They do not hold any finished goods inventory, and material and supplies inventories consist only of operating expenses (rent, electricity, packaging, etc.) without purchases for resale.

		Agriculture	Manufacturing	Services	Final Demand: Employed	Final Demand: Unemployed	Final Demand: Exports	Output
	Agriculture	5,129	27,147	788	13,107	713	5,917	52,801
	Manufacturing	9,192	121,491	38,735	127,063	3,959	42,109	342,549
	Services	3,084	44,835	76,574	233,534	4,043	13,367	375,436
Imports	Agriculture	387	2,459	743	1,724	57	-	
Imports	Manufacturing	967	7,378	5,940	7,760	257	-	
Imports	Services	580	14,757	743	7,760	257	-	
	Taxes	1,632	16,353	12,535	24,527	1,180	4,067	
	Value Added (Labor)	31,831	108,130	239,378				
	Output	52,801	342,549	375,436				
	Employment	4,906	3,700	11,905				
	Area (thousand sqft)	817	812	823				

Fig. 7.4 Pre-disaster IO Table, flow values in thousands of dollars

Table 7.1 Regional characteristics

Variable	Description	Value
τ	Labor force participation rate	0.60
σ	Expectations' adjustment parameter	0.05
σ^M	Foreign sectors expectations' adjustment parameter	0.01
ε	Error allowed for JIT and responsive industries	0.01
p	Resident population	40,000
$\bar{l}^E$	External labor force available	1000
s	Unemployment benefits per period	\$3000

7.4 Application Example

We illustrate the GDIO with a 3-sector example for a small economy. The pre-disaster IO table for the region is presented in Fig. 7.4 and its parametrization in Tables 7.1 and 7.2. The model runs for 36 periods and we assume an unexpected event in period 13 when 15% of manufacturing becomes inoperable. There is no population displacement. Recovery happens during the subsequent 5 periods (Table 7.2). In this example, we compare the effects of trade restrictions to losses in the region, simulating a fully flexible scenario and a restricted one. These import constraints are implemented using the amount of foreign inventories/external available capacity at each period as proxies ($\theta = 100$ and $\theta = 1.5$ respectively).[25]

Figures 7.5, 7.6 and 7.7 compare the results of both scenarios. Overall, under full trade flexibility, production losses are lower and recovery occurs faster than in the second scenario, since imports mitigate part of the supply restrictions in the economy. The model illustrates the major role that inventories and uncertainty have on losses and, especially, on their duration.

The initial periods post-disaster follow a similar pattern in both scenarios: first, manufacturing production declines due to capacity constraints causing a reduction in local income (due to layoffs) and a subsequent small impact on Services. Agriculture maintains the same level of production since it is anticipatory, thus overproducing

[25]The code and data for this example are available upon request.

Table 7.2 Industrial characteristics

	Agriculture	Manufacturing	Services
Production mode	Long anticipatory (2 months)	Short anticipatory (1 month)	Just-in-time
Hold inventories	Yes	Yes	No
ρ	0.99	0.98	0.98
Wages (per period)	$ 6488	$ 29,224	$ 20,107
Capital inoperability	0%	15%	0%
Capital recovery time	–	5	–

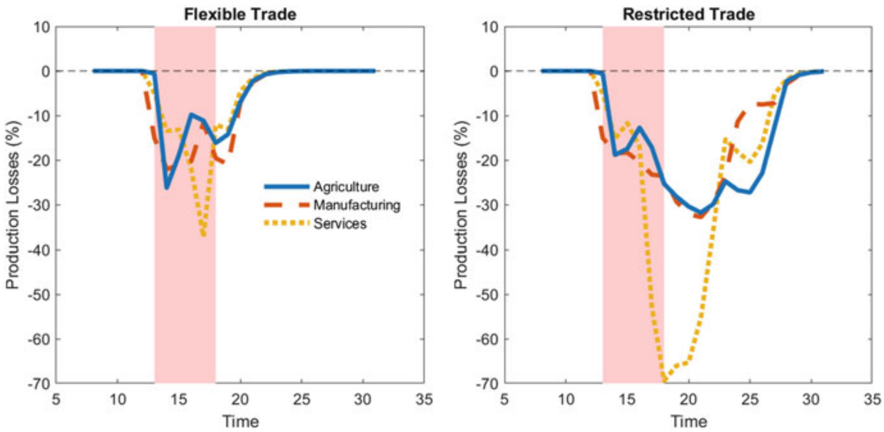


Fig. 7.5 Production losses by industry

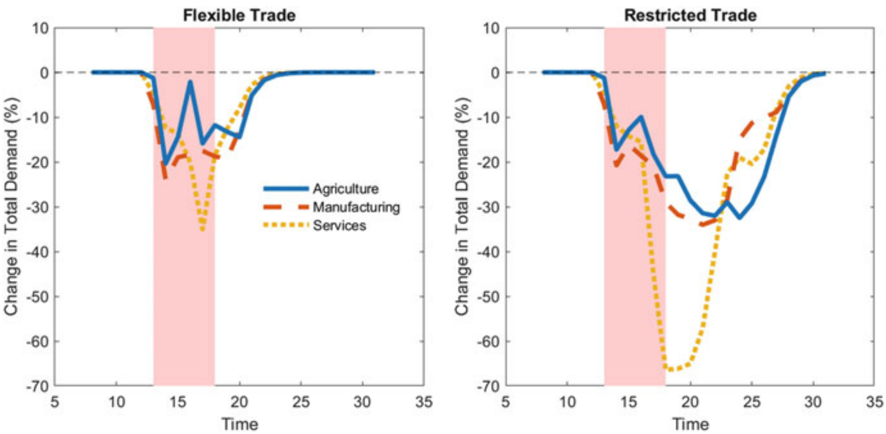


Fig. 7.6 Evolution of total demand (intermediate + final) by industry

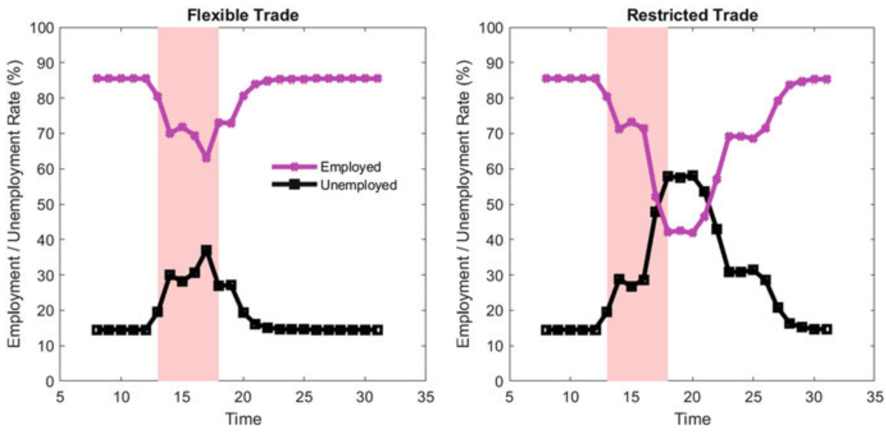


Fig. 7.7 Evolution of demographic indicators

and building up inventories. In the next period, a substantial decline is observed in all sectors due to supply constraints from manufacturing (indirect effects), available inventories in Agriculture, and lower final demand. Lower outputs also translate into increasing unemployment in the region, shifting the final demand mix towards less services and more agricultural goods.

Capacity restoration, expectation adjustments and enough inventories of intermediate goods allow a reduction in losses in periods 15–16 during which most of the inventory created in the previous two periods is consumed. The depletion of inventories, however, leads to insufficient intermediate local supply to support production from the service sector in the next period (when capacity is almost fully restored in the manufacturing sector). The negative impact in Services is exacerbated by the increase in unemployed residents who spend a significantly smaller share of their income in this sector than employed residents. As the most labor intensive sector in the economy, this leads to a negative inertial effect that exacerbates output losses until period 17. The two scenarios diverge from this point forward. The flexibility in trade in the first scenario, combined with the recovery experienced by Agriculture and Manufacturing, allows the Service sector to overcome local input supply restrictions and break its inertial effect, rebounding in the next periods. Conversely, trade restrictions in the second scenario slow such adjustment, especially for anticipatory industries in which supply-demand unbalances increase the uncertainty in the economy, compromising their expectations' correction. This longer realignment process permeates the system for several periods, feeding the negative inertial effect in Services, expanding unemployment and reducing final demand. In time, inventory and final demand heteroscedasticity decline, allowing the economy to rebound.

Services is the most sensitive sector in this example due to 2/3 of its output being consumed by the local final demand. Hence, changes in the composition and volume of household's demand have a crucial role in the dynamics of this sector.

By embedding intertemporal expectation adjustments via the SIM, and the demo-economic framework, this model reflects a non-smooth recovery process in contrast to other models currently available. We compare our estimates in the "flexible trade"

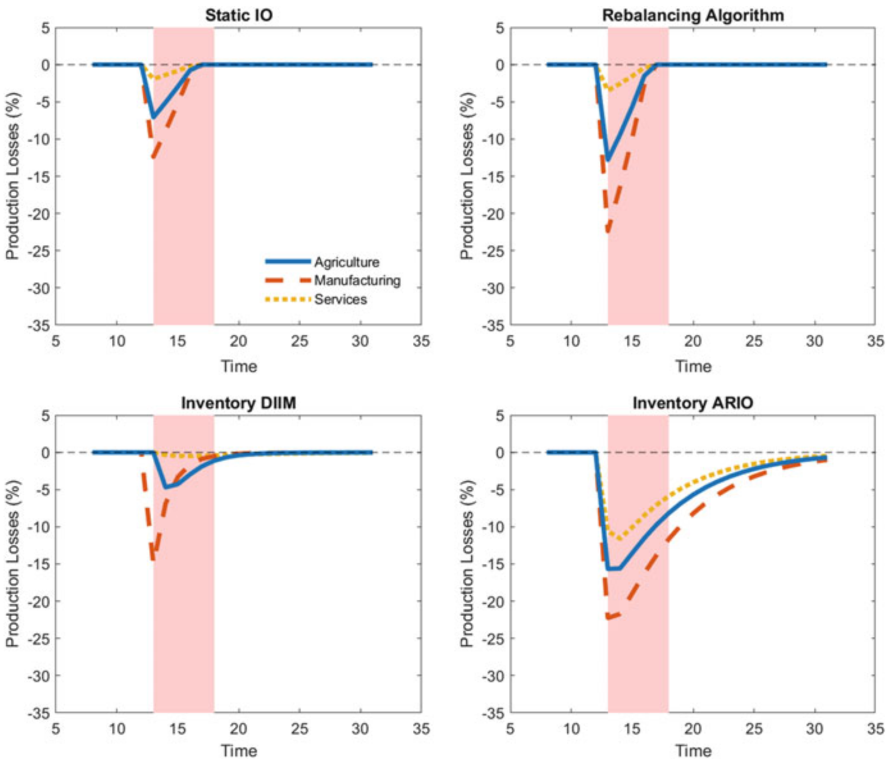


Fig. 7.8 Production losses and final demand, other models

scenario with four commonly used single-region models in the literature: the traditional Leontief model, a simplified version of Cochrane's rebalancing model, the Inventory DIIM, and the Inventory ARIO model (see Appendix 7.2 for details on their specifications, induced effects not considered).

Overall, the recovery curve is monotonic increasing and similarly smooth across all models (Fig. 7.8). Since there is no change in demand composition nor heterogeneous production chronology, the recovery path is very homogeneous between sectors, which is in clear contrast with Fig. 7.5, in which the SIM framework, combined with the explicit consideration of labor market changes, influences the amount and timing of impacts. Moreover, by not considering labor market conditions and their effect on final demand, Services is the least impacted sector in these models. The simulations shown in Fig. 7.8 do not consider induced effects, however, which may partially explain the smaller total losses in relation to our model.

Because of their static formulations, both the Leontief and rebalancing models have no disruption spillovers beyond the 5-period recovery time for Manufacturing. Since each period's inoperability is contained within itself, the resulting recovery path is completely dependent on the exogenous recovery timing imposed, and therefore linear. The rebalancing model shows larger losses than the Leontief model, as it captures part of the forward effects besides backward impacts.

Conversely, both dynamic models portrayed in the bottom of Fig. 7.8 account for intertemporal inoperability, resulting in longer recovery paths. In the Inventory-DIIM, the restoration pace is endogenously determined by the size of unbalance between supply-demand in each period, as well as the resilience and repair coefficient of the sectors. The Inventory-ARIO model operates in a somewhat similar fashion as the GDIO, however, without considering final demand mix changes nor different types of production modes. It is the model that generates the closest amount of total losses to our estimates (94.9%)[26] although the shape of the recovery curve differs substantially from our model due to the aforementioned differences.

7.5 Conclusions

Disaster events present unique challenges to economic assessment due to its time-compression characteristic that creates a structural break followed by simultaneous and intense recovery efforts in the affected areas. Due to modern "lean" production systems with high specialization, little spare capacity (to exploit scale economies), and longer production chains, disruptions and subsequent production delays in one node of a network can quickly spread to other chains and create lingering disruptive effects. Thus, there is a need to assess these transient phenomena in an industrial network perspective, accounting for the spatio-temporal spillovers within and between affected and unaffected regions.

Modeling these interdependent industrial linkages has been the main advantage of the IO framework, especially due to its relatively low data requirements, tractability and connectivity to external models. Given the simplicity and inadequacy of some of the assumptions in the traditional Leontief demand-driven model, several extensions have been proposed to address issues of supply constraints, dynamics and spatio-temporal limitations, but these contributions are still fragmentation in different models.

In a step towards a more complete methodology, the GDIO model is proposed in this chapter. It combines insights from the past literature, building upon the Inventory ARIO model, while also accounting for production scheduling, seasonality and demographic changes in a single framework. The GDIO, thus, encompasses the virtues of intertemporal dynamic models with the explicit intratemporal modeling of production and market clearing, thus allowing supply and demand constraints to be simultaneously analyzed. The key roles of inventories, expectation adjustments, timing of the event, displacement, primary inputs and physical assets are addressed. Seasonality can be included by using *intra-year* IO tables that can be derived via the T-EURO method (Avelino 2017). Through a demo-economic extension, we include induced effects post-disaster, accounting for level and mix changes in labor force and household income/expenditure patterns. The GDIO is "general" in the sense that simpler models as the Leontief formulation, SIM and demo-economic models can be easily derived by using

---

[26]Total losses from the other models amount to 11.9% (Leontief), 22.0% (rebalancing) and 12.5% (Inv-DIIM) of the total estimates for the GDIO.

simplifying assumptions. The model also allows for the extraction of balanced IO tables at each time step; this option might be advantageous in optimizing recovery efforts.

Despite these advances in modeling disaster events, the current version of the GDIO has several limitations. We are still restricted to assessing short-term effects, as in the long term the underlying socio-economic structure might exhibit significant changes [e.g., New Orleans after Hurricane Katrina (The Data Center 2015)]. The model also does not consider the impact of business cycles, when excess capacity might be extremely reduced (Hallegatte and Ghil 2008), nor does it endogenize the recovery process according to local conditions in each period (the recovery schedule is exogenously imposed). Related to the latter, although we account for the impact of labor force availability in the region, this constraint needs to be modeled exogenously accounting for accessibility and housing stock. Moreover, additional mitigation strategies beyond inventories need to be implemented in future developments of the GDIO, as those suggested by Rose and Wei (2013).

A simple application showed the advantage of the GDIO in capturing the impact of uncertainty in the recovery process, through intertemporal expectation adjustments that are affected by heteroscedasticity in inventory levels and final demand (endogenous in our model). The new system offers a more natural recovery curve in which breaks in the recovery process are common. Further research will be needed, especially for an application of the model in a real natural disaster situation in a multi-region context with seasonal IO tables, and where comparison of the results with existing methodologies can be made.

Acknowledgments The authors would like to thank Yasuhide Okuyama, Adam Rose and the two anonymous reviewers for providing substantial feedback and suggestions to improve this work. Any remaining errors are our own.

Funding This research was supported in part by an appointment to the U.S. Army Corps of Engineers (USACE) Research Participation Program administered by the Oak Ridge Institute for Science and Education (ORISE) through an interagency agreement between the U.S. Department of Energy (DOE) and the U.S. Army Corps of Engineers (USACE). ORISE is managed by ORAU under DOE contract number DE-SC0014664. All opinions expressed in this chapter are the author's and do not necessarily reflect the policies and views of USACE, DOE or ORAU/ORISE.

Appendix 7.1: Simplified Model IV (Batey and Weeks 1989)

$$\begin{pmatrix} \mathbf{I}-\tilde{\mathbf{A}} & -\mathbf{h}_{\mathrm{c}}^{\mathrm{E}} & -s\times\mathbf{h}_{\mathrm{c}}^{\mathrm{U}} \\ -\mathbf{h}_{\mathrm{r}}^{\mathrm{E}} & \mathbf{1} & \mathbf{0} \\ \mathbf{a}^{\mathrm{L}}\times\hat{\boldsymbol{\rho}} & \mathbf{0} & \mathbf{1} \end{pmatrix} \begin{pmatrix} \mathbf{x}^{\mathrm{A}} \\ x_{\mathrm{H}}^{\mathrm{E}} \\ u \end{pmatrix} = \begin{pmatrix} \mathbf{f}^{\mathrm{A}} \\ f_H \\ l^{\mathrm{T}} \end{pmatrix} \tag{7.26}$$

where:

$\tilde{\mathbf{A}}$: is a matrix ($n \times n$) of local direct input requirements
$\mathbf{x}^{\mathrm{A}}$: is a column vector ($n \times 1$) of total output by industry
$\mathbf{f}^{\mathrm{A}}$: is a column vector ($n \times 1$) of total final demand by industry

$\mathbf{h}_c^E$: is a column vector ($n \times 1$) of employed households' expenditure pattern
$\mathbf{h}_c^U$: is a column vector ($n \times 1$) of unemployed households' expenditure pattern
$\mathbf{h}_r^E$: is a row vector ($1 \times n$) of wage income from employment coefficients
$\mathbf{a}^L$: is a row vector ($1 \times n$) of employment/output ratios
$\boldsymbol{\rho}$: is a column vector ($n \times 1$) of probabilities indicating the likelihood of previously unemployed indigenous workers filling opened vacancies
s: unemployment benefits
x_H^E: total employed household income
f_H: income from exogenous sources to employed households
u: unemployment level
l^T: total labor supply

Appendix 7.2: Additional Models' Specification

Model	Assumptions
Static Leontief demand-driven model	Supply constraints converted into demand constraints via: $\mathbf{f}^A(t) = (\mathbf{I} - \boldsymbol{\Gamma}(t)) * \mathbf{f}^A(0)$ Where $\mathbf{I} - \boldsymbol{\Gamma}(t)$ represents the amount of inoperability by sector at time t.
Cochrane's model	No trade restrictions. Rebalance estimated using: $\mathbf{x}^A(t) = \left(\mathbf{I} - (\mathbf{I} - \boldsymbol{\Gamma}(t))\tilde{\mathbf{A}}\right)^{-1} * \mathbf{f}^A$
Inventory DIIM	Resilience coefficients (l) assumed 0.55 (agriculture) and 0.16 (services).[a] Manufacture's resilience coefficient estimated following Barker and Santos (2010) at 0.54.[a] Repair coefficients (k) estimated following Barker and Santos (2010).[a] No initial inventories.
Inventory ARIO (version 4.1)	Same parametrization from Hallegatte (2014), except: • Maximum overproducing capacity[b]: $\alpha_{max} = 1$ • Number of days of stock: $n_j^i = 60$ • Size of direct losses: 1 • Reconstruction timescale: 5 years • Production reduction parameter[b]: $\psi = 1$

[a]The Inv-DIIM is very sensitive to these parameters, as they inform the speed with which the supply-demand gap closes in each period
[b]The Inv-ARIO model is very sensitive to these parameters, see complete discussion on Hallegatte (2014)

References

Aulin-Ahmavaara P (1990) Dynamic input-output and time. Econ Syst Res 2(4):329–344
Avelino A (2017) Disaggregating input-output tables in time: the temporal input-output framework. Econ Syst Res 29(3):313–334
Barker K, Santos J (2010) Measuring the efficacy of inventory with a dynamic input-output model. Int J Prod Econ 126:130–143
Batey P (2018) What can demographic–economic modeling tell us about the consequences of regional decline? Int Reg Sci Rev 41:256–281
Batey P, Weeks M (1989) The effects of household disaggregation in extended input-output models. In: Miller R, Polenske K, Rose A (eds) Frontiers of input-output analysis. Oxford University Press, New York, pp 119–133
Batey P, Bazzazan F, Madden M (2001) Dynamic extended input-output models: some initial thoughts. In: Felsentein D, Mcquaid R, McCann P, Shefer D (eds) Public investment and regional development. Edward Elgar, Northampton, pp 26–39
Bénassy J (2002) The macroeconomics of imperfect competition and nonclearing markets. MIT Press, Cambridge
Bočkarjova M (2007) Major disasters in modern economies: an input-output based approach at modelling imbalances and disproportions. Doctoral Thesis – University of Twente, The Netherlands
Cochrane H (1997) Forecasting the economic impact of a Midwest earthquake. In: Jones B (ed) Economic consequences of earthquakes: preparing for the unexpected. NCEER, Buffalo, pp 223–247
Cole S (1988) The delayed impacts of plant closures in a reformulated Leontief model. Pap Reg Sci Assoc 65:135–149
Cole S (1989) Expenditure lags in impact analysis. Reg Stud 23(2):105–116
Debreu G (1959) Theory of value. Yale University Press, New Haven
Dietzenbacher E, Miller R (2015) Reflections on the inoperability input-output model. Econ Syst Res 27(4):1–9
Duchin F, Levine S (2011) Sectors may use multiple technologies simultaneously: the rectangular choice-of-technology model with binding factor constraints. Econ Syst Res 23(3):281–302
Hallegatte S (2008) An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. Risk Anal 28(3):779–799
Hallegatte S (2014) Modeling the role of inventories and heterogeneity in the assessment of the economic costs of natural disasters. Risk Anal 34(1):152–167
Hallegatte S, Ghil M (2008) Natural disasters impacting a macroeconomic model with endogenous dynamics. Ecol Econ 68:582–592
Hendricks K, Singhal V (2005) An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. Prod Oper Manag 14(1):35–52
Jackson R, Madden M (1999) Closing the case on closure in Cole's model. Pap Reg Sci 78 (4):423–427
Jackson R, Madden M, Bowman H (1997) Closure in Cole's reformulated Leontief model. Pap Reg Sci 76(1):21–28
Kim K, Hewings G (2019) Bayesian estimation of labor demand by age: theoretical consistency and an application to an input-output model. Econ Syst Res 31:44–69
Kim K, Kratena K, Hewings G (2014) The extended econometric input-output model with heterogeneous household demand system. Econ Syst Res 27(2):257–285
Koks E, Thissen M (2016) A multiregional impact assessment model for disaster analysis. Econ Syst Res 29(4):429–449
Leontief W (1970) The dynamic inverse. In: Carter A, Bródy A (eds) Contributions to input-output analysis I. North-Holland, London, pp 17–46
Li J, Crawford-Brown D, Syddall M, Guan D (2013) Modeling imbalanced economic recovery following a natural disaster using input-output analysis. Risk Anal 33(10):1908–1923

Lian C, Haimes Y (2006) Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input-output model. Syst Eng 9(3):241–258

Madden M (1993) Welfare payments and migration in a nonlinear, extended input-output model with an application to Scotland. Pap Reg Sci 72(2):177–199

Mules T (1983) Some simulations with a sequential input-output model. Pap Reg Sci Assoc 51:197–204

Okuyama Y (2007) Economic modeling for disaster impact analysis: past, present, and future. Econ Syst Res 19(2):115–124

Okuyama Y (2009) Critical review of methodologies on disaster impact estimation. https://www.gfdrr.org/sites/gfdrr/files/Okuyama_Critical_Review.pdf

Okuyama Y, Lim H (2002) Linking economic model and engineering model: application of sequential interindustry model (SIM). Research Paper 2002–12, REAL

Okuyama Y, Santos J (2014) Disaster impact and input-output analysis. Econ Syst Res 26(1):1–12

Okuyama Y, Hewings G, Kim T, Boyce D, Ham H, Sohn J (1999) Economic impacts of an earthquake in the New Madrid seismic zone: a multiregional analysis. In: Elliot W, McDonough P (eds) Optimizing post-earthquake lifeline system reliability: Proceedings of the 5th U.S. conference on lifeline earthquake engineering, August 12–14, 1999. American Society of Civil Engineers, Reston, pp 592–601

Okuyama Y, Hewings G, Sonis M (2002) Economic impacts of unscheduled events: sequential interindustry model (SIM) approach. Research Paper 2002–11, REAL

Okuyama Y, Hewings G, Sonis M (2004) Measuring economic impacts of disasters: interregional input-output analysis using sequential interindustry model. In: Okuyama Y, Chang S (eds) Modeling spatial and economic impacts of disasters. Springer, Berlin, pp 77–102

Olshansky R, Hopkins L, Johnson L (2012) Disaster and recovery: processes compressed in time. Nat Hazard Rev 13:173–178

Oosterhaven J (2000) Lessons from the debate on Cole's model closure. Pap Reg Sci 79 (2):233–242

Oosterhaven J (2017) On the limited usability of the inoperability IO model. Econ Syst Res 29 (3):452–461

Oosterhaven J, Bouwmeester M (2016) A new approach to modelling the impacts of disruptive events. J Reg Sci 56(4):583–595

Oosterhaven J, Többen J (2017) Wider economic impacts of heavy flooding in Germany: a non-linear programming approach. Spat Econ Anal 12(4):404–428

Przyluski V, Hallegatte S (2011) Indirect costs of natural hazards. CONHAZ Consortium, Paris

Ptak C, Smith C (2011) Orlicky's material requirements planning, 3rd edn. McGraw-Hill, New York

Richardson H, Park J, Moore J II, Pan Q (2014) National economic impact analysis of terrorist attacks and natural disasters. Edward Elgar, Cheltenham

Richardson H, Pan Q, Park J, Moore J II (2015) Regional economic impacts of terrorist attacks, natural disasters and metropolitan policies. Springer, New York

Romanoff E, Levine S (1977) Interregional sequential interindustry model: a preliminary analysis of regional growth and decline in a two region case. Northeast Reg Sci Rev 7:87–101

Romanoff E, Levine S (1981) Anticipatory and responsive sequential interindustry models. IEE Trans Syst Man Cybern 11(3):181–186

Romanoff E, Levine S (1990) Technical change in production processes of the sequential interindustry model. Metroeconomica 41(1):1–18

Rose A (2004) Economic principles, issues, and research priorities in hazard loss estimation. In: Okuyama Y, Chang S (eds) Modeling spatial and economic impacts of disasters. Springer, Berlin, pp 13–36

Rose A, Benavides J (1998) Regional economic impacts. In: Shinozuka M, Rose A, Eguchi R (eds) Engineering and socioeconomic impacts of earthquakes: an analysis of electricity lifeline disruptions in the New Madrid area. MCEER, Buffalo, pp 95–124

Rose A, Wei D (2013) Estimating the economic consequences of a port shutdown: the special role of resilience. Econ Syst Res 25(2):212–232

Santos J (2003) Interdependency analysis: extensions to demand reduction inoperability input-output modeling and portfolio selection (Unpublished doctoral dissertation). University of Virginia, Charlottesville, VA

Santos J, Haimes Y (2004) Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures. Risk Anal 24(6):1437–1451

Sohn J, Hewings G, Kim T, Lee J, Jang S (2004) Analysis of economic impacts of an earthquake on transportation network. In: Okuyama Y, Chang S (eds) Modeling spatial and economic impacts of disasters. Springer, Berlin, pp 233–256

ten Raa T (1986) Dynamic input-output analysis with distributed activities. Rev Econ Stat 68 (2):300–310

The Data Center (2015) Facts for features: Katrina recovery. Retrieved from https://www.datacenterresearch.org/data-resources/katrina/facts-for-features-katrina-recovery/

United Nations (2009) System of national accounts 2008. United Nations, New York

University of Tennessee (2014) Managing risk in the global supply chain. Global Supply Chain Institute, Knoxville

van Dijk J, Oosterhaven J (1986) Regional impacts of migrants' expenditures: an input-output/vacancy-chain approach. In: Batey P, Madden M (eds) Integrated analysis of regional systems. Pion, London, pp 122–147

Andre F. T. Avelino is a post-doctoral research associate at the University of Illinois at Urbana-Champaign (United States). His research encompasses several interdisciplinary topics related to human-environmental interactions, especially focused on natural disasters, environmentally extended input-output models, economic impacts of climate change, and seasonality in interindustrial relationships. Dr. Avelino earned his doctoral degree in Agricultural and Applied Economics with specialization in Regional Development and Policy from the University of Illinois at Urbana-Champaign in 2018.

Geoffrey Hewings is a Professor Emeritus in the University of Illinois at Urbana-Champaign. His main interests are in the modeling of urban and regional economies; for the last 30 years, these interests have been centered in the Regional Economics Applications Laboratory at Illinois. He was previously at the University of Kent (UK) and the University of Toronto. His PhD is from the University of Washington.

Chapter 8
Multiregional Disaster Impact Models: Recent Advances and Comparison of Outcomes

Elco Koks, Raghav Pant, Trond Husby, Johannes Többen, and Jan Oosterhaven

Abstract This chapter provides an overview of several multiregional modelling approaches used for disaster impact analysis. The chapter specifically focuses on the multiregional supply-use model, the dynamic multiregional inoperability input-output model, the multiregional impact assessment model and the non-linear programming model. Whereas the first two approaches have been applied widely over the last years, the latter two are recently developed methods which aim to improve the estimation of a disruption in the economic system by, amongst others, allowing for a supply shock and spatial substitution effects. Our outcomes show significantly distinct results for the demand-driven multiregional supply-use model and the dynamic multiregional inoperability input-output model on the one hand, and for the non-linear programming model and the multiregional impact assessment model, on the other hand. Whereas for the former only negative impacts in all German

E. Koks (✉)
Environmental Change Institute, University of Oxford, Oxford, UK

Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands
e-mail: elco.koks@vu.nl

R. Pant
Environmental Change Institute, University of Oxford, Oxford, UK
e-mail: raghav.pant@ouce.ox.ac.uk

T. Husby
PBL Netherlands Environmental Assessment Agency, The Hague, The Netherlands
e-mail: Trond.husby@pbl.nl

J. Többen
Norwegian University of Science and Technology, Trondheim, Norway
e-mail: johannes.tobben@ntnu.no

J. Oosterhaven
Faculty of Economics and Business, University of Groningen, Groningen, The Netherlands
e-mail: j.oosterhaven@rug.nl

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_8

regions and foreign countries are observed, the latter also shows positive impacts in several only indirectly impacted regions in addition to different negative impacts.

8.1 Introduction

Although the field of disaster impact modelling has traditionally been dominated by engineering-type of studies, there is a growing interest in understanding the multi-faceted economic impacts of disaster risks. For example, one recent strand of literature investigates empirically the long-term impacts of disasters on aggregate economic growth (e.g., Cavallo et al. 2013; Klomp and Valckx 2014; Lazzaroni and van Bergeijk 2014). Other recent empirical papers exploit the exogenous variation in weather extremes over time within a given spatial area to study local disaster impacts (for a summary, see Dell et al. 2014). Finally, a range of studies employing newly developed economic models investigate the systemic effects of disaster risks (e.g. Okuyama 2015; Oosterhaven and Bouwmeester 2016; Wenz et al. 2014). Many of the latter studies make use of the well-established input-output (IO) modelling approach.

In this chapter we discuss how the traditional IO model has evolved over the years to multiregional and flexible approaches, such as the newly developed models by Oosterhaven and Bouwmeester (2016) and Koks and Thissen (2016). Besides the newly developed models, we discuss the widely used multiregional input-output (MRIO) model, the Inoperability IO Model (IIM) and its multiregional version (MRIIM). In addition to the theoretical discussion, we run these models on a case-study of floods in Germany. The economic impacts for Germany of the 2013 Danube and Elbe floods are estimated with all models, using the German multiregional supply-use table for 2007 (Többen 2017). The applied economic disruptions are based on direct supply and demand losses as a result of reduced labor production capacities due to the aforementioned floods (In den Baumen et al. 2015; Oosterhaven and Többen 2017).

Next to the explanation and comparison of the various IO modelling frameworks, we argue in this paper that the traditional IO approaches have methodological difficulties in estimating the effects of a supply-side disruptions. As these traditional approaches are still widely used in disaster impact analysis, we cannot simply ignore them. Hence, to show how both the traditional and the more recently developed modelling approaches should be interpreted relative to each other, we estimate the total effects for all models. By showing the outcomes side-by-side, we make a case that traditional IO approaches may be less suitable in estimating the impacts of a natural disaster.

In this study we focus on direct flow effects and indirect flow effects. We refer to the impacts as effects, as they could be both positive and negative. The direct (flow) effects are defined as the impacts which occur to businesses directly affected. The indirect (flow) effects are defined as the system-wide effects to other firms and industries via backward and/or forward linkages (Okuyama and Santos 2014).

The chapter proceeds as follows. In Sect. 8.2 we provide a concise summary of the traditional IO model and the rationale behind using IO modelling in disaster impact analysis. In Sect. 8.3 we discuss some common multiregional modelling approaches, which all use the IO framework as the starting point. Section 8.4 shows the outcomes of the various models by means of a German case study. Following, Sect. 8.5 discusses the outcomes and the interpretation of the various models. Finally, Sect. 8.6 concludes the chapter.

Throughout this chapter, unless otherwise stated, matrices are denoted by bold capitals, vectors by bold small types, and scalars by italics; $\mathbf{x}'$ indicates the transpose of $\mathbf{x}$, $\hat{\mathbf{x}}$ a diagonal matrix of $\mathbf{x}$, $\mathbf{i}'$ a summation row with ones, and $\mathbf{I} = \hat{\mathbf{i}}$ the identity matrix, while a • represents an index over which a summation has been applied. Furthermore, superscripts r and s refer to regions/nations, subscripts i and j to industries and subscript p to products.

8.2 Background

The most commonly used approaches to assess the economic impacts of disasters are IO and Computable General Equilibrium (CGE) models.[1] An IO model is an analytical technique for explaining the economic system (Christ 1955). In its most simple form, an IO model is a linear system of equations, in which product flows from each of the sectors (as a producer/seller) to each of the sectors (as a purchaser/buyer) are explained. CGE models have the same analytical purpose as IO models, only more sophisticated. CGE models allow for more flexibility in the production and consumption technology (i.e., alternative production and utility functions) and are therefore capable of analyzing more complex changes in the economy compared to IO models.

When modelling the economic effects of disasters, it is essential to understand how a specific disaster may disrupt the economic system. Several papers (Koks and Thissen 2016; Oosterhaven and Bouwmeester 2016; Rose and Wei 2013) argue that shocks from natural disasters primarily affect the supply-side of the economy, and should, as such, be seen as a supply-side shock. Therefore, using a demand-driven modelling technique, such as the traditional IO model models, has been proven to cause difficulties in assessing the impacts of such events. Some have tried to overcome this issue by re-interpreting the disaster as a demand shock (Santos and Haimes 2004). However, in a recent contribution, Oosterhaven (2017) shows that demand (MR)IO models are unsuited to simulate the impacts of supply shocks. The core, but not the only problem, is double counting the endogenous intermediate demand in open (i.e., Type I) IO models and, additionally, double counting endogenous consumption demand in semi-closed (i.e., Type II) IO models. A special problem is posed by industries like the mining sector that have (close to) zero exogenous final demand. An adequate solution of the core problem may require ad hoc dealing with import and export substitution, along with using allocation

[1]For the sake of unnecessary repetition, this chapter will not provide a full comparison between IO and CGE models. For a more comprehensive comparison between the models and an overview in the field, please refer to, for instance, Okuyama and Santos (2014) and Koks et al. (2016).

coefficients for the destination of output and processing (i.e., reciprocal technical) coefficients for the impact on output in the processing sectors (Oosterhaven 1988; Rose and Wei 2013). Others have made use of a (altered) version of the supply-driven model (Ghosh 1958), which however is shown to be a theoretically implausible approach (Oosterhaven 1988, 2012).

Traditional IO models and the variants mentioned above are mostly static models that estimate annual economic losses. Numerous studies have developed dynamic IO models and their variants to assess the short-run economic effects that occur from a natural disaster within an affected area (e.g., Hallegatte 2008; Rose et al. 2011; Santos and Haimes 2004). Recently, more research focuses on assessing the indirect losses outside the affected region in more detail as well. To this end a few studies have emphasized the multiregional effects of natural disasters in using both static and dynamic IO modelling approaches (MacKenzie et al. 2012a; Arto et al. 2015; Bierkandt et al. 2014; In den Baumen et al. 2015; Okuyama 2004). These studies show that substantial losses can occur outside the directly affected regions.

The additional insights one can get by incorporating trade and interregional spillovers in the multiregional IO modelling framework have been picked up over the last years in the research community. This is exemplified by the large amount of publications, based around large global multiregional datasets which have been developed in the last decade (i.e. WIOD, EORA and EXIOBASE[2]). These new datasets have been the starting point of the development of various models (i.e., Koks and Thissen 2016) and will allow for a much more complete impact analysis in the future. However, before we dive into the capabilities of such frameworks, let us go briefly through the basics of the traditional input-output model.

The coefficients of an IO model can be calibrated from an input-output table (IOT) as well as from a supply-use table (SUT) (Oosterhaven 1984). The most important part of an IOT describes the transaction flows between pairs of sectors (from sector i to sector j), denoted as z_{ij}. Besides these interindustry flows, each sector also sells goods to other users that, in the base IO model, are all assumed to behave exogenously; these actors can be, for instance, households or governments. These exogenous flows, generally referred to as final demand, are denoted as f_{iq}. Let's assume that the economy can be categorized into n sectors. And let's denote x_i as the total output (production) of sector i. Then we can rewrite the above as a simple equation in which sector i distributes its products through sales to other sectors and to final demand:

$$x_i = \sum\nolimits_j z_{ij} + \sum\nolimits_q f_{iq} \tag{8.1}$$

This equation symbolizes that the IO model assumes that demand determines the size of total output. To this base assumption, the base IO model only adds one additional behavioral equation that states that each sector uses its intermediate inputs

[2]Please refer to Moran and Wood (2014) for an overview of these datasets and how they relate to each other.

in a fixed proportion to its total output; an assumption that can be derived from a cost minimization under a Walras-Leontief production function (Oosterhaven 1996):

$$z_{ij} = a_{ij} x_j \tag{8.2}$$

Substituting (8.2) in (8.1) and rewriting the result in matrix form gives the standard IO model:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \tag{8.3}$$

Its solution for a given a set of final demand requirements reads as follows:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} \tag{8.4}$$

where:

$\mathbf{x} = n \times 1$ vector of total output

$\mathbf{f} = n \times 1$ vector of final demand

$\mathbf{A} = n \times n$ matrix with technical coefficients

In Eq. (8.4), $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief Inverse, which indicates how much each sector must produce in order to deliver a unit of final goods and services. In the case of assessing how a change in final demand ($\Delta\mathbf{f}$) may impact the production levels of each sector ($\Delta\mathbf{x}$), Eq. (8.4) can be easily used in the form of $\Delta\mathbf{x} = \mathbf{L}\,\Delta\mathbf{f}$.

8.3 Methods

8.3.1 Multiregional Input-Output (MRIO) Model

Considering the increasing globalization and interdependencies between nations and regions, only looking at a single region/nation, disregarding its imports and exports, may result in suboptimal outcomes of an impact analysis. It may not be so much the case of underestimated total single region outcomes (research has shown that including interregional feedbacks increases single-region estimates by no more than 3–10%, (Miller 1969; Oosterhaven 1981), but mainly about understanding the dynamics of the impacts through our economy. As such, it is clear that one of the core foci in our field should lie in a further development of the incorporation of the interregional spillover effects of disasters in our modelling frameworks.

In an ideal world, the single-region IO model would be extended in full detail to an interregional IO model. An IRIO table provides full information on regional supply, demand and trade of all regions included in the table and is often referred to as the Isard (1951) model. The construction of these tables, however, requires a tremendous amount of data, often not available or too difficult to estimate. Hence, much research has focused on the estimation of multiregional IO (MRIO) tables. In the literature, three main versions of limited information MRIO models are being distinguished, besides the full information Isard model: (1) The column-coefficient model, the so-called Chenery et al. (1953) and Moses (1955) model, which uses uniform geographical trade origin shares calculated from the columns of the trade matrices; (2) the row-coefficient model, the so-called Polenske (1970) model, which uses uniform trade destination shares calculated from the rows of the trade matrices and; (3) the gravity model, the so-called Leontief and Strout (1963) model, which combines origin, destination and distance information. The difference between the three versions mainly lies in how trade is being dealt with. As shown in Polenske (1970), the column coefficient model (i.e., the Chenery-Moses model) performs best and has, therefore, been used for the construction of the US MRIO tables. Subsequently, this version became considered as the basic MRIO model (see e.g. Miller and Blair 2009; Oosterhaven and Hewings 2014), and this version will be briefly discussed in this chapter.

The core difference between the traditional IO model and its multiregional extension is the inclusion of trade between regions. We assume that there are R regions trading between each other. First we define the trade flows between regions, which in the MRIO model are estimated by sector. For sector i, the trade coefficient can be defined as:

$$t_{i\bullet}^{rs} = \frac{c_{i\bullet}^{rs}}{\sum^{r} c_{i\bullet}^{rs}} \tag{8.5}$$

where c is defined as the flow of products from sector i from region r to region s, irrespective of the sector of destination in the receiving region, as indicated by the aggregation dot. In the literature, the intraregional trade coefficient $t_{i\bullet}^{rr}$ is often referred to as the regional purchase coefficient (RPC, Stevens and Trainer 1980). In contrast to the single-region IO model that has no exports or imports, the intraregional input coefficient a_{ij}^{rr} is not a technical coefficient anymore. It now becomes the product of the technical IO coefficient and the trade coefficient, and the same holds for the interregional input coefficients a_{ij}^{sr}:

$$a_{ij}^{rr} = t_{i\bullet}^{rr} a_{ij}^{\bullet r} \text{ and } a_{ij}^{sr} = t_{i\bullet}^{sr} a_{ij}^{\bullet r} \text{ with } \sum^{s} t_{i\bullet}^{sr} = 1 \tag{8.6}$$

For one region in the MRIO model, Eq. (8.2) can then be rewritten as:

$$x_i^r = \sum^{s} \sum_{j} t_{i\bullet}^{rs} a_{ij}^{\bullet s} x_j^s + \sum^{s} t_{i\bullet}^{rs} \sum_{q} f_{iq}^{s}, \forall i, r \tag{8.7}$$

Reading Eq. (8.7) from left to right illustrates the core of the multiregional model. First, the output of sector i in region r is equal to the sum of intermediate sales across all regions plus the sum of the sales to final consumption across all regions. Second, intermediate use of any sector in any region is proportional to its production output;

that is, the coefficient $a_{ij}^{rs} = t_{i\bullet}^{rs} a_{ij}^{\bullet s}$ represents the intermediate use of products from sector i in region r by sector j in region s per unit of output of that sector.

In matrix algebra, where for n industries across R regions, $\mathbf{x}$ is now the $rn \times 1$ vector of outputs, $\mathbf{A}$ is now the $rn \times rn$ diagonal block matrix of regional technical coefficients, $\mathbf{T}$ is the $rn \times rn$ block matrix of with trade coefficients on the diagonals of its blocks, and $\mathbf{f}$ is the $rn \times 1$ vector of regional final demands, Eq. (8.7) can be written as:

$$\mathbf{x} = \mathbf{TAx} + \mathbf{Tf} \tag{8.8}$$

Or rewritten into the form of the solution Eq. (8.4):

$$\mathbf{x} = (\mathbf{I} - \mathbf{TA})^{-1}\mathbf{Tf} \tag{8.9}$$

The matrix **(I-TA)** is constructed such that it is invertible, so that a solution for $\mathbf{x}$ exists. In matrix form, including r regions, Eq. (8.9) reads as:

$$\begin{bmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^r \end{bmatrix} = \left(\begin{bmatrix} \mathbf{I} & 0 & \cdots & 0 \\ 0 & \mathbf{I} & \cdots & 0 \\ \vdots & \vdots & & \\ 0 & 0 & \cdots & \mathbf{I} \end{bmatrix} - \begin{bmatrix} \hat{\mathbf{t}}^{11} & \cdots & \hat{\mathbf{t}}^{1r} \\ \hat{\mathbf{t}}^{21} & \cdots & \hat{\mathbf{t}}^{2r} \\ \vdots & & \\ \hat{\mathbf{t}}^{r1} & \cdots & \hat{\mathbf{t}}^{rr} \end{bmatrix} \begin{bmatrix} \mathbf{A}^1 & 0 & \cdots & 0 \\ 0 & \mathbf{A}^1 & \cdots & 0 \\ \vdots & \vdots & & \\ 0 & 0 & \cdots & \mathbf{A}^r \end{bmatrix} \right)^{-1} \begin{bmatrix} \hat{\mathbf{t}}^{11} & \cdots & \hat{\mathbf{t}}^{1r} \\ \hat{\mathbf{t}}^{21} & \cdots & \hat{\mathbf{t}}^{2r} \\ \vdots & & \\ \hat{\mathbf{t}}^{r1} & \cdots & \hat{\mathbf{t}}^{rr} \end{bmatrix} \begin{bmatrix} \mathbf{f}^1 \\ \mathbf{f}^2 \\ \vdots \\ \mathbf{f}^r \end{bmatrix} \tag{8.10}$$

Again, similar as shown in Sect. 8.2, Eq. (8.9) can be written in the form of $\Delta\mathbf{x} = (\mathbf{I} - \mathbf{TA})^{-1}\mathbf{T}\Delta\mathbf{f}$ to assess how a change in final demand ($\Delta\mathbf{f}$) alters the endogenous total production of the economy ($\Delta\mathbf{x}$). This means that the MRIO model allows us to investigate how a change in final demand in one region may impact production volumes by sector in all regions.

8.3.2 Multiregional Supply-Use (MRSU) Model

The discussed traditional IO models either implicitly or explicitly assume that each industry produces a single homogenous output (Oosterhaven 1996). In reality, however, industries produce a mix of products, which complicates the construction of IO tables. This is why, nowadays, so-called supply-use tables (SUTs) are assembled more frequently than IOTs. The advantage of SUTs over IOTs is that they explicitly distinguish products from industries, and therefore abstain from the problematic assignment of byproducts of other industries to the industry that has this product as its main output. Due to the greater availability of supply-use tables, this type of accounting framework is now more and more used in the field of disaster impact modelling too.

A SUT consists of two main sub-tables, the supply table and the use table. The supply table has industries on its rows and the products produced by each of these industries on its columns. The use table, on the other hand, has industries (and final demand categories) on its columns and the products that are used by of each of these industries (and final demand categories) on its rows. With relatively easy matrix algebra (Eurostat 2008; Miller and Blair 2009), a usually rectangular SUT (with usually more products than industries) can be transformed into a symmetric industry-by-industry or product-by-product IOT, allowing for an impact analysis as in Eqs. (8.4) and (8.9).

However, as exogenous changes in the IO model refer to changes in final demand (see Sect. 8.2) they will usually be operationalized as changes in the demand for products and not in the changed demand for *all* products of a certain industry. This gives the use of SUTs an additional advantage over IOTs. In the IO case, demand for products has to be allocated to industries which may pose problems when limited information is available about product flows and their use by industries (Oosterhaven 1984).

Fortunately, instead of transforming a rectangular SUT into a symmetric IOT, one may also directly base an IO model on a SUT accounting framework (Oosterhaven 1984). Let's denote the Use matrix with $\mathbf{U}$ where u_{pj} is the value of purchases of product p by industry j. Similar to technical coefficients a_{ij}, the SUT technical coefficients can be estimated in matrix form as:

$$\mathbf{B} = \mathbf{U}\hat{\mathbf{x}}^{-1} \tag{8.11}$$

The supply or make matrix, on the other hand shows which products are being made by each industry. This matrix is usually denoted $\mathbf{V}$ with v_{ip} showing the value of the output of product p that is produced by industry i. When the assumption is made that each industry has a fixed market share in the supply of each product:

$$\mathbf{D} = \mathbf{V}\hat{\mathbf{s}}^{-1} \tag{8.12}$$

then the use of products by industry can be linked to the making of products by industry. Following Lenzen and Rueda-Cantuche (2012), the system of equations of the SUT can be easily rewritten into a form usable for impact analysis. The SUT accounting identities for total industry output $\mathbf{x}$ and total product supply $\mathbf{s}$ read as:

$$\begin{bmatrix} \mathbf{s} \\ \mathbf{x} \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{U} \\ \mathbf{V} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{i}_p \\ \mathbf{i}_i \end{bmatrix} + \begin{bmatrix} \mathbf{f}_p \\ 0 \end{bmatrix} \tag{8.13}$$

Substitution of the behavioral Eqs. (8.11) and (8.12) in (8.13) gives:

$$\begin{bmatrix} \mathbf{s} \\ \mathbf{x} \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{B} \\ \mathbf{D} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{s} \\ \mathbf{x} \end{bmatrix} + \begin{bmatrix} \mathbf{f}_p \\ 0 \end{bmatrix} \tag{8.14}$$

which has the following solution:

$$\begin{bmatrix} \mathbf{s} \\ \mathbf{x} \end{bmatrix} = \left(\mathbf{I} - \begin{bmatrix} 0 & \mathbf{B} \\ \mathbf{D} & 0 \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{f}_p \\ 0 \end{bmatrix} \tag{8.15}$$

In the case of assessing how a change in final demand may impact both the total production and the total commodity use/supply, Eq. (8.15) can be rewritten as:

$$\begin{bmatrix} \Delta\mathbf{s} \\ \Delta\mathbf{x} \end{bmatrix} = \left(\mathbf{I} - \begin{bmatrix} 0 & \mathbf{B} \\ \mathbf{D} & 0 \end{bmatrix} \right)^{-1} \begin{bmatrix} \Delta\mathbf{f}_p \\ 0 \end{bmatrix} \begin{bmatrix} \Delta\mathbf{s} \\ \Delta\mathbf{x} \end{bmatrix} = \left(\mathbf{I} - \begin{bmatrix} 0 & \mathbf{B} \\ \mathbf{D} & 0 \end{bmatrix} \right)^{-1} \begin{bmatrix} \Delta\mathbf{f}_p \\ 0 \end{bmatrix} \tag{8.16}$$

Similar to the IO model, the SU model can also be extended to a multiregional version. Here we present how an impact analysis can be performed, considering the simplest possible variant of multi-regional SUT frameworks, in which only information about the spatial origin and destination of trade flows is given (see Oosterhaven 1984, for all variants). Within this framework two accounting identities must hold. The first one is the *product supply-demand balance*, which states that total supply of products has to equal to total use of products within a region:

$$\mathbf{s}^r = (\mathbf{i}'\mathbf{V}^r)' + (\mathbf{i}'\mathbf{T}^{\bullet r})' + \mathbf{m}^r = \mathbf{U}^r\mathbf{i} + \mathbf{f}^r + \mathbf{T}^{r\bullet}\mathbf{i} + \mathbf{e}^r \tag{8.17}$$

where $\mathbf{m}^r$ and $\mathbf{e}^r$, respectively, denote foreign imports and foreign exports of region r by product, and $\mathbf{T}^{\bullet r}$ and $\mathbf{T}^{r\bullet}$, respectively, denote the block column for region r and the block row for region r of the block matrix with interregional trade flows by product on the diagonals of the blocks, with the intra-regional blocks being equal to $\mathbf{0}$. The second identity states that total output by industry has to be equal to the sum of intermediate inputs and primary inputs (value added $\mathbf{w}^r$) and is thus called the *industry input-output balance*:

$$\mathbf{x}^r = \mathbf{V}^r\mathbf{i} = (\mathbf{i}'\mathbf{U}^r)' + \mathbf{w}^r \tag{8.18}$$

Similar to the MRIO model, trade coefficients have to be estimated to allocate total regional purchases by product to their geographical origin of production. Define $\hat{\mathbf{P}}$ as the block diagonal matrix with $\mathbf{p}' = \mathbf{i}'\mathbf{V}^r$, i.e., the intra-regional supply of products, on the diagonals of the diagonal blocks and $\mathbf{0}$ elsewhere, then the block matrix with both intra-regional and interregional trade coefficients on the diagonals of its blocks can be estimated as follows:

$$\mathbf{C} = \left(\hat{\mathbf{P}} + \mathbf{T}\right)\hat{\mathbf{s}}^{-1} \tag{8.19}$$

For products, that are also imported from the rest of the world, column sums of **C** will be smaller than one. For products without foreign imports the column sums of **C** will equal **1**. Introducing **C** along with technical coefficients **B** and industry market shares **D**, and assuming for each product equal average import propensity for all types of use, the stacked vector with the intra-regional supply of products, i.e., the first term of Eq. (8.17) may be rewritten as:

$$\mathbf{p} = \mathbf{C}\left(\mathbf{B}\overline{\mathbf{D}}\mathbf{p} + \mathbf{f}\right) \tag{8.20}$$

Thereby, product $\mathbf{CB}\overline{\mathbf{D}}\mathbf{p}$ has the following properties: The industry market shares matrix **D** allocates the demand for regional products **p** to regional industries and determines, therefore, regional output by industry. Regional industry output further determines intermediate consumption of products by industries according to the technical coefficients' matrix **B** assuming *industry technology*. Thereafter, regional intermediate consumption is allocated to the regional origin of products according to the trade coefficients' matrix **C**.

Solving Eq. (8.20) for product output yields the solution of a multi-regional supply-use (MRSU) model, which describes the relationship between regional final demand and regional product output:

$$\mathbf{p} = \left(\mathbf{I} - \mathbf{CB}\overline{\mathbf{D}}\mathbf{p}\right)^{-1}\mathbf{Cf} \tag{8.21}$$

The corresponding solution for regional industry output read as:

$$\mathbf{x} = \left(\mathbf{I} - \overline{\mathbf{D}}\mathbf{CB}\right)^{-1}\overline{\mathbf{D}}\mathbf{Cf} \tag{8.22}$$

In this case pre-multiplying final demand by $\overline{\mathbf{D}}\mathbf{C}$, first, transfers final demand for products to purchases from a specific region and, second, transfers this demand further to the specific industries that deliver that product in that region of origin. This model is comparable to Eq. (8.10) in the sense that information about the spatial origin and destination of products is used to derive a matrix of (column) trade coefficients, which distributes spatial purchases of industries and categories of (domestic) final demand within a region to different regional sources according to their market share in product supply (Oosterhaven 1984).

8.3.3 Multiregional Inoperability Input-Output Model (MRIIM)

A commonly used approach in the disaster impact literature is the Inoperability Input-Output Model. The IIM introduces the notion of an inoperability index, q_i, which is the ratio between the post-disaster loss of production and the pre-disaster level of production in industry i. Hence q_i is a dimensionless number ranging between 0 and 1. Haimes and Jiang (2001) laid the conceptual and theoretical foundations for the IIM, while Santos and Haimes (2004) and Santos (2006) developed a process in which the IIM is derived from the Leontief IO model to study the higher order effects of inoperability across interdependent economic systems. The IIM has been applied now in various cases studies including, among others, the North East US blackouts (Anderson et al. 2007), cyber threats (Andrijcic and Horowitz 2006), and influenza epidemics (Santos et al. 2013). The core equation of the IIM can be described as:

$$\mathbf{q} = \mathbf{A}^*\mathbf{q} + \mathbf{f}^* \Leftrightarrow \mathbf{q} = (\mathbf{I} - \mathbf{A}^*)^{-1}\mathbf{f}^* \tag{8.23}$$

where:

$$\mathbf{q} = \hat{\mathbf{x}}^{-1}\Delta\mathbf{x}$$

$$\mathbf{A}^* = \hat{\mathbf{x}}^{-1}\mathbf{A}\hat{\mathbf{x}}$$

$$\mathbf{f}^* = \hat{\mathbf{x}}^{-1}\Delta\mathbf{f}$$

Here, as is evident, $\mathbf{q}$ and $\mathbf{f}^*$ are $n \times 1$ vectors, $\mathbf{A}^*$ a $n \times n$ matrix, and the inverse of $(\mathbf{I} - \mathbf{A}^*)$ exists. As shown in Dietzenbacher and Miller (2015), the IIM is a rewritten version of the traditional IO model expressed in relative changes instead of the usual expression in absolute changes. Hence the outcomes are exactly the same as the outcomes of a traditional IO model, but then measured in an inoperability index between 0 and 1, i.e. measured in a relative output reduction of, respectively, 100% or 0%. In the IIM direct disruptions are modelled as demand-side effects, which are quantified in the vector $\mathbf{f}^* = \hat{\mathbf{x}}^{-1}\Delta\mathbf{f}$, called the demand perturbation vector. It is important to note that the exogenous variable of the IIM ($\mathbf{f}^*$) does not range from 0 to 1, but from 0 to the share of final demand in total output by sector, i.e. to $\hat{\mathbf{x}}^{-1}\mathbf{f}$ (see Oosterhaven 2017, for the complications involved).

A dynamic version of the IIM, called the Dynamic Inoperability Input-Output Model (DIIM) has also been proposed (Haimes et al. 2005; Lian and Haimes 2006), and has been widely applied in multiple contexts such as, among others, supply chain risk assessments (Barker and Santos 2010), systems resilience estimation (Pant et al. 2014), and critical infrastructure failures (Jonkeren and Giannopoulos 2014). The DIIM, written in discrete time steps 1, . . . , k, k + 1, . . . is expressed as:

$$\mathbf{q}(k+1) = \mathbf{q}(k) + \hat{\mathbf{k}}\left[\mathbf{A}^*\mathbf{q}(k) + \mathbf{f}^*(k) - \mathbf{q}(k)\right] \tag{8.24}$$

where $\mathbf{q}(k)$ and $\mathbf{f}^*(k)$ have the same meaning as in the IIM, but are now expressed in time steps, $\hat{\mathbf{k}}$ is a $n \times n$ diagonal matrix referred to as the resilience coefficients matrix. The diagonal values of, $\hat{\mathbf{k}}$ ranging between between 0 and 1, represent the ability of sectors to recover following disruptions, where greater values correspond to faster recoveries. Different ways of deriving values for $\hat{\mathbf{k}}$ are explained in Haimes et al. (2005) and Lian and Haimes (2006). The DIIM ultimately converges towards the IIM when it reaches the equilibrium condition. Though the DIIM looks similar to the dynamic input-output model (see Miller and Blair 2009), the two models have different meanings. While the DIIM models recovery following disruption leading towards the original stable equilibrium, the dynamic input-output model describes the long-term expansion of outputs due to investments (Dietzenbacher and Miller 2015).

The multiregional version of the IIM, the MRIIM, has also been developed (Crowther and Haimes 2010) and has been applied in a case-study on port disruptions in the US (Pant et al. 2011). The MRIIM can be obtained by including $\mathbf{T}^*$, which is defined as the multiregional interdependencies matrix, and similarly calculated as $\mathbf{A}^*$:

$$\mathbf{T}^* = \hat{\mathbf{x}}^{-1}\mathbf{T}\hat{\mathbf{x}} \tag{8.25}$$

The multiregional form the MRIIM reads very similar as the multiregional IO model:

$$\mathbf{q} = \mathbf{T}^*\mathbf{A}^*\mathbf{q} + \mathbf{T}^*\mathbf{f}^* \tag{8.26}$$

Where now $\mathbf{f}^*$ are $rn \times 1$ vectors and $\mathbf{A}^*$ is a $rn \times rn$ multiregional inoperability matrix, and $\mathbf{T}^*$ is a $rn \times rn$ matrix defined as the multiregional interdependencies matrix. Rewritten in the same form as Eq. (8.10), the solution of the MRIIM is given in Eq. (8.27),with $(\mathbf{I} - \mathbf{T}^*\mathbf{A}^*)$ being an invertible matrix:

$$\mathbf{q} = (\mathbf{I} - \mathbf{T}^*\mathbf{A}^*)^{-1}\mathbf{T}^*\mathbf{f}^* \tag{8.27}$$

The dynamic version of the MRIIM has also been developed and applied in studies of multiregional impacts of inland waterway disruptions in the US (MacKenzie et al. 2012a; Pant et al. 2015). The dynamic MRIIM (DMRIIM), expressed in discrete time steps 1, . . . , k, k + 1, . . ., is written as:

$$\mathbf{q}(k+1) = \mathbf{q}(k) + \hat{\mathbf{k}}\left[\mathbf{T}^*\mathbf{A}^*\mathbf{q}(k) + \mathbf{T}^*\mathbf{f}^*(k) - \mathbf{q}(k)\right] \tag{8.28}$$

Due to the wide use of the DMRIIIM, we will use this version in the comparison with the other modelling frameworks. The model will be run for a one-year period, to allow for a consistent comparison with the yearly outputs of the other models. If $\mathbf{f}^*(k) = \mathbf{f}^*$, $\forall k$ then for $k \to \infty$ the DMRIIM reaches an equilibrium state, which converges towards the MRIIM. This can be also achieved by setting the values of $\hat{\mathbf{k}}$ such that the model converges quickly over finite time steps (see Haimes et al. 2005).

8.3.4 Multiregional Impact Assessment (MRIA) Model

The MRIA model uses all the information available in a MRSUT. In contrast to the MRSU model, this model allows for an endogenously determined new post-disaster optimum with shifts between main suppliers within the boundaries of the existing (trade and) production structure of the (regional) economy. The objective function of the model, Eq. (8.29), minimizes total production over all regions. Each industry in each region aims to minimize its costs given the demand for products and the available technologies to produce the products. These technologies describe how industries can make a mix of products out of a specific set of inputs. Technologies are specific and unique to each of the industries in the different regions and are therefore only available to them. The mix of inputs that each industry requires to make its specific mix of products represents its production technology and is described by the use table. The mix of products that each industry can make using this technology is described by the supply table.

The complete MRIA Model can be described by the following set of equations:

$$\mathrm{Min} \sum\nolimits^{r} \mathbf{i}'\mathbf{x}^r \tag{8.29}$$

$$\mathbf{s}^r \geq \left(\mathbf{I} - \hat{\boldsymbol{\eta}}^r\right)\left(\mathbf{U}^r\mathbf{i} + \mathbf{f}^r + \mathbf{v}^r\right) - \boldsymbol{\omega}^r + \mathbf{e}^{r,EU} + \mathbf{e}^{r,ROW}, \forall r \tag{8.30}$$

$$\boldsymbol{\omega}^r = \mathrm{Max}\left[0, \left(\mathbf{I} - \hat{\boldsymbol{\eta}}^r\right)\left(\mathbf{U}^r\mathbf{i} + \mathbf{f}^r + \mathbf{v}^r\right) - \boldsymbol{\omega}^r + \mathbf{e}^{r,EU} + \mathbf{e}^{r,ROW} - \delta\mathbf{s}^{r,max}\right]\forall r \tag{8.31}$$

$$\mathbf{e}^{r,EU} = \sum\nolimits^{s} \mathbf{T}^s\boldsymbol{\mu}^s\left(\mathbf{U}\mathbf{i}^s + \mathbf{f}^s + \mathbf{v}^s\right) + \sum\nolimits^{s} \mathbf{T}^s\boldsymbol{\mu}^s\boldsymbol{\omega}^s\forall r \tag{8.32}$$

where

$$x_i^r \geq 0, x_i^r \leq x_i^{r,max}, \omega_p^r \geq 0, v_p^r \geq 0,$$

$$\mathbf{V}\mathbf{i}^{r,max} = \mathbf{D}^r\mathbf{x}^{r,max},$$

$$\boldsymbol{\eta}^r = \left(\hat{\mathbf{m}}^{r,EU} + \hat{\mathbf{m}}^{r,ROW}\right)\left(\mathbf{U}\mathbf{i}^{r,ex} + \hat{\mathbf{f}}^{r,ex}\right)^{-1}$$

$$\boldsymbol{\mu}^r = \left(\hat{\mathbf{m}}^{r,EU}\right)\left(\mathbf{u}^{r,ex} + \hat{\mathbf{f}}^{r,ex}\right)^{-1}$$

In line with traditional IO modelling, the model assumes a demand-determined economy. In other words, the total demand from all the regions in the model have to be satisfied by the total supply in all regions. This means that if there is a supply restriction in a region, the model aims to substitute to a non-affected supplier to satisfy demand. The supply of products in all regions should be equal to or larger than demand for these products from all regions [Eq. (8.30)]. The possibility of total demand to be lower than the total production capacity is an essential element in the model that allows for modelling inefficiencies in the economy due to limits in the production capacity in the disaster affected area. The production in all regions will take place at the lowest possible costs (industries minimize costs) given demand, the available technologies and the maximum capacity of industries. The vector $\boldsymbol{\eta}$ defines the total import share (EU + world) for product p demanded from region r, vector $\mathbf{v}$ defines the total reconstruction demand in region r and vector $\boldsymbol{\omega}$ defines the required additional import of the affected regions from other regions to satisfy the demand for products which cannot be satisfied due to lost production capacity in the own region [Eq. (8.31)]. The last term in Eq. (8.31) consists of the maximum regional capacity of a region to produce goods given the available production technologies. Factor δ describes to what extent the regions will exhaust all of their technology to produce a demanded product before it starts to import additional products. If δ equals one, the region will only start importing a product when all possible technologies have been used with very large inefficiencies as a consequence. Equation (8.32) closes the model by ensuring that additional imports due to limits in regional production capacity or increased production are produced by the exporting regions. The vector $\boldsymbol{\mu}^s$ defines the European import share for product p demanded from region r.

8.3.5 Non-linear Programming (NLP) Approach

Parallel to the MRIA model, Oosterhaven and Bouwmeester (2016) have developed a non-linear programming (NLP) model based on a full-information multiregional input-output framework, which was extended towards a full-information multiregional supply-use framework in Oosterhaven and Többen (2017). Here we present the multiregional supply-use based variant. The model is set up to predict the interregional and interindustry impacts of disruptive events. The core idea of the model is that economic actors (firms, households, and governments), in the short run after a disruptive event, primarily try to re-establish the old size and pattern of their transactions. In the model, the difference between the pre-event and post-event economic situation is measured by means of the following adaptation of the information measure of Kullback (1959) and Theil (1967):

$$
\begin{aligned}
&\text{Min} \sum\nolimits_{ip}^{r} v_{ip}^{r}\left(ln\frac{v_{ip}^{r}}{v_{ip}^{r,ex}}-1\right)+\sum\nolimits_{pj}^{r,s} u_{pj}^{rs}\left(ln\frac{u_{pj}^{rs}}{u_{pj}^{rs,ex}}-1\right)\\
&+\sum\nolimits_{p}^{r,s} y_{p\bullet}^{rs}\left(ln\frac{y_{p\bullet}^{rs}}{y_{p\bullet}^{r,ex}}-1\right)+\sum\nolimits_{p}^{r} e_{p}^{r}\left(ln\frac{e_{p}^{r}}{e_{p}^{r,ex}}-1\right)\\
&+\sum\nolimits_{j}^{r} w_{\bullet j}^{r}\left(ln\frac{w_{\bullet j}^{r}}{w_{\bullet j}^{r,ex}}-1\right)
\end{aligned}
\tag{8.33}
$$

In Eq. (8.33), the summation over r in the terms with intermediate use u_{pj}^{rs} and local final use $y_{p\bullet}^{rs}$ (i.e., in the fully regionalized Use table) includes the Rest of the World (RoW). The • in the terms $y_{p\bullet}^{rs}$ and $w_{\bullet j}^{r}$ indicates an aggregation over the categories of final demand and the categories of value added of the MRSUT, respectively. The superscript *ex* indicates exogenous data (i.e., the actual values from the base scenario MRSUT).

The first restriction to minimize Eq. (8.33) is that all transactions should be semi-positive. This implies that changes in stocks are excluded from the model. This exclusion is justified by the fact that changes in stocks, as a rule, do not represent economic transactions for which it is assumed that economic actors try to maintain them as much as possible. The pre-disaster levels of stocks, however, do represent important ultra-short run adaptation possibilities (see Hallegatte 2008; MacKenzie et al. 2012b). Hence, these are ignored in this model; partly because they only delay the adjustments that are modelled, and partly because a MRSUT only gives information about the historic changes in these levels and not about the levels themselves. Furthermore, in all scenarios, Eq. (8.33) is minimized subject to the following additional constraints.

First, and foremost, prices changes are assumed in such a fashion that the economy remains in short run equilibrium, i.e., it is assumed that demand equals supply, per product, per region:

$$
\sum\nolimits_{i}^{s} u_{pi}^{rs}+\sum\nolimits^{s} y_{p\bullet}^{rs}+e_{p}^{r}=\sum\nolimits_{i} v_{ip}^{r}, \forall p, r \tag{8.34}
$$

This approach thus concentrates on the volume changes, i.e., all variables are measured in base scenario prices equal to unity.

Second, and equally important, it is assumed that total output equals total input for each regional industry:

$$
\sum\nolimits_{p} v_{jp}^{s} == \sum\nolimits_{p}^{r} u_{pj}^{rs}+w_{\bullet j}^{s}, \forall j, s \tag{8.35}
$$

This assumption is similar to the traditional MRSUT approach [Eq. (8.23)] and the first constraint [Eq. (8.30)] of the MRIA modelling framework. The core difference between the constraints of this approach and the MRIA model is that the MRIA model assumes that supply is allowed to be greater or equal than demand (see Sect. 8.6 for a more elaborate discussion).

The third constraint is the assumption of cost minimization under a Walras-Leontief production function, per input, per industry, per region, which results in (Oosterhaven 1996):

$$\sum\nolimits^{r} u_{pi}^{rs} = a_{pi}^{\bullet s} x_i^s, \forall p, i, s, \text{and } w_{\bullet i}^s = c_i^s x_i^s, \forall i, s \tag{8.36}$$

In Eq. (8.36), additionally, $a_{ji}^{\bullet s}$ denote fixed technical coefficients, i.e. intermediate inputs regardless of spatial origin per unit of output, and c_i^s denotes fixed value added per unit of output, with the $a_{ji}^{\bullet s}$ and c_i^s being calculated from the base-year MRSUT as $a_{pi}^{\bullet s} = \left(\sum^r u_{pi}^{rs,ex}\right)/x_i^{s,ex}\right)$ and $c_i^s = (w_{\bullet i}^{s,ex})/(x_i^{s,ex})$. Note that $\sum_p a_{pi}^{\bullet s} + c_i^s = 1, \forall i, s$, by definition and, therefore, that r in Eq. (8.36) as well as the summation • includes foreign imports.

Fourth, the same assumption is used to model a fixed product mix of final demand:

$$\sum\nolimits^{r} y_{p\bullet}^{rs} = p_p^s y^s, \forall s \tag{8.37}$$

In Eq. (8.37), additionally, y^s denotes total regional final demand (i.e., $\mathbf{i}'\mathbf{y}^s$), and the p_p^s denote package coefficients (i.e., final demand regardless of spatial origin per unit of total final demand), with the p being calculated from the base-year MRSUT as $p_p^s = \left(\sum^r y_p^{rs,ex}\right)/y^{s,ex}$, with $\sum_p p_p^s = 1$. Note that Eq. (8.37) may be derived from a cost minimizing assumption under a Walras-Leontief utility function, and note again that r includes foreign imports.

8.4 Case-Study

For a test case, we use the 2013 floods of the Danube and Elbe rivers in Germany, which in particular hit the southern state of Bayern (Danube) and the eastern states of Sachsen, Sachsen-Anhalt and Thüringen (Elbe). The direct impacts of these floods to the production capacities of the directly affected industries are taken from Schulte In den Baumen et al. (2015). They are estimated on the basis of data from the public unemployment insurance reporting the number of workers by industries who are working less than full-time. We note that using asset losses is a more commonly used approach to estimate the economic disruption and capacity loss-rates. We have, however, two reasons for using employment loss data. First, it is empirically observed data, allowing us to estimate losses which may come closer to reality. Besides, much is also still unknown about the relation between asset losses and flow losses, due to a lack of empirically available information. Second, and perhaps even more important, we have to translate the supply-side disruption into a demand-side disruption to estimate the impacts with the MRSU and DMRIIM models. Assuming that a reduction in employment results in a reduction in final demand (as done below) is easier to justify than translating an asset loss disruption into a final demand reduction.

Assuming that the labor intensities of production are fixed in the short run allows using the shares of workers working less than full-time in the total number of workers by industry as production capacity loss-rates γ_i^r. Thus, the post-disaster production capacities in the MRIA and NLP models can be expressed as:

$$x_i^r \leq \left(1 - \gamma_i^r\right) x_i^{r,ex}, \forall i, r \tag{8.38}$$

The estimation of post-disaster production capacities for the (traditional) MRSU model is more complicated. Up till now, there is no simple analytical solution within a traditional IO modelling framework for this problem. In most literature, the post-disaster situation is modelled through a reduction in final demand. To see how this assumption behaves versus the approaches in which we can model the supply constraint directly (MRIA, NLP), we make the assumption that the reduction in employees results in proportionally lower levels of all categories of exogenous final demand, including interregional and foreign exports (the latter are shown in Fig. 8.6). As such, in the MRSU and the DMRIIM the disruptions are translated into demand-side effects. Here we assume that the labor losses result in lower demand for the products from industry i, which also decreases as per the rates γ_i^r. Thus, the post-disaster demand reductions in the MRIO and DMRIIM are expressed as:

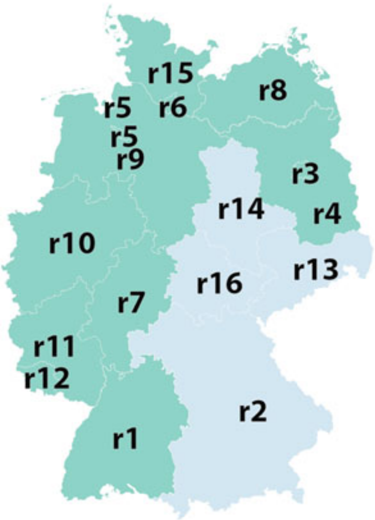
$$\Delta f_i^r = \left(1 - \gamma_i^r\right) f_i^r, \forall i, r \tag{8.39}$$

Also in the DMRIIM we assume that at each time step the demand reductions remain, and we set the values of the $\hat{\mathbf{k}}$ matrix such that the model converges towards a stable equilibrium in 365 time-steps, i.e., 1 year. As noted earlier, the model then converges towards the MRIIM solution.

Figure 8.1 presents an overview of the case-study country and the average disruption in each of the flooded regions. In this case study, the models are calibrated on the aggregated version of German MRSUT for 2007 (Többen 2017, Chap. 4) that has already been used for the disaster impact analysis in Oosterhaven and Többen (2017). The aggregated MRSUT features 16 regions (federal states) with 12 industries and 19 products per region (see Appendix B).

8.5 Illustration of Model Outcomes

Figures 8.2 and 8.3 present the results for Germany as a whole at the industry level, aggregated to three sectors. First, note the difference in the size of the direct impacts, in the middle panels of Figs. 8.2 and 8.3, in the two sets of models. The explanation for this difference can be found in the assumptions made in Eqs. (8.38) and (8.39). As exogenous local final demand constitutes about 2/3 to 3/4 of total output in the



	Region	GDP (% of total)	Disruption
r1	Baden-Württemberg	14.7%	
r2	Bayern	17.9%	0.13%
r3	Berlin	3.5%	
r4	Brandenburg	2.2%	
r5	Bremen	1.1%	
r6	Hamburg	3.4%	
r7	Hessen	8.8%	
r8	Mecklenburg-Vorpommern	1.4%	
r9	Niedersachsen	8.5%	
r10	Nordrhein-Westfalen	21.8%	
r11	Rheinland-Pfalz	4.3%	
r12	Saarland	1.2%	
r13	Sachsen	3.9%	0.51%
r14	Sachsen-Anhalt	2.3%	0.72%
r15	Schleswig-Holstein	3.0%	
r16	Thüringen	2.0%	0.40%

Fig. 8.1 Overview of regions and aggregate disruptions

German MRSUT, the direct effect in case of the two models (MRSU and DMRIIM) that translate the supply constraint of the NLP and MRIA models into a final demand reduction, is about 2/3 to 3/4 of the direct effect in the last two models. Second and equally important, note that the indirect effects of the two demand-driven IO models are much larger than the indirect effects of the two models that handle the supply shock as a supply shock and allow for substitution effects. This holds in absolute terms, and holds even more when the indirect effects are taken as a percentage of the direct effects, as is done when calculating disaster impact multipliers (cf. Oosterhaven and Többen 2017). The result of these two opposing differences is that the total impacts are more or less comparable between all four models.

For all models, the manufacturing sectors endure the highest total impacts, followed by the service sectors. The manufacturing sector shows the most similar total impacts (in sign and magnitude) for all models. For agriculture and mining and, especially, for the services sector, the MRIA model shows much lower total impacts. The indirect effects in the right-most panel of Figs. 8.2 and 8.3 indicate that substitution effects in the NLP and MRIA models result in a dampening effect on the negative impacts due to the floods. The MRIA model even shows positive indirect effects for the services and agricultural sector. Overall losses remain negative. When Figs. 8.2 and 8.3 are compared, the size of the positive impacts on the services sector with the MRIA model in case of the actual combined floods of the Elbe and Danube is both absolutely and relatively much larger than for the scenario in which only the Danube flood is considered. The reason for this difference is found in the Figs. 8.4 and 8.5 that provide details of the spatial composition of the total impacts.

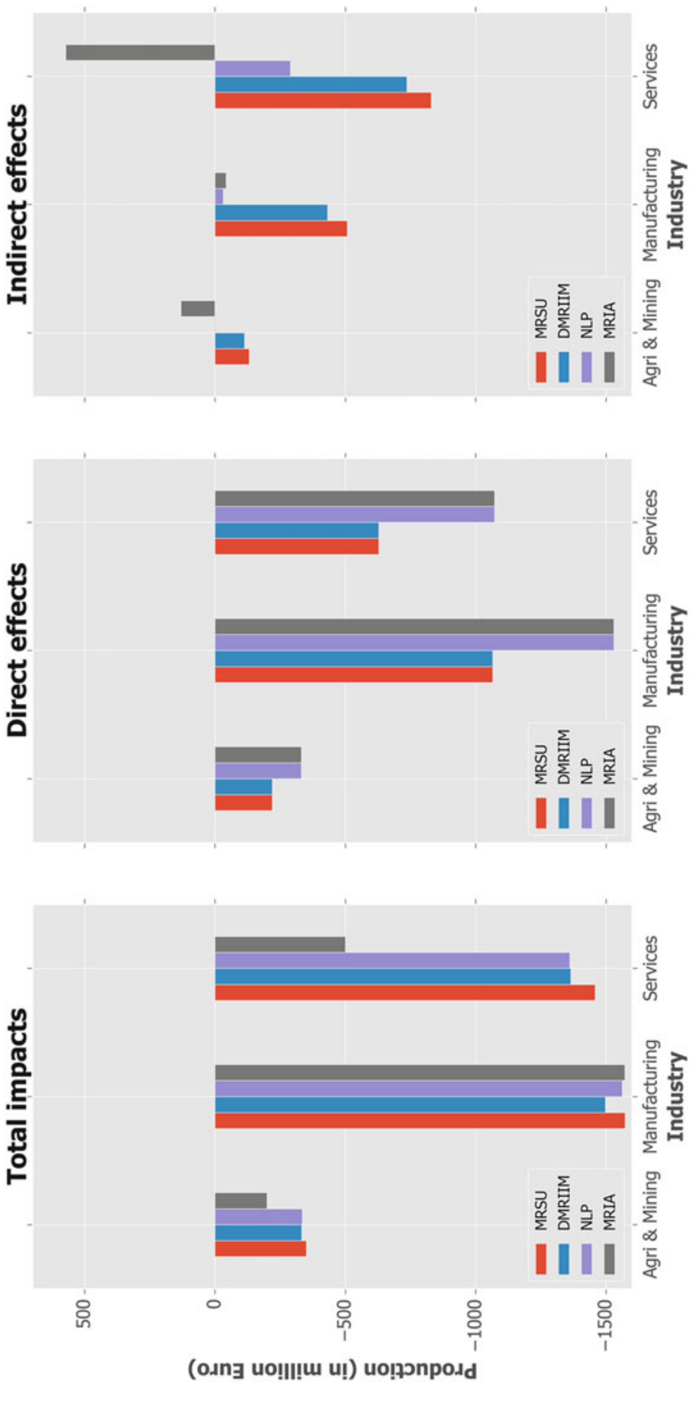


Fig. 8.2 Aggregated national outcomes per industry for a combined flood of the Danube and Elbe rivers

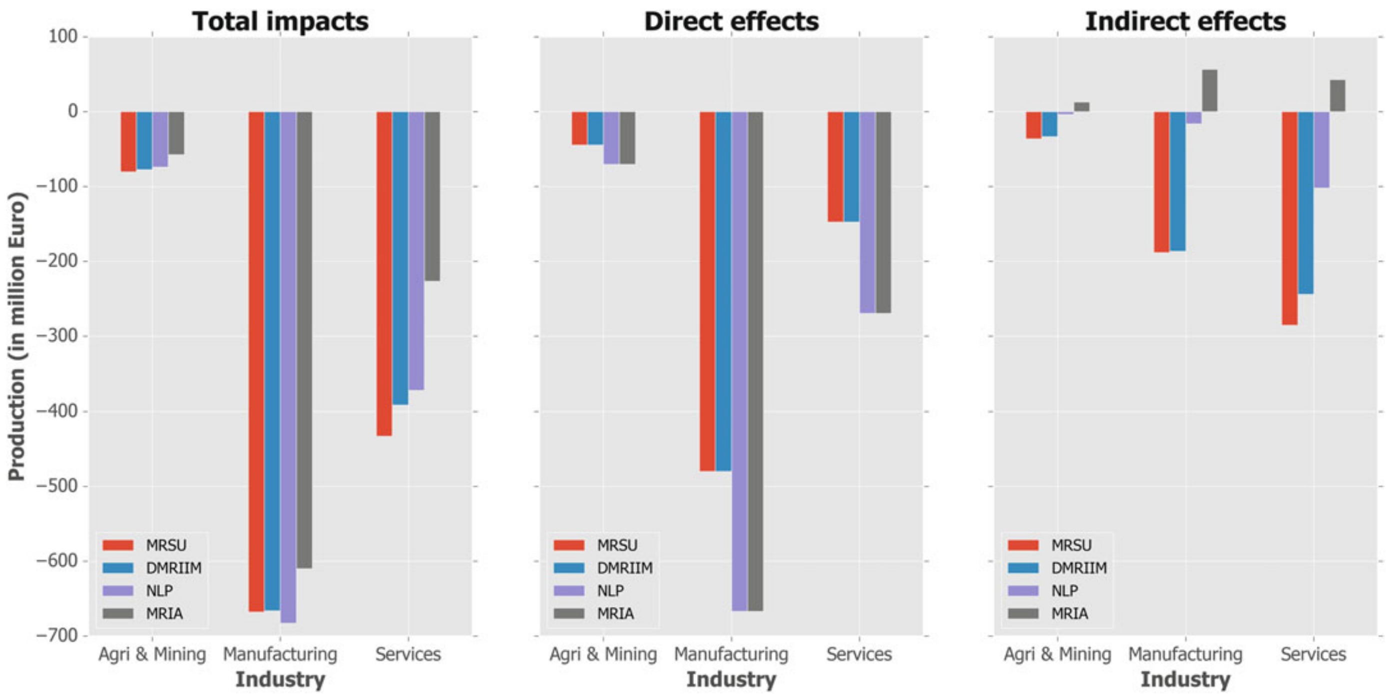


Fig. 8.3 Aggregated national outcomes per industry for each model for a flood of the Danube River only

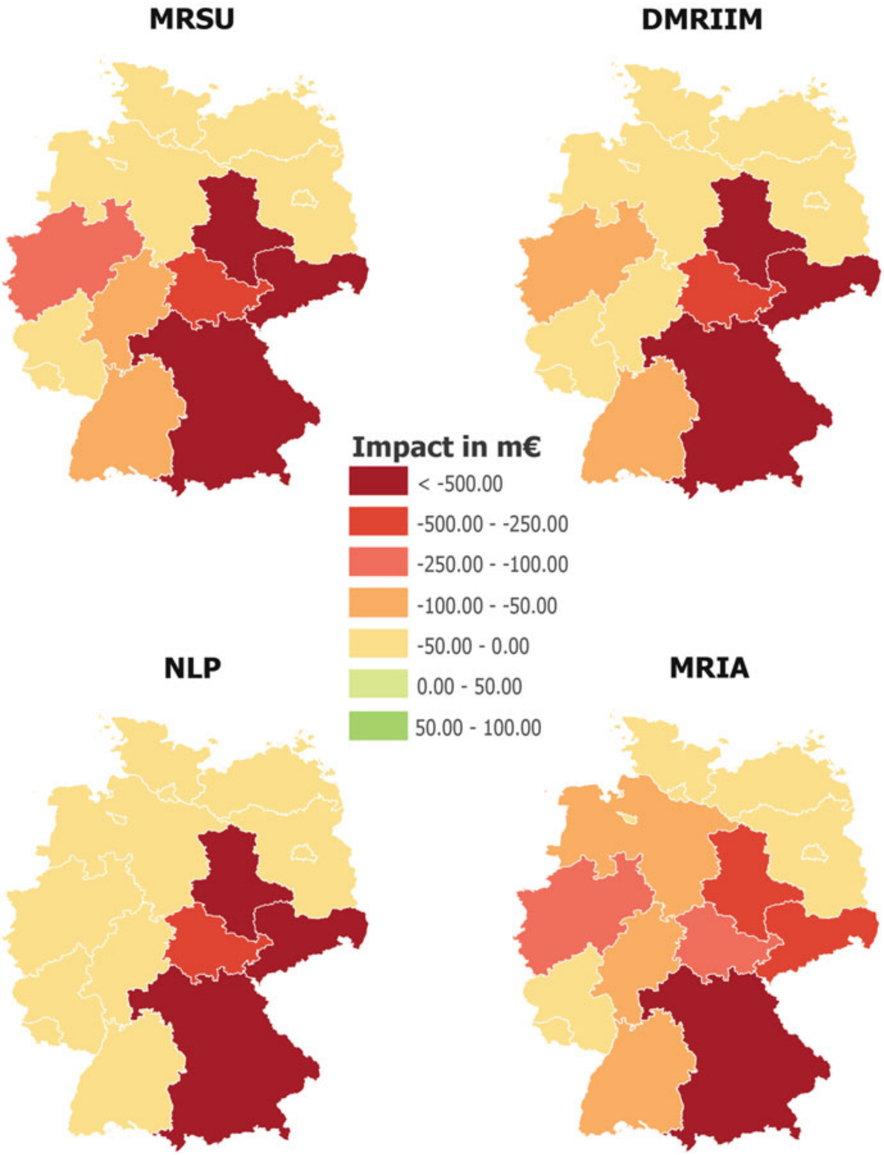


Fig. 8.4 Changes in total production output in each region for a combined flood of the Danube and Elbe rivers

Figure 8.4 presents the regional impacts on the yearly production for a combined flood of the Danube and the Elbe rivers, including the direct impacts in the four regions indicated in Fig. 8.1. All models predict negative impacts in both the flooded regions and the rest of Germany. The relative magnitude of the impacts, however, differs. Compared to the other models, the MRIA model estimates the lowest losses

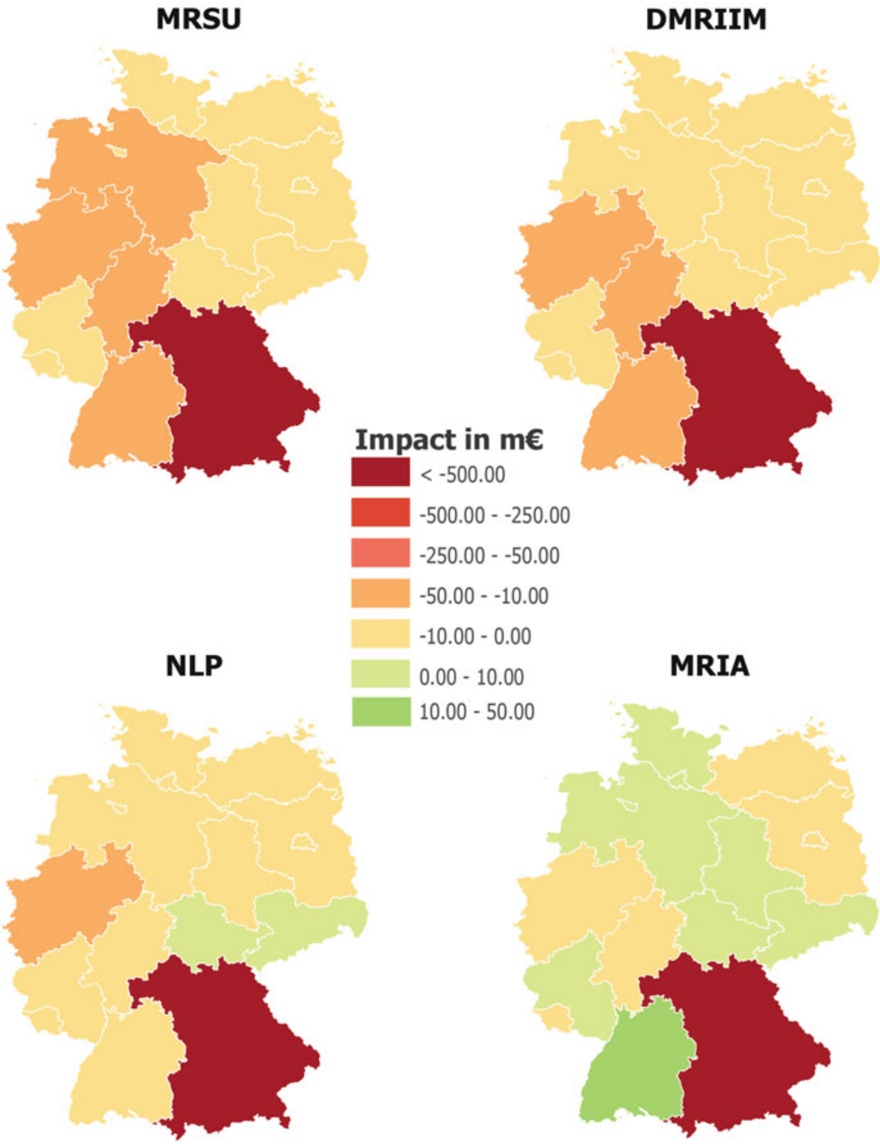


Fig. 8.5 Changes in total production output in each region for a flood of the Danube River only

in the flooded regions, but slightly higher losses in Nordrhein-Westfalen (r10) and Niedersachsen (r9). This is the result of re-allocation of intermediate supply in the flooded regions that is not used due to reduced use in the affected regions. The model aims to use this remaining production as efficiently as possible (by trying to keep waste production at a minimum) and re-allocates this supply through existing trade relations to other regions where demand has not been reduced. For Nordrhein-

Westfalen and Niedersachsen, this results in some competition towards their own supply and results in slightly lower local production in these areas. As shown in the right-most diagram of Fig. 8.2, this effect mainly occurs within the services sector, indicating that substitution in trade is easiest within more labor intensive sectors. The NLP model shows both positive and negative impacts whereby the negative ones dominate. As a result, the NLP model still shows negative impacts in the surrounding regions, but lower due to its spatial substitution possibilities. The indirect effects presented in Fig. 8.2 indicate that the NLP predicts a similar redistribution effect as the MRIA model, but less profound.

Figure 8.5 presents the results for a flood of the Danube, which only includes direct flood impacts in Bavaria. The most notable differences are the small positive impacts that can be observed in the outcomes of the NLP and MRIA models. With a smaller disruption, the NLP and MRIA models show more strongly that spatial substitution can offset the negative impacts of a disaster in the non-flooded regions. Due to the linear nature of the MRSU model [Eq. (8.18)] and the convergence of our DMRIIM to the linear MRIIM [Eq. (8.30)], all regions are negatively impacted with those models. And, consequently, the regions that trade the most with the flooded regions, will endure the highest losses. In the MRIA model, the economy aims to re-optimize to a new optimal outcome, aiming to satisfy as much final demand as possible [Eq. (8.33)]. As a result, the region with the largest (existing) trade will try to satisfy as much as possible what cannot be satisfied in the flooded region and may see a slight offset in negative impacts. The NLP model, which aims to re-balance the economy in such a way that it will be as similar as possible to the pre-disaster situation, shows lower negative impacts compared to the MRSU and DMRIIM, and lower positive impacts compared to the MRIA model.

Figure 8.6 presents the impacts on foreign imports and foreign exports. All models, and both scenarios, show that foreign exports are more strongly impacted than the foreign imports. The results show especially strong negative impacts on foreign exports with the MRSU and DMRIIM models. But the reasons are quite different. In case of these two demand-driven models the change in foreign exports is exogenously determined by Eq. (8.39), whereas in the two models that handle a supply shock as it is, the drop in foreign exports is endogenous and serves to indirectly substitute for lacking domestic supply. This effect is larger in the MRIA model than in the NLP model, whereas it is smaller in the case of the drop in foreign imports, because the NLP model, compared to the MRIA model, allows for much more flexibility in import patterns. But even with the NLP model the negative demand effects dominate the positive substitution effects, resulting in a net negative effect on foreign imports.

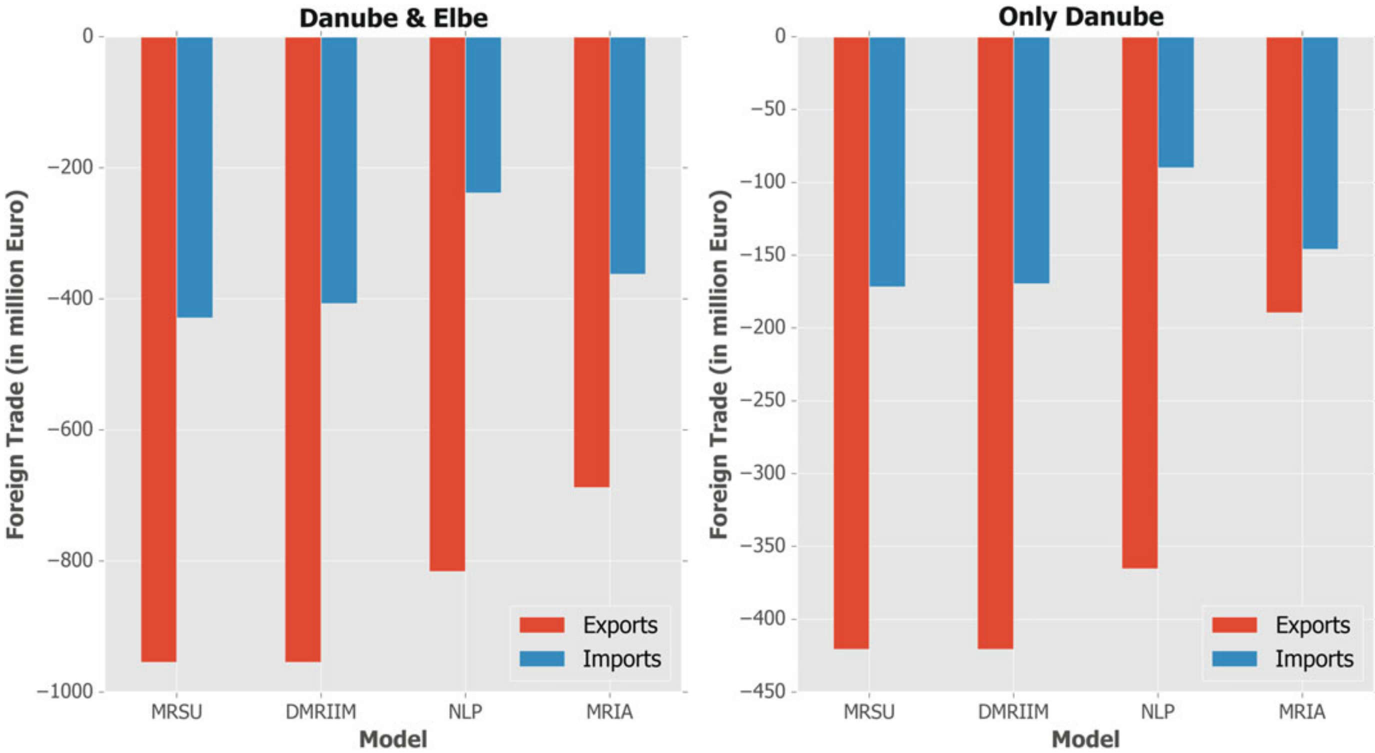


Fig. 8.6 Aggregated national outcomes on foreign trade for each model in both flood scenarios. Note the different scales on the y-axis

8.6 Discussion and Concluding Remarks

IO models are one of the main tools used for disaster impact analysis. A key advantage of this type of models is that they allow for investigating the systemic effects of disasters: they can capture the indirect effects from disasters on sectors and regions that are not directly affected. On the basis of a theoretical discussion we argue that the traditional demand-driven IO model and the IIM models may be suitable for modelling man-made disasters, such as a terrorist attack, which will mainly result in spatial and product shifts in final demand (i.e., effect on tourism and consumer demand). For the modelling of natural disasters such as earthquakes or floods, which primarily affect the supply-side of economy, we argue that the IO models are unsuitable, as they suffer from shortcomings in representing supply-side shocks. These shortcomings include: (1) double-counting issues that arise when supply-shocks are transformed into supposedly equivalent demand-shocks; (2) the inability to take substitution of lost supply into account, due to the assumption of fixed trade origin coefficients. In this chapter we have explained these shortcomings and discussed how the newly developed NLP and MRIA models by Oosterhaven and Bouwmeester (2016) and Koks and Thissen (2016) try to overcome them.

In Sect. 8.5 we estimated the economic impacts in Germany of the 2013 Danube and Elbe floods with the aforementioned models, using the German multiregional supply-use table for 2007 (Többen 2017). Our outcomes showed significantly distinct results for the demand-driven MRSU model and DMRIIM (which converges towards the MRIIM), on the one hand, and for the NLP and MRIA models, on the other hand. Whereas for the former only negative impacts in all German regions and foreign countries could be observed, the latter also showed positive impacts in several only indirectly impacted regions in addition to negative ones. These differences are directly explained by the fixed linear coefficients' nature of the MRSU model and the MRIIM versus the more flexible non-linear behavior of the MRIA and NLP models, which allow for positive indirect impacts in those industries and regions that deliver substitutes to replace the lost supply of others. In our simulations the MRSU, DMRIIM and NLP models show similar total production losses, but the reasons are quite different and reflect the issue of transforming actual supply-shocks into demand shocks. In the two demand-driven models, the direct impacts are much smaller, but are compensated by much larger indirect impacts than in case of the NLP model. In the MRIA model the indirect impacts are even positive for some sectors, which results in the lowest total impacts across the nation. This could be explained by the greater than or equal sign in Eq. (8.32). As shown in Koks et al. (2016), the MRIA model shows very similar results to a CGE model with free movement of capital and labor.

In the end, an essential next research step is to validate the model outcomes. From a theoretical point of view, it is relatively clear which models may or may not produce sensible outcomes for a certain question. Much is unknown, however, about how the outputs should be interpreted and which models can simulate the most realistic post-disaster behavior. As such, benchmark data to compare model outcomes is essential to improve the current disaster impact modelling approaches. Hence, the next focus in the field should be on model validation to know which modelling approach produces the most realistic and sensible outcomes to be used for disaster risk management.

References

Anderson CW, Santos JR, Haimes YY (2007) A risk-based input–output methodology for measuring the effects of the august 2003 northeast blackout. Econ Syst Res 19(2):183–204

Andrijcic E, Horowitz B (2006) A macro-economic framework for evaluation of cyber security risks related to protection of intellectual property. Risk Anal 26(4):907–923

Arto I, Andreoni V, Rueda Cantuche JM (2015) Global impacts of the automotive supply chain disruption following the japanese earthquake of 2011. Econ Syst Res 27(3):306–323

Barker K, Santos JR (2010) Measuring the efficacy of inventory with a dynamic input–output model. Int J Prod Econ 126(1):130–143

Bierkandt R, Wenz L, Willner SN, Levermann A (2014) Acclimate—a model for economic damage propagation. part 1: basic formulation of damage transfer within a global supply network and damage conserving dynamics. Environ Syst Decis 34(4):507–524

Cavallo E, Galiani S, Noy I, Pantano J (2013) Catastrophic natural disasters and economic growth. Rev Econ Stat 95(5):1549–1561

Chenery HB, Clark PG, Pinna VC (1953) The structure and growth of the Italian economy. U. S. Mutual Security Agency, Special Mission to Italy for Economic Cooperation, Rome

Christ CF (1955) A review of input-output analysis. In: Input-output analysis: an appraisal. Princeton University Press, Princeton, pp 137–182

Crowther KG, Haimes YY (2010) Development of the multiregional inoperability input-output model (MRIIM) for spatial explicitness in preparedness of interdependent regions. Syst Eng 13(1):28–46

Dell M, Jones BF, Olken BA (2014) What do we learn from the weather? The new climate–economy literature. J Econ Lit 52(3):740–798

Dietzenbacher E, Miller RE (2015) Reflections on the inoperability input–output model. Econ Syst Res 27(4):478–486

Eurostat (2008) Eurostat manual of supply, use and input-output tables. Office for Official Publications of the European Communities, Luxembourg

Ghosh A (1958) Input-output approach in an allocation system. Economica 25(4):58–64

Haimes YY, Jiang P (2001) Leontief-based model of risk in complex interconnected infrastructures. J Infrastruct Syst 7(1):1–12

Haimes YY, Horowitz BM, Lambert JH, Santos JR, Lian C, Crowther KG (2005) Inoperability input-output model for interdependent infrastructure sectors. I: Theory and methodology. J Infrastruct Syst 11(2):67–79

Hallegatte S (2008) An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. Risk Anal 28(3):779–799. https://doi.org/10.1111/j.1539-6924.2008.01046.x

In den Baumen HS, Többen J, Lenzen M (2015) Labour forced impacts and production losses due to the 2013 flood in germany. J Hydrol 527(0):142–150. https://doi.org/10.1016/j.jhydrol.2015.04.030

Isard W (1951) Interregional and regional input-output analysis: a model of a space-economy. Rev Econ Stat 33(4):318–328

Jonkeren O, Giannopoulos G (2014) Analysing critical infrastructure failure with a resilience inoperability input–output model. Econ Syst Res 26(1):39–59

Klomp J, Valckx K (2014) Natural disasters and economic growth: a meta-analysis. Glob Environ Chang 26:183–195

Koks EE, Thissen M (2016) A multiregional impact assessment model for disaster analysis. Econ Syst Res 28(4):1–21

Koks EE, Carrera L, Jonkeren O, Aerts JCJH, Husby TG, Thissen M et al (2016) Regional disaster impact analysis: comparing input–output and computable general equilibrium models. Nat Hazards Earth Syst Sci 16(8):1911–1924

Kullback S (1959) Information and statistics. Wiley, New York

Lazzaroni S, van Bergeijk PA (2014) Natural disasters' impact, factors of resilience and development: a meta-analysis of the macroeconomic literature. Ecol Econ 107:333–346

Lenzen M, Rueda-Cantuche JM (2012) A note on the use of supply-use tables in impact analyses. SORT 36(2):139–152

Leontief W, Strout A (1963) Multiregional input-output analysis. In: Structural interdependence and economic development. Springer, Heidelberg, pp 119–150

Lian C, Haimes YY (2006) Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input–output model. Syst Eng 9(3):241–258

MacKenzie CA, Barker K, Grant FH (2012a) Evaluating the consequences of an inland waterway port closure with a dynamic multiregional interdependence model. IEEE Trans Syst Man Cybern Part A Syst Humans 42(2):359–370

MacKenzie CA, Santos JR, Barker K (2012b) Measuring changes in international production from a disruption: case study of the Japanese earthquake and tsunami. Int J Prod Econ 138(2):293–302. https://doi.org/10.1016/j.ijpe.2012.03.032

Miller RE (1969) Interregional feedbacks in input-output models: some experimental results. Econ Inq 7(1):41–50

Miller RE, Blair PD (2009) Input-output analysis: foundations and extensions. Cambridge University Press, Cambridge

Moran D, Wood R (2014) Convergence between the eora, wiod, exiobase, and openeu's consumption-based carbon accounts. Econ Syst Res 26(3):245–261

Moses LN (1955) The stability of interregional trading patterns and input-output analysis. Am Econ Rev 45(5):803–826

Okuyama Y (2004) Modeling spatial economic impacts of an earthquake: input-output approaches. Disaster Prev Manag 13(4):297–306

Okuyama Y (2015) How shaky was the regional economy after the 1995 kobe earthquake? A multiplicative decomposition analysis of disaster impact. Ann Reg Sci 55(2–3):289–312

Okuyama Y, Santos JR (2014) Disaster impact and input-output analysis. Econ Syst Res 26(1):1–12

Oosterhaven J (1981) Interregional input-output analysis and Dutch regional policy problems. Gower, Aldershot

Oosterhaven J (1984) A family of square and rectangular interregional input-output tables and models. Reg Sci Urban Econ 14(4):565–582

Oosterhaven J (1988) On the plausibility of the supply-driven input-output model. J Reg Sci 28(2):203–217

Oosterhaven J (1996) Leontief versus Ghoshian price and quantity models. South Econ J 62(3): 750–759

Oosterhaven J (2012) Adding supply-driven consumption makes the Ghosh model even more implausible. Econ Syst Res 24(1):101–111

Oosterhaven J (2017) On the limited usability of the inoperability IO model. Econ Syst Res 29(3): 452–461

Oosterhaven J, Bouwmeester MC (2016) A new approach to modeling the impact of disruptive events. J Reg Sci 56(4):583–595

Oosterhaven J, Hewings GJ (2014) Interregional input–output models. In: Handbook of regional science. Springer, Berlin, pp 875–901

Oosterhaven J, Többen J (2017) Wider economic impacts of heavy flooding in Germany: a non-linear programming approach. Spat Econ Anal 12(4):404–428

Pant R, Barker K, Grant FH, Landers TL (2011) Interdependent impacts of inoperability at multimodal transportation container terminals. Transport Res E-Log 47(5):722–737

Pant R, Barker K, Zobel CW (2014) Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. Reliab Eng Syst Saf 125:92–102

Pant R, Barker K, Landers TL (2015) Dynamic impacts of commodity flow disruptions in inland waterway networks. Comput Ind Eng 89:137–149

Polenske KR (1970) An empirical test of interregional input-output models: estimation of 1963 Japanese production. Am Econ Rev 60:76–82

Rose A, Wei D (2013) Estimating the economic consequences of a port shutdown: the special role of resilience. Econ Syst Res 25(2):212–232

Rose A, Liao S-Y, Bonneau A (2011) Regional economic impacts of a Verdugo scenario earthquake disruption of Los Angeles water supplies: a computable general equilibrium analysis. Earthquake Spectra 27(3):881–906

Santos JR (2006) Inoperability input-output modeling of disruptions to interdependent economic systems. Syst Eng 9(1):20–34

Santos JR, Haimes YY (2004) Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures. Risk Anal 24(6):1437–1451

Santos JR, May L, Haimar AE (2013) Risk-based input-output analysis of influenza epidemic consequences on interdependent workforce sectors. Risk Anal 33(9):1620–1635

Stevens BH, Trainer GA (1980) Error generation in regional input-output analysis and its implications for nonsurvey models. In: Economic impact analysis: methodology and applications. Springer, Berlin, pp 68–84

Theil H (1967) Economics and information theory. North-Holland/Elsevier, Amsterdam

Többen J (2017) Effects of energy and climate policy in Germany: a multiregional analysis. PhD thesis, Faculty of Economics and Business, University of Groningen

Wenz L, Willner SN, Bierkandt R, Levermann A (2014) Acclimate—a model for economic damage propagation. part ii: a dynamic formulation of the backward effects of disaster-induced production failures in the global supply network. Environ Syst Decis 34(4):525–539

Elco Koks is Assistant Professor at the Vrije Universiteit Amsterdam and Postdoctoral Researcher at the Environmental Change Institute (ECI) at the University of Oxford. His key research domain is the modelling of the economy-wide consequences of natural disasters on both a regional and interregional level, focusing on industrial impacts and infrastructure systems.

Raghav Pant is a Senior Postdoctoral Researcher at the Environmental Change Institute (ECI) at the University of Oxford. He has 12 years of academic and professional experience on infrastructure and economic risk and resilience modelling, and leads the risk and resilience analysis research in the Infrastructure Transitions Research Consortium (ITRC).

Trond Husby works as a researcher at the Netherlands Environmental Assessment Agency. He investigated the general equilibrium effects of behavioural responses to flood risk in his PhD thesis. His current work focusses primarily on interregional mobility and population change.

Johannes Tobben is a Postdoctoral Fellow in the Industrial Ecology Programme at the Norwegian University of Science and Technology. His key research domain lies in the intersection of econometrics, inter-industry and regional economics, with a strong focus on interdisciplinary applications to questions of sustainable development.

Jan Oosterhaven is emeritus professor of spatial economics at the University of Groningen. His research focuses on interregional input-output analysis, demo-economic modeling, indirect economic effects of transport infrastructure, and integral cost-benefit analysis of spatial policy measures.

Chapter 9
On the Sensitivity of Impact Estimates for Fixed Ratio Assumptions

Johannes Többen and Jan Oosterhaven

Abstract Firms react to shortages in the supply of their inputs by looking for substitutes. We investigate the impact of finding such substitutes on estimates of the size of regional and national disaster impacts. To investigate this issue, we use the German multiregional supply-use table (MRSUT) for 2007, together with data on the direct impacts of the 2013 heavy floods of the German Elbe and the Danube rivers. Our analysis starts with a non-linear programming model that allows for maximum substitution possibilities. In that case there are little to no indirect damages in the directly affected regions, whereas negative indirect impacts of a magnitude of 5–7% and of up to 34% of the direct impact occur in other German regions and abroad, respectively. Adding the increasingly less plausible fixed ratios commonly used in standard Type I and extended Type II multiregional input-output and MRSUT models, results in (1) substantial increases in the magnitude of negative indirect impacts and (2) a significant shift in the intra-regional versus interregional and international distribution of these impacts. Our conclusion is that both demand-driven and supply-driven input-output and supply-use models tend to grossly overstate the indirect damages of negative supply shocks, which are part and parcel of most disasters.

9.1 Introduction

The core economic property of most disasters is that it primarily constitutes a shock to the supply-side of the economy. Most naturally, economic actors that are subjected to a negative shock in the supply of their intermediate, land, capital or

J. Többen (✉)
Industrial Ecology Programme (Indecol), Norwegian University of Science and Technology, Trondheim, Norway
e-mail: toebben@gws-os.com

J. Oosterhaven
Faculty of Economics and Business, University of Groningen, Groningen, The Netherlands
e-mail: j.oosterhaven@rug.nl

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_9

labour inputs will react by looking for substitutes. Whether they are able to find such substitutes at acceptable prices determines whether or not they will have to diminish or even stop their production and sales. Consequently, besides the negative impacts on directly affected actors, other actors delivering the substitutes will experience positive impacts, while the size of the negative impacts on actors that are faced with supply shortages mainly depends on their ability to substitute for their lacking inputs. Hence, estimates of the size of an important part of both the positive and the negative wider economic impacts of disasters will strongly depend on the assumptions made with regard to the ease with which various actors are able to find such substitutes.

Different models make different assumptions in this regard. Typically, input-output (IO) and supply-use (SU) models assume that firms, governments and households purchase their inputs in fixed proportions, whereas computable general equilibrium (CGE) models assume that substitution is possible and that some types of substitution are more easily made than others, which is reflected in using different substitution elasticities. Recently, Koks et al. (2015) compared the regional and national disaster impacts of two flooding scenarios for the Italian Po river delta, as estimated with, respectively, the adaptive regional input-output (ARIO) model developed by Hallegate (2008), a regionalized version of the CGE model developed Standardi et al. (2014), as applied in Carerra et al. (2015), and the multi-regional impact assessment (MRIA) model of Koks and Thissen (2016). Both with a convex and with a linear recovery path, the fixed ratio ARIO approach predicts national economic losses that are 1.5–3 times larger than those of the more flexible MRIA and CGE models. With a concave recovery path, the ARIO model outcomes are 4.5–7 times larger than those of the MRIA model and almost 6 times larger than those of the CGE approach. Without the mitigating positive impact of the recovery path assumptions, the differences would be even larger.

Standard demand-driven IO models, which includes the widely used Inoperability IO model (IIM, Santos and Haimes 2004; Santos 2006; Anderson et al. 2007), can be expected to generate even larger indirect impacts for basically two reasons. Firstly, when one makes an attempt to analyse supply shocks, it is necessary to transform the supply shock into a shock to final demand. Oosterhaven (2017) shows that the transformation typically used in IIM applications causes double-counting and, hence, inflated indirect impact estimates. Secondly, the assumptions of fixed ratios, especially regarding trade origins, underlying these models exclude any adaption possibilities. Nonetheless, the IIM appears to be the most widely used model for disaster impact studies. The main reason for this might be its much lower data requirements compared to the above mentioned approaches, especially compared to CGE models. In fact, the advantage of spatial CGE models (cf. Tsuchiya et al. 2007), in terms of allowing for substitution effects, requires the availability of all kinds of elasticities. Moreover, modelling impacts in the short run as opposed to the long run requires different versions of the model, as short run substitution elasticities are much closer to zero than their longer run equivalents (Rose and Guha 2004).

In a recent application to the Danube and Elbe flooding 2013 in Germany, Oosterhaven and Többen (2017) find that the simplicity of standard IO models comes at a price, as they show that fixed trade origin and fixed industry market shares lead to significantly inflated indirect impact estimates compared to the base non-linear programming (NLP) model proposed in Oosterhaven and Bouwmeester (2016). This base model has been developed with the goal to allow for a more realistic representation of the adaption behaviour of economic actors at research costs, in terms of data requirements, that are comparable to those of standard IO models. This is achieved by assuming that, in the event of a disaster, economic actors try to maintain their old transaction patterns as much as possible. In addition, their NLP model allows for accounting for supply shocks directly, without the need for any transformation, by setting constraints on production capacities of directly affected industries.

Interpreting the differences in outcomes between all these different models, however, is problematic as it is almost impossible to attribute the total difference to all the individual aspects that differ between each of them. In this chapter we approach this problem by working with a single model, i.e., the one proposed in Oosterhaven and Bouwmeester (2016), which allows for maximum substitution flexibility, and by sequentially adding increasingly less plausible fixed ratios to this base model. In this way, the cumulative impact of each individual fixed ratio becomes separately clear. The NLP model that is used as the base model will be discussed in Sect. 9.2, along with the multi-regional supply-use (MRSU) accounting framework to which it is applied, and the four simultaneously occurring heavy German floods of 2013 that are simulated with this model. The various fixed ratios that are most often used in the literature are discussed in Sect. 9.3, while Sect. 9.4 discusses the impact of sequentially adding these fixed ratios to the base model. Section 9.5 concludes that economies that possess maximal flexibility (resilience) will experience only little wider economic damages, whereas assuming all kind of fixed ratios substantially increases the magnitude of wider economic impact estimates, while it substantially changes its spatial distribution. In an Appendix we discuss the similar results that occur when the fixed ratios of a supply-driven MRSU model are added to our base model.

9.2 Accounting Scheme, Base Model and Disaster Scenarios

All eight models used here are calibrated on the use-regionalized multi-regional supply-use table (MRSUT) for Germany for 2007 (Többen 2017a, Ch. 4), with value added split-up in regional labour income and other value added, and domestic final demand split-up in consumption from regional labour income and other regional final demand. In order to keep the computational requirements at a reasonable level the MRSUT covering the 16 German states is aggregated to 12 industries and 19 products. See Table 9.1 for the set-up of this database.

Table 9.1 Accounting framework of the use-regionalized MRSUT for Germany for 2007

		Region 1				Region r				RoW	Total
		Products	Industries	Work. households	Other final demand	Products	Industries	Work. households	Other final demand		
Region 1	Products		$\mathbf{U}^{\mathbf{11}}$	$\mathbf{y}^{\mathbf{11}}$	$\mathbf{f}^{\mathbf{11}}$		$\mathbf{U}^{\mathbf{1r}}$	$\mathbf{y}^{\mathbf{1r}}$	$\mathbf{f}^{\mathbf{1r}}$	$\mathbf{e}^{\mathbf{1}}$	$\mathbf{g}^{\mathbf{1}}$
	Industries	$\mathbf{V}^{\mathbf{1}}$									$\mathbf{x}^{\mathbf{1}}$
Region r	Products		$\mathbf{U}^{\mathbf{r1}}$	$\mathbf{y}^{\mathbf{r1}}$	$\mathbf{f}^{\mathbf{r1}}$		$\mathbf{U}^{\mathbf{rr}}$	$\mathbf{y}^{\mathbf{rr}}$	$\mathbf{f}^{\mathbf{rr}}$	$\mathbf{e}^{\mathbf{r}}$	$\mathbf{g}^{\mathbf{r}}$
	Industries					$\mathbf{V}^{\mathbf{r}}$					$\mathbf{x}^{\mathbf{r}}$
Rest of World			$\mathbf{U}^{\mathbf{RoW1}}$	$\mathbf{y}^{\mathbf{RoW1}}$	$\mathbf{f}^{\mathbf{RoW1}}$		$\mathbf{U}^{\mathbf{RoWr}}$	$\mathbf{y}^{\mathbf{RoWr}}$	$\mathbf{f}^{\mathbf{RoWr}}$		$\mathbf{m}^{\bullet}$
Labour income			$\mathbf{l}^{\mathbf{1}}$	$\mathbf{0}$	$\mathbf{0}$		$\mathbf{l}^{\mathbf{r}}$	$\mathbf{0}$	$\mathbf{0}$		$y^{\bullet}$
Other value added			$\mathbf{w}^{\mathbf{1}}$	$\mathbf{0}$	$\mathbf{0}$		$\mathbf{w}^{\mathbf{r}}$	$\mathbf{0}$	$\mathbf{0}$		$w^{\bullet}$
Total		$\mathbf{g}^{\mathbf{1}}$	$\mathbf{x}^{\mathbf{1}}$	y^{1}	f^{1}	$\mathbf{g}^{\mathbf{r}}$	$\mathbf{x}^{\mathbf{r}}$	y^{r}	f^{r}	$e^{\bullet}$	

The symbols in Table 9.1 and in the upcoming equations have the following meaning, with bold faces indicating vectors and matrices, and italics indicating scalars:

$v_{ip}^{r} \in \mathbf{V^r}$ = supply of product p by industry i in region r (= origin),

$u_{pi}^{rs} \in \mathbf{U^{rs}}$ = use of product p from region r by industry i in region s (= destination),

$y_{p}^{rs} \in \mathbf{y^{rs}}$ = use of product p from region r by households working and living in s,

$f_{p}^{rs} \in \mathbf{f^{rs}}$ = use of product p from region r by other final demand in region s,

$e_{p}^{r} \in \mathbf{e^{r}}$ = foreign exports of product p by region r,

$l_{i}^{r} \in \mathbf{l^{r}}$ = labour compensation by industry i in region r,

$w_{i}^{r} \in \mathbf{w^{r}}$ = other value added of industry i in region r,

$g_{p}^{r} \in \mathbf{g^{r}}$ = total supply = total demand of product p by region r,

$x_{i}^{r} \in \mathbf{x^{r}}$ = total output = total input by industry i in region r,

$u_{pi}^{RoW,s} \in \mathbf{U^{row,s}}$ = foreign imports of product p by industry i in region s,

$y_{p}^{RoW,s} \in \mathbf{y^{RoW,s}}$ = foreign imports of product p of households working and living in region s,

$f_{p}^{RoW,s} \in \mathbf{f^{RoW,s}}$ = foreign imports of product p for other final demand in region s,

$*$ = summation over the index concerned.

The base model uses the minimal amount of assumptions possible. First, it assumes that market prices react such, to the disaster-induced shocks to the supply and demand of products, that the accounting identities of the MRSUT are maintained. Second, it assumes that all economic actors try to maintain their old pattern of economic transactions as much as possible (see Oosterhaven and Bouwmeester 2016, for an extended discussion of this approach, and Oosterhaven and Többen 2017, for a first application with a MRSUT accounting framework).

To simulate the consequences of assumption that all economic actors try to maintain their pre-disaster pattern of economic transactions, as much as possible, the *objective function* of our non-linear programming (NLP) model minimizes the information gain of the transaction values of the post-disaster MRSUT, compared to the corresponding values of the pre-disaster MRSUT, which are indicated by the superscripts *ex*:

$$
\begin{aligned}
&Minimize\ \sum\nolimits_{ip}^{r}\left(v_{ip}^{r}\left(\ln\frac{v_{ip}^{r}}{v_{ip}^{r,ex}}-1\right)\right)+\sum\nolimits_{pj}^{rs}\left(u_{pj}^{rs}\left(\ln\frac{u_{pj}^{rs}}{u_{pj}^{rs,ex}}-1\right)\right)\\
&\quad+\sum\nolimits_{p}^{rs}\left(y_{p}^{rs}\left(\ln\frac{y_{p}^{rs}}{y_{p}^{r,ex}}-1\right)\right)+\sum\nolimits_{p}^{rs}\left(f_{p}^{rs}\left(\ln\frac{f_{p}^{rs}}{f_{p}^{r,ex}}-1\right)\right)\\
&\quad+\sum\nolimits_{p}^{r}\left(e_{p}^{r}\left(\ln\frac{e_{p}^{r}}{e_{p}^{r,ex}}-1\right)\right)+\sum\nolimits_{i}^{r}\left(l_{i}^{r}\left(\ln\frac{l_{i}^{r}}{l_{i}^{r,ex}}-1\right)\right)\\
&\quad+\sum\nolimits_{i}^{r}\left(w_{i}^{r}\left(\ln\frac{w_{i}^{r}}{w_{i}^{r,ex}}-1\right)\right) \qquad (9.1)
\end{aligned}
$$

In all scenarios this objection function is minimized subject to three accounting type constraints.

First, we assume that prices change in such a way that the economy remains in market equilibrium, i.e., we assume that *supply equals demand* by product by region:

$$\sum_i v_{ip}^r = \sum_i^s u_{pi}^{rs} + \sum^s y_p^{rs} + \sum^s f_p^{rs} + e_p^r, \forall p, r \tag{9.2}$$

This means that all variables represent quantities measured in pre-disaster (base year) prices. Implicitly, we also assume in (9.2) that the ultra-short run adaptation possibilities of depleting stocks of inputs have already taken place or are impossible, as is the case with most services. This assumption assures that total sales, i.e., the second term of (9.2), equals total output.

Second, we assume *total output equals total input* by regional industry:

$$\sum_p v_{ip}^s = \sum_p^r u_{pi}^{rs} + l_i^s + w_i^s, \forall i, s \tag{9.3}$$

Note that these two constraints represent the equality of the corresponding rows and columns of Table 9.1.

Third, we assume that total *consumption* from labour income *is tied to* total labour *income* by region:

$$\sum_p^r y_p^{rs} = h^s \sum_i l_i^s, \forall s \tag{9.4}$$

where $h^s = \sum_p^r y_p^{rs,ex} / \sum_i l_i^{s,ex}$ denotes the ratio of total household consumption from labour income of people living and working in region s to total labour income of the same people in the pre-disaster MRSUT. Note that $h^s = (1 - t^s)$, where t^s is the labour income tax rate plus savings rate of these households. Consequently, (9.4) assumes that households living from labour incomes are not able to change their (anyhow small) savings rate and that government will not change its tax rate in face of a disaster. Moreover, (9.4) implies that the labour income accruing to commuters is part of *Other value added* in region s, while the consumption expenditures of commuters are part of *Other final demand* in other regions $r \neq s$. Strictly taken, (9.4) is neither an accounting identity nor a market equilibrium condition. Instead, it models the budget constraint of regional households that only have regional labour incomes as income source, which represents the majority of all regional households (Többen 2017b).

When the base model (9.1)–(9.4) is run to simulate the pre-disaster equilibrium, the 2007 MRSUT for Germany is reproduced exactly, as it should. The outcomes for regional and national total output as well as for foreign exports in this base scenario will be compared with two main disaster scenarios, namely, with the 2013 heavy flooding of the Danube and its tributaries, which directly impacted the German region of Bayern, and with the 2013 heavy flooding of the Elbe and its tributaries, which directed impacted the German regions of Sachsen, Sachsen-Anhalt and

Thüringen (see Oosterhaven and Többen 2017, for details). However, for the Elbe flooding we do not treat all of the three directly affected regions simultaneously, but rather compute outcomes for the direct shocks to one of the regions separately. We do so in order to prevent that the indirect impacts triggered by each region's direct impact offset each other. In this way, we actually defined four independent disaster scenarios.

We assume that the flooding imposes constraints on the production capacities of industries in the directly affected regions. These direct damages to production capacities are modelled by:

$$x_d^d \leq \left(1 - \gamma_d^d\right) x_d^{d,ex} \tag{9.5}$$

where d indicates the directly impacted industries and γ_d^d their capacity loss rates. The direct loss of production capacities is taken from Schulte in den Bäumen et al. (2015), where they are estimated by means of monthly data about the number of workers working "less than normally" by region and industry.

Generally, such indirect approaches to estimate the direct impact of a disaster are not ideal, as they are based on assumptions, whose impacts are difficult to assess. In our case, our estimate of the direct impact may very well include some indirect impacts too. In his critique of disaster impact analysis, Albala-Bertrand (2013) distinguishes three stages to arrive at a conclusion, namely, input data, modelling technique and interpretation of results, whereby assumptions made at each stage compound the assumptions made at former stages. This chapter examines the role of modelling assumptions typically used in standard demand- and supply-driven IO and SU models given an arbitrary direct shock to the supply-side of an economy. In the sense of this hierarchy, we, thus, only deal with those assumptions added at the second tier of the whole assumption-compound, while taking the errors made in the first tier for granted.

9.3 Adding Fixed Ratios to the Base Model

Next, we describe the fixed ratios that we will cumulatively add to the base scenario (9.1)–(9.5), in the order in which we consider them less and less plausible.

First, we add *fixed* intermediate and primary *technical coefficients* for each industry in each region, i.e., we assume that firms minimize their cost under a Leontief-Walras production function, which gives (Oosterhaven 1996):

$$\sum\nolimits^r u_{pi}^{rs} = a_{pi}^{*s} x_i^s, \forall p, i, s, l_i^s = b_i^s x_i^s, \forall i, s, \text{ and } w_{*i}^s = c_i^s x_i^s, \ \forall i, s \tag{9.6}$$

where a_{pi}^{*s} denote technical intermediate input coefficients, i.e., intermediate inputs regardless of their spatial origin per unit of output, b_i^s denote regional labour incomes per unit of output, and c_i^s denote other value added per unit of output, with a_{pi}^{*s}, b_i^s and

c_i^s being calculated from the 2007 MRSUT as $a_{pi}^{*s} = \sum^r u_{pi}^{rs,ex}/x_i^{s,ex}$, $b_i^s = l_i^{s,ex}/x_i^{s,ex}$ and $c_i^s = w_i^{s,ex}/x_i^{s,ex}$. Note that $\sum_p a_{pi}^{*s} + b_i^s + c_i^s = 1, \forall i, s$, by definition. Thus, (9.6) assumes that technical substitution of, e.g., metal subparts for plastic subparts, to be impossible. In the short run after a disaster this is a very reasonable assumption. However, the longer the period after a disaster, the less plausible this assumption becomes.

Second, we add *fixed trade origin coefficients* for intermediate inputs, which are commonly used in all demand-driven MRIO and MRSU models (cf. Oosterhaven 1984). As the data are available, we use the cell-specific, so-called interregional version of this assumption (Isard 1951), instead of the less data demanding row-specific, so-called multi-regional version (Chenery 1953; Moses 1955). Formally, the cell-specific version is written as

$$\mathrm{t}_{pi}^{\mathrm{rs}} = u_{pi}^{rs}/u_{pi}^{*s}, \forall r, s, p, i \tag{9.7}$$

where t_{pi}^{rs} = trade origin shares, i.e., use of product p from region r per unit of total use of product p by industry i in region s. These shares are calculated from the MRSUT, with $\sum^r t_{pi}^{rs} = 1$ by definition, as r includes *RoW*. The row-specific version of (9.7) assumes that the trade origin shares for all purchasing industries i in region s are equal.

The assumption of fixed trade origin ratios extends the fixed technology ratios (9.6) to the geographical origin of intermediate inputs (cf. Oosterhaven and Polenske 2009). In the context of negative demand shocks, it is more or less plausible to assume that firms proportionally purchase less inputs from all their established suppliers. In the case of a negative supply shock, however, firms will immediately search for different sources for their inputs. In an extreme case, assuming fixed trade origin ratios implies that firms have to shut down their own production completely if only one of their suppliers is not able to deliver the required inputs. Hence, this assumption definitely leads to overstating the negative impacts of disasters.

Note that, from a calculation point of view, it is not efficient to add both (9.6) and (9.7) to the base scenario (9.1)–(9.5). It more efficient to combine (9.6) and (9.7), which gives:

$$u_{ij}^{rs} = a_{ij}^{rs} x_j^s \; \forall r, s, i, j \tag{9.8}$$

with a_{ij}^{rs} representing the *fixed interregional input coefficients*.

Third, the assumption of *fixed industry market shares* is commonly used in input-output (IO) models based on industry-by-industry transaction matrices, both in the case when such models are based on supply-use tables (SUTs) and when they are based on symmetric industry-by-industry IO tables. In the first case the assumption needs to be made explicitly in order to derive an operational IO model (Oosterhaven 1984), while, in the second case, the assumption is implicitly embodied in the symmetric IO table itself, which nowadays typically is derived from supply-use accounts (see Miller and Blair 2009). Formally, this assumption is written as:

$$v_{ip}^{r} = d_{ip}^{r} g_{p}^{r}, \forall i, p, r, \tag{9.9}$$

where d_{ip}^{r} = market share of industry i in the regional supply of product p, calculated from the MRSUT, with $\sum_{i} d_{ip}^{r} = 1$.

While this assumption is plausible, to some extent, when used in the context of a positive demand shock, it is highly implausible when the economy is faced with a negative supply shock. This can be easily shown with an example. Assume the extreme case where a certain product is produced by two industries only. Say that the first industry provides 90% of the total supply, whereas the market share of the second industry is only 10%. If this second industry is forced to shut down its production because of a disaster while the first industry is unaffected, fixed market shares would imply that the first industry will also not be able to sell that product. Therefore, the assumption of fixed industry market shares can be expected to inflate the outcomes of any model artificially.

The assumptions (9.8) and (9.9) together present the combination of fixed ratios used by the basic interregional IO model and the interregional Inoperability IO Model (IIM), which are equivalent (Dietzenbacher and Miller 2015).

Fourth, we cumulatively add the assumption for household consumption from labour incomes that corresponds with the fixed technical coefficients for intermediate demand, namely *fixed technical consumption package coefficients*:

$$\sum\nolimits^{r} y_{p}^{rs} = p_{py}^{s} y_{*}^{*s}, \forall s, p \tag{9.10}$$

where p_{py}^{s} denote technical package coefficients (i.e., household consumption of product p regardless of its spatial origin per unit of total household consumption), with the p_{j}^{s} being calculated from the base-year MRSUT as $p_{py}^{s} = \sum\nolimits^{r} y_{py}^{rs,ex} / y_{*}^{*s,ex}$, with $\sum_{p} p_{py}^{s} = 1$. We consider assuming fixed ratios for consumption demand much less plausible than assuming fixed ratios for intermediate demand, as their nature is more behavioural than technical, although private cars, of course, also cannot drive without gasoline. More importantly, in face of a severe drop in income, households will consciously change their consumption in the direction of consuming relatively more food and shelter.

Fifth, we add *fixed consumption trade origin shares* for household consumption demand:

$$t_{py}^{rs} = y_{p}^{rs} / y_{p}^{*s}, \forall r, s, p \tag{9.11}$$

where t_{py}^{rs} = trade origin shares, i.e., household consumption of product p from region r per unit of total household consumption of product p in region s. These shares are calculated from the MRSUT, with $\sum\nolimits^{r} t_{py}^{rs} = 1$, by definition, as r includes RoW.

Again, for calculation efficiency reasons, we do not add both (9.10) and (9.11) to the earlier set of fixed ratios, but instead add their combination, i.e., *fixed interregional consumption package coefficients*:

$$y_p^{rs} = p_{py}^{rs}\, y_*^{*s}, \forall r, s, p \tag{9.12}$$

where $p_{py}^{rs} = y_p^{rs,ex}/y_*^{*s,ex}$ denotes household consumption of product j from region r per total consumption of households in region s, with $\sum_j^r p_j^{rs} = 1$.

The assumptions (9.8)–(9.9) plus (9.12), in fact, represent the combination of fixed ratio assumptions of the extended (i.e., Type II) interregional IO and IIM models.

Sixth and seventh, we add the same two assumption, as (9.10) and (9.12), for *other regional final demand*, namely *fixed technical package coefficients*,

$$\sum\nolimits^r f_p^{rs} = p_{pf}^{s} f_*^{*s}, \forall s, p \tag{9.13}$$

and *fixed interregional package shares*:

$$f_p^{rs} = p_{pf}^{rs}\, f_*^{*s}, \forall r, s, p \tag{9.14}$$

These two assumptions are not commonly found in the disaster impact literature. Probably because they are very implausible. Other regional final demand comprises of government consumption demand, and government and private investment demand. Each of these three types of demands will react very differently to supply shocks. In all cases, this will imply a conscious change in the composition of each type of demand, which is why assuming fixed (technical or trade) ratios is very unrealistic. Only in the case of government consumption demand, assuming fixed technical package coefficients will have some credibility, as bureaucrats will still need their bureaus, computers and papers in combination.

9.4 Impacts of Fixed Ratios on Modelling Outcomes

The comparison of running the cumulatively extended base model for the four flooding scenarios with the base scenario (9.1)–(9.4) is made in terms of the *ratio* of the regional and national indirect impacts to the direct impacts on gross output. The regional ratios are defined as:

$$M^{R,d} = \sum\nolimits_i \left(x_i^{d,ex} - x_i^d - \gamma_i^d x_i^{d,ex}\right) / \sum\nolimits_i \gamma_i^d x_i^{d,ex}, \forall d \tag{9.15}$$

where the numerator measures the indirect change in regional gross output in the flooded region, while the denominator measures the direct loss of gross output due to the floods in that same region. The corresponding national ratios are defined as:

$$M^{N,d} = \left(\left(\sum\nolimits_i^s x_i^{s,ex} - x_i^s\right) - \sum\nolimits_i \gamma_i^d x_i^{d,ex}\right) / \sum\nolimits_i \gamma_i^d x_i^{d,ex}, \forall d \tag{9.16}$$

where the numerator represents the indirect change in national gross output due to the flooding in region d.

The first row of Tables 9.2, 9.3, 9.4 and 9.5 shows these ratios for the flooding of, respectively, the Danube in Bayern and the Elbe in Sachsen, Sachsen-Anhalt and Thüringen, separately, under the assumption of maximal economic flexibility. Most remarkable is the very small size of *all* indirect impacts and especially of those occurring in the directly affected regions. While the floods cause zero (or close to zero) intra-regional indirect impacts, the effect on other German regions is in the range of about 5–7% of the size of the direct shock (i.e., loss of production capacity). Apart from Thüringen, the drop of foreign exports is much larger compared to the effects occurring in Germany itself. The very small positive indirect impacts in the not directly affected regions suggest that the loss of intermediate inputs is predominantly substituted by increasing the foreign imports and decreasing the foreign exports. This indicates that economies with a very high degree of economic flexibility, as assumed in (9.1)–(9.5), will experience negligible indirect economic damages of whatever disaster. Such economies obviously need to direct their attempts to reduce the overall cost of disasters at diminishing their direct cost, and leave the size of the indirect cost to the market.

The second to fourth row show the indirect impacts for adding the first set of fixed ratios, which, taken together, constitute the assumptions used in Type I multi-regional IO and SU models.

Surprisingly, adding fixed *technical coefficients* (second row) has no impact of scale of indirect impacts in the case of the Danube flooding in Bayern, neither in Bayern itself nor in the rest of Germany or abroad. In contrast, in the three, economically less diversified and much smaller eastern German states fixed

Table 9.2 Indirect impacts in permilles of direct gross output impact of Danube floods, while adding fixed ratios to the base model

Impacts in permilles on	Bayern	Rest of Germany		All of Germany	Foreign exports
		Negative	Positive		
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	−1.7	−51	0.11	−52	−338
+ fixed technical coefficients	−1.7	−51	0.11	−52	−338
+ fixed intermediate trade origin ratios	−9.1	−82	0.10	−91	−447
+ fixed industry market shares[a]	−44.6	−86	0.00	−131	−491
+ fixed consumption package coefficients	−44.6	−86	0.00	−131	−505
+ fixed consumption trade origin ratios[b]	−62.9	−88	0.09	−150	−514
+ fixed other final demand package coeff.	−69.9	−96	0.08	−166	−540
+ fixed other final demand trade origins	−509.0	−136	10.88	−635	−582

[a]These three assumptions are used in Type I input-output and supply-use models
[b]These five assumptions are used in Type II input-output and supply-use models

Table 9.3 Indirect impacts in permilles of direct gross output impact of Elbe floods in Sachsen, while adding fixed ratios to the base model

Impacts in permilles on	Sachsen	Rest of Germany		All of Germany	Foreign exports
		Negative	Positive		
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	−0.08	−48	0.01	−48	−189
+ fixed technical coefficients	−0.13	−45	1.64	−43	−197
+ fixed intermediate trade origin ratios	−0.15	−81	0.08	−81	−254
+ fixed industry market shares[a]	−22.66	−80	0.37	−103	−260
+ fixed consumption package coefficients	−24.60	−81	0.80	−105	−263
+ fixed consumption trade origin ratios[b]	−26.11	−96	1.00	−121	−284
+ fixed other final demand package coeff.	−101.10	−189	90.99	−199	−289
+ fixed other final demand trade origins	−751.51	−521	25.62	−1247	−264

[a]These three assumptions are used in Type I input-output and supply-use models
[b]These five assumptions are used in Type II input-output and supply-use models

Table 9.4 Indirect impacts in permilles of direct gross output impact of Elbe floods in Sachsen-Anhalt, while adding fixed ratios to the base model

Impacts in permilles on	Sachsen-Anhalt	Rest of Germany		All of Germany	Foreign exports
		Negative	Positive		
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	0.00	−65	0.07	−65	−250
+ fixed technical coefficients	−0.00	−61	0.96	−60	−257
+ fixed intermediate trade origin ratios	−0.20	−113	0.04	−114	−346
+ fixed industry market shares[a]	−8.88	−115	0.06	−124	−374
+ fixed consumption package coefficients	−9.98	−117	0.03	−127	−375
+ fixed consumption trade origin ratios[b]	−10.99	−138	0.00	−149	−403
+ fixed other final demand package coeff.	−14.00	−208	62.62	−159	−407
+ fixed other final demand trade origins	−552.88	−605	16.17	−1141	−473

[a]These three assumptions are used in Type I input-output and supply-use models
[b]These five assumptions are used in Type II input-output and supply-use models

technical coefficients tend to increase intraregional indirect impacts and the drops of foreign exports, but decrease negative indirect impacts occurring in the rest of Germany. At the same time, some industries in the rest of Germany increase their production, in order to compensate for the loss of inputs caused by, especially, the floods in these three eastern states.

Table 9.5 Indirect impacts in permilles of direct gross output impact of Elbe floods in Thüringen, while adding fixed ratios to the base model

Impacts in permilles on	Thüringen	Rest of Germany Negative	Rest of Germany Positive	All of Germany	Foreign exports
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	0.00	−67	0.09	−67	−5
+ fixed technical coefficients	0.00	−63	0.59	−62	−7
+ fixed intermediate trade origin ratios	−1.49	−111	0.31	−112	−94
+ fixed industry market shares[a]	−6.47	−116	0.13	−122	−142
+ fixed consumption package coefficients	−8.47	−119	0.32	−127	−144
+ fixed consumption trade origin ratios[b]	−9.99	−132	0.42	−142	−168
+ fixed other final demand package coeff.	−60.73	−193	48.58	−205	−172
+ fixed other final demand trade origins	−445.48	−504	14.20	−934	−228

[a]These three assumptions are used in Type I input-output and supply-use models
[b]These five assumptions are used in Type II input-output and supply-use models

When fixed origin-specific *trade coefficients* are added to the technical coefficients (third row), negative impacts occurring in the directly affected regions and in the rest of Germany as well as abroad increase significantly. However, especially in the three eastern states affected by the Elbe flooding, the intra-regional effects are still very small compared to the impacts occurring in the rest of Germany and particularly abroad. Compared to adding fixed technical coefficients only, the strongest relative increase can be observed for intra-regional indirect impacts followed by interregional impacts occurring in the rest of Germany and impacts to foreign countries due to a drop of exports.

Adding fixed *industry market shares*, completes the set of assumptions on which multi-regional Type I IO and SU models are build. This additional assumption leads to the strongest increases in indirect disaster impacts in the directly affected regions themselves compared to the cases discussed before. Intra-regionally, the indirect impacts increase at least by a factor of about 4–5 in Thüringen and Bayern. Nonetheless, compared to the indirect impact occurring in the Rest of Germany and compared to the drop of exports, the intraregional effects are still small. In Bayern, Sachsen-Anhalt and Thüringen the negative indirect effects in the Rest of Germany increase only slightly by less than 5%, or, in the case of Sachsen, even decrease by a small amount. Similarly, the increases in the drop of exports to foreign countries are relatively small compared to the change in the scale in the intra-regional impacts. In Bayern, Sachsen and Sachsen-Anhalt this increase is less than 10%, while only Thüringen shows a more significant drop of foreign exports of a about 50%.

The fifth and sixth rows of Tables 9.2, 9.3, and 9.4 show the outcomes of adding fixed ratios for the final consumption of households. Fixed consumption package and fixed consumption trade origin ratios taken together with the three earlier fixed ratios constitute the assumptions of the multi-regional Type II input-output and supply-use models.

Adding fixed *consumption package coefficients* (fifth row) results in very similar outcomes compared to the case where fixed technical coefficients have been added to the NLP base model (second row). Indeed, the intra-regional and interregional effects caused by the Danube flooding in Bayern do not change at all, whereas the impacts caused by the Elbe floods in Sachsen, Sachsen-Anhalt and Thüringen increase only slightly. In Bayern, the only difference to adding fixed technical coefficients is that the drops of foreign exports increase slightly, while it did not in the case of adding fixed technical coefficients.

Adding fixed *trade origin ratios* for consumption expenditures leads to significantly different outcomes in the four regions under study. In Bayern, especially the intra-regional indirect impact increases strongly by about more than 40%, whereas the changes in indirect impacts in the rest of Germany and on exports are much smaller with less than 2% each. In Sachsen, by contrast, intraregional indirect impacts only increase by about 6% and those on exports by about 7%, while the increase in the indirect impact on the rest of Germany is the dominant one with about 18%. Sachsen-Anhalt shows a similar impact as Sachsen, although the change in the interregional impacts of the former is not as dominant as that of the latter. In Thüringen, finally, the increase in the intraregional impacts changes most with about 17%. However, compared to Bayern the relative changes in interregional indirect impacts and in impacts on exports to foreign countries are much stronger with about 11% and 16.6% respectively.

The seventh and eighth rows, finally, show the outcomes, when fixed ratios on other final demand are imposed in addition to the assumptions of the Type I and Type II multiregional IO and SU models.

In the case of fixed *other final demand package coefficients* only relatively slight increases of indirect disaster impacts can be observed for the Danube flooding in Bayern. Compared to that the changes in the indirect impacts caused by the Elbe floods in Sachsen, Sachsen-Anhalt and Thüringen are much different. First of all, the intra-regional indirect impacts increase strongly. While this increase is relatively moderate in Sachsen-Anhalt with about 27%, they are about four to six times larger in Sachsen and Thüringen respectively. Strong increases can also be observed for the negative indirect impacts on the rest of Germany, but contrary to cases before, these negative impacts on some industries are now accompanied by significant positive impacts on the output of other industries.

Whereas the indirect impacts observed before all have been significantly smaller than what one would expect from Type I and Type II IO and SU models, adding fixed other final demand *trade origin ratios* eventually generates results of the expected order. In particular the indirect intra-regional impacts increase drastically by a factor of about seven in Bayern, Sachsen and Thüringen and even become about 40 times larger in the case of Sachsen-Anhalt. Another remarkable outcome is that the negative indirect interregional impacts also increase drastically due to the floods in the three eastern German states by factors of about 2.6 in Thüringen to about 3 in Sachsen-Anhalt. Compared to that, the increase in the negative interregional impacts caused by the flooding in Bayern increases only moderately by about 40%.

From these quite diverse outcomes observed for the four different regions two main patterns can be deduced. Firstly, as expected, the more fixed ratios are added to the model, the larger is the indirect impact felt in the directly affected regions themselves, in the rest of Germany and abroad. Especially in the most extreme case, fixed ratios lead to indirect impacts that are many times larger as in the case with maximal substitution possibilities (i.e., the base model). Secondly, however, our outcomes clearly show that the way in which these fixed ratios affect the intraregional, interregional and international indirect impacts seems to depend strongly on the economic structure of the region under study.

On the one hand, Bayern is by far the largest of the four economies with a strong specialization on exports and as well as strong intra-regional interrelations of its industries. As a consequence, this region shows the largest impact on exports to foreign countries throughout all cases as well as the largest intra-regional indirect effects. Compared to the other regions adding fixed ratios has the strongest impact on the intra-regional output relative to the interregional and international output. In the three eastern regions, on the other hand, the intra-regional interrelations are much weaker and as a consequence the interregional effects caused by their flooding remain dominant compared to the intra-regional impacts, except for the case of added fixed other final demand trade origins in Sachsen.

Another remarkable difference between Bayern and the three eastern regions is their reaction to fixed ratios imposed on consumption demand and other final demand. Fixed ratios for consumption only results in a relatively small increase in indirect impacts in the three eastern states, whereas the increase in indirect impacts in Bayern is much stronger. For imposing fixed ratios on other final demand, the opposite is true. The relative increase in indirect impacts is much larger in the eastern states compared to that in Bayern. This can be explained by the degree to which regional industries depend on final demand of households compared to other final demand, which in particular contains the final demand of governments. As the three eastern German regions are still economically underdeveloped, the latter makes out a much larger share of total final demand compared to Bayern.

9.5 Conclusion

In this chapter we examined the impacts of the fixed ratio assumptions commonly used in standard demand-driven Type I and extended Type II multiregional input-output and supply-use models on the magnitude of indirect disaster impact estimates. By adding increasingly less plausible fixed ratios to the base non-linear programming model that allows for maximal substitution possibilities, we are able to examine the relative contribution of each assumption to the magnitude of indirect impacts. Our outcomes allow us to draw three main conclusions.[1]

Firstly, a supply shock to a highly resilient economy does not cause significant indirect impacts compared to the magnitude of the direct ones, as the possibility of both producers and consumers to substitute lacking inputs mitigates the negative cascading effects rippling through the interregional supply chains, and adds positive impacts elsewhere. Since the accounting framework used here, is more detailed in terms of value added and final demand, additional possibilities to adapt lead to even smaller indirect impacts compared to a previous application of this model in Oosterhaven and Többen (2017).

Secondly, we find that fixed ratio assumptions not only inflate the magnitude of indirect impact estimates substantially, but that it also has a significant impact on the spatial distribution of these impacts. While in the base model with maximum substitution possibilities intra-regional indirect impacts make out only a negligible portion of the total, adding fixed ratios shifts this portion more and more towards the disaster regions themselves. Our findings suggest that the spatial distribution of these impacts should be subject to further investigation.

Thirdly, our results also suggest that the consequences of a fixed ratio assumption are highly dependent on the characteristics of the regions under study. The four regions in our study are quite different in terms of economic size, strength of intra-regional linkages and dependency on private consumption, other final demand and regional exports. Therefore, disaster impact assessments require a realistic representation of the economy under study and of its interrelations with other economies. The disaster itself is often bound to a relatively small geographic area at the subnational level. At the same time, IO data at that level of spatial resolution is practically always scarce, which highlights the importance of plausible regional supply-use data as a prerequisite for realistic modelling outcomes.

Finally, similar to the outcomes in Oosterhaven and Többen (2017), our results show that the indirect impacts of a disaster may be only a minor concern if sufficient substitution possibilities exist. This implies that disaster impact mitigating policies targeting at the enhancement of the resilience of an economy as a whole, may not be justified, at least not in high-income countries such as Germany. Instead of focussing on indirect impacts, emphasis should rather be put on policies mitigating and preventing the negative direct impacts of disasters.

[1]Adding the extremely implausible fixed ratios of the newly formulated *supply-driven* multi-regional supply-use model to the base NLP model, in the Appendix, leads to more or less comparable conclusions.

Appendix

A.1 Impact of Adding Supply-Driven Fixed IO and SU Ratios to the NLP Model

A.1.1 A Supply-Driven Multiregional Supply-Use Model

The secondary question we investigate here, is whether adding the fixed ratios assumed in the supply-driven IO model produces a different outcome compared to adding the ratios of the demand-driven IO model, as discussed in the main text. First and foremost, it needs to be reiterated that the original quantity interpretation of the supply-driven IO model (Ghosh 1958) is generally considered extremely implausible (Oosterhaven 1988, 2012; Dietzenbacher 1997; DeMesnard 2009). In sum: the single homogeneous input assumption of this model implies that cars may drive without gasoline and factories may work without labour. Nevertheless, we discuss it here because, especially, natural disasters primarily constitute a shock to the supply-side of the economy, and because the name of this model suggests that it might be suited to simulate the quantity impacts of supply shocks (see Crowther and Haimes 2005, for at least one disaster application).[2]

As our base model is calibrated on a use-regionalized MRSU table (labelled as *purchase only* by Oosterhaven 1984, who describes a whole family of MRSUTs), we first need to formulate a supply-driven MRSU model that fits these detailed data (see Table 9.1). DeMesnard (2009) already formulated a supply-driven SU model for a closed economy when he discussed the unfitness of the commodity technology assumption while constructing a demand-driven SU model. Here, we will extend his SU model to fit to a use-regionalized MRSUT. It will be the mathematical mirror of the existing demand-driven MRSU model based on a use-regionalized MRSUT (Oosterhaven 1984). For briefness sake, we put the model directly in matrix notation.

First, any change in the supply of exogenous primary inputs $\mathbf{w}'$ or endogenous intermediate inputs $\mathbf{i}'\mathbf{U}$ of any regional industry leads to an equally large change in its total input $\mathbf{x}'$:

$$\mathbf{x}' = \mathbf{i}'\mathbf{U} + \mathbf{w}' \tag{9.17}$$

where the vectors and matrices follow the layout of Table 9.1. In Eq. (9.17) all inputs are treated as perfect substitute for one another, just as the demand-driven model assumes that all outputs are perfect substitutes for one another.

Second, any change in total inputs $\mathbf{x}'$ leads to an equally large change in the total supply of products by that industry $\mathbf{Vi}$, while the latter are produced in a *fixed product mix*:

[2]Dietzenbacher's (1997) reinterpretation of the Ghosh model as a cost-push price model that is equivalent to the Leontief (1951) price model is irrelevant here, as disaster impact studies are primarily interested in the volume changes in the economy and not in the price changes.

$$\mathbf{V} = \widehat{\mathbf{x}}\,\mathbf{M} \tag{9.18}$$

where $m_{ip}^{r} \in \mathbf{M}$ is calculated from the base-year MRSUT as $v_{ip}^{r,ex}/x_{i}^{r,ex}$. Note that Eq. (9.18) may technically be only realistic in case of some chemical industries. For other industries it must be based on the wish to service all purchasers proportionally, irrespective of their demand, which consequently is assumed to be perfectly elastic, just as the demand-driven model assumes supply to be perfectly elastic (Oosterhaven 1996, 2012).

Third, any change in the regional supply of any product $\mathbf{i}'\mathbf{V}$ leads to an equally large change in the total supply $\mathbf{g}$ of that product:

$$\mathbf{g}' = \mathbf{i}'\mathbf{V} \tag{9.19}$$

Fourth, any change in the total regional supply of any product leads to a proportional increase (i.e., with fixed allocation coefficients) in the use of that product by all industries $\mathbf{U}$ and the use of that product by all final demand categories $\mathbf{Y}$. Here a distinction between technical allocation coefficients $\mathbf{B}$ and spatial allocation coefficients $\mathbf{T^g}$ clarifies the multi-regional nature of the extension of the closed single-region SU model:

$$\mathbf{U} = \widehat{\mathbf{g}}\,\mathbf{B} \otimes \mathbf{T^g} \text{ and } \mathbf{Y} = \widehat{\mathbf{g}}\,\mathbf{B^y} \otimes \mathbf{T^{gy}} \tag{9.20}$$

where $\otimes$ indicates a cell-by-cell multiplication. The *technical allocation ratios* (i.e., technical output or sales coefficients) $b_{pj}^{r*} \in \mathbf{B}$ are calculated from the base-year MRSUT as $b_{pj}^{r*} = u_{pj}^{r*,ex}/g_{p}^{r,ex}$, with the $b_{py}^{r*} \in \mathbf{B^y}$ calculated analogously. The *trade destination ratios* $t_{pj}^{r*} \in \mathbf{T^g}$ are calculated as $t_{pj}^{rs} = u_{pj}^{rs,ex}/u_{pj}^{r*,ex}$, with the $t_{py}^{rs} \in \mathbf{T^{gy}}$ calculated analogously. Note again the importance of the assumption of a perfectly elastic demand in all markets, as opposed to the assumption of a perfectly elastic supply in the demand-driven IO model.

Appropriate sequential substitution leads to, respectively, the following base equation and subsequent solution for *total industry input*:

$$\mathbf{x}' = \mathbf{x}'\mathbf{M}\,\mathbf{B} \otimes \mathbf{T^g} + \mathbf{w}' \Rightarrow \mathbf{x}' = \mathbf{w}'(\mathbf{I} - \mathbf{M}\,\mathbf{B} \otimes \mathbf{T^g})^{-1} \tag{9.21}$$

In Eq. (9.21) both coefficient matrices $\mathbf{M}$ and $\mathbf{B} \otimes \mathbf{T^g}$ may be rectangular, but their product $\mathbf{M}\;\mathbf{B} \otimes \mathbf{T^g}$ is square and has an industry-by-industry dimension. $\mathbf{G} = (\mathbf{I} - \mathbf{M}\,\mathbf{B} \otimes \mathbf{T^g})^{-1}$ represents the multi-regional generalization of the Ghosh-inverse.

The solution for *total product supply* may, then, be calculated simply by means of:

$$\mathbf{g}' = \mathbf{x}'\mathbf{M} \tag{9.22}$$

A.1.2 The Impact of Adding Supply-Driven Fixed Ratios to the Base Model

The above supply-driven MRSU model, specifies the fixed ratio assumptions that we will sequentially add to the base model (9.1)–(9.5).

First, the fixed *product mix ratios* by regional industry:

$$v_{ip}^r = x_i^r m_{ip}^r, \forall i, p, r. \tag{9.23}$$

where m_{ip}^r = share of product p in the output of regional industry i, with $\sum_p m_{ip}^r = 1$.

Second, the fixed industry and final demand *allocation ratios* for regional product supply, now written out in full:

$$\sum\nolimits^s u_{pj}^{rs} = g_p^r b_{pj}^{r*}, \sum\nolimits^s y_p^{rs} = g_p^r h_p^{r*}, \sum\nolimits^s f_p^{rs} = g_p^r d_p^{r*} \text{ and } e_p^r = g_p^r k_p^r, \forall p, j, r \tag{9.24}$$

where b_{pi}^{r*}, h_p^{r*} and d_p^{r*} denote the technical allocation coefficients, i.e., sales regardless of their spatial destination per unit of regional supply as calculated from the rows of the MRSUT. The k_p^r denote foreign export allocation coefficients, which do not need to be added separately as $\sum_i b_{pi}^{r*} + h_p^{r*} + d_p^{r*} + k_p^r = 1, \forall p, r$, holds because of Eq. (9.2) in the main text.

Third, the *cell-specific* fixed intermediate and final output *trade destination ratios*, now again written out in full:

$$t_{pi}^{rs} = u_{pi}^{rs}/u_{pi}^{r*}, t_{py}^{rs} = y_p^{rs}/y_p^{r*}, t_{pf}^{rs} = f_p^{rs}/f_p^{r*}, \forall r, s, p, i \tag{9.25}$$

where t_{pi}^{rs}, t_{py}^{rs} and t_{pf}^{rs} represent the use of product p from region r per unit of total use of product p by i, y and f in region s. These shares are calculated from the rows of the MRSUT, with $\sum^s t_{pi}^{rs} = 1$ by definition. The *column-specific* version of (9.25), which we do not use, as we have detailed cell-specific MRSUT information, would assume that the trade destination ratios for all different products p from region r are equal (cf. the *FI multiregional SUT* in Oosterhaven 1984).

Note that, from a calculation point of view, it is not efficient to add both (9.24) and (9.25) to the base scenario (9.1)–(9.5). It is more efficient to combine them, which gives:

$$u_{pj}^{rs} = g_p^r b_{pj}^{rs}, y_p^{rs} = g_p^r h_p^{rs} \text{ and } f_p^{rs} = g_p^r d_p^{rs}, \forall p, j, r, s \tag{9.26}$$

and to then add (9.26), with its *fixed interregional allocation coefficients*, to the base scenario instead.

Tables 9.6, 9.7, 9.8, 9.9 describe the impact of this sequential adding of fixed ratios to the base model. The first rows, again, show the outcomes of the base model as defined by the Eqs. (9.1)–(9.5), while the second to fourth rows show the outcomes for the sequential adding of fixed product mix ratios by industry, fixed technical allocation ratios and, finally, fixed trade destination ratios. As opposed to

Table 9.6 Indirect impacts in permilles of direct gross output impact of Danube floods, while adding fixed ratios to the base model

Impacts in permilles on	Bayern	Rest of Germany Negative	Rest of Germany Positive	All of Germany	Imports
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	−1.7	−51	0.1	−52	−170
+ fixed product mix ratios/industry	−1.9	−52	0.2	−53	−173
+ fixed technical allocation coefficients	−9.6	−39	21.1	−27	−219
+ fixed spatial allocation coefficients[a]	−29.6	−121	1.5	−149	−301

[a]These three assumptions are used in supply-driven MRIO and MRSU models

Table 9.7 Indirect impacts in permilles of direct gross output impact of Elbe floods in Sachsen, while adding fixed ratios to the base model

Impacts in permilles on	Sachsen	Rest of Germany Negative	Rest of Germany Positive	All of Germany	Imports
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	−0.08	−48	0.01	−48	−161
+ fixed product mix ratios/industry	−0.24	−48	0.03	−48	−162
+ fixed technical allocation coefficients	−0.60	−46	33.95	−12	−180
+ fixed spatial allocation coefficients[a]	−4.39	−127	0.15	−132	−238

[a]These three assumptions are used in supply-driven MRIO and MRSU models

Tables 9.1, 9.2, 9.3, 9.4 in the main text, which include the impacts on foreign exports, Tables 9.6, 9.7, 9.8, 9.9 include the impacts on foreign imports. The reason is that adding input ratios in the main text fixes the structure of the columns of the MRSUT, leaving exports relatively unconstrained, whereas adding output ratios in the Appendix fixes the structure of the rows of the MRSUT, leaving imports relatively unconstrained.

As to the impact of adding fixed product mix ratios per regional industry, it can be observed that the intra-regional indirect impact in all four regions increase by at least 11% (Bayern), whereas the interregional impacts change less and show a mixed behaviour. On the one hand, the interregional impacts in Bayern and Thüringen increase slightly by about 2%, while, on the other hand, a slight decrease 0.6% and 2% can be observed for Sachsen and Sachsen-Anhalt, respectively. The drop of imports from foreign countries changes uniformly across the four regions, whereby the largest drop can be observed in Bayern (1.5%) and the lowest in Sachsen (0.3%).

When fixed technical allocation coefficients are added on top of the fixed product mix ratios, the change in the indirect impacts is more uniform across the four regions. It can be observed that the intra-regional impacts increase substantially and are at least about 2.5 times (Sachsen and Sachsen-Anhalt) up to 10 times (Thüringen) larger than before. At the same time, the indirect impacts in all of Germany decrease

Table 9.8 Indirect impacts in permilles of direct gross output impact of Elbe floods in Sachsen-Anhalt, while adding fixed ratios to the base model

Impacts in permilles on	Sachsen-Anhalt	Rest of Germany		All of Germany	Imports
		Negative	Positive		
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	0.00	−67	0.09	−67	−129
+ fixed product mix ratios/ industry	−0.24	−66	0.12	−66	−130
+ fixed technical allocation coefficients	−0.58	−49	20.16	−29	−148
+ fixed spatial allocation coefficients[a]	−0.56	−156	0.50	−157	−203

[a]These three assumptions are used in supply-driven MRIO and MRSU models

Table 9.9 Indirect impacts in permilles of direct gross output impact of Elbe floods in Thüringen, while adding fixed ratios to the base model

Impacts in permilles on	Thüringen	Rest of Germany		All of Germany	Imports
		Negative	Positive		
Ratios with max. Substitution = NLP base model (9.1)–(9.5)	0.00	−67	0.09	−67	−60
+ fixed product mix ratios/ industry	−0.07	−68	0.00	−69	−61
+ fixed technical allocation coefficients	−0.66	−54	29.51	−25	−70
+ fixed spatial allocation coefficients[a]	−3.17	−182	0.03	−185	−104

[a]These three assumptions are used in supply-driven MRIO and MRSU models

significantly by about 49% for Bayern to about 75% for Sachsen. Separating industries that experience a positive indirect impact from those with a negative impact (second and third column), shows that this is due to an decrease in the negative indirect impacts combined with a substantial increase in the positive indirect impacts in the rest of Germany. In contrast, the drop of imports again increases uniformly, but is much larger compared to the case where only fixed product mix ratios by industry are imposed. As before, the largest changes apply to Bayern (27%) and the lowest to Sachsen (11%).

Adding fixed spatial allocation coefficients, finally, leads to a substantial increase in the indirect impacts, both, intra-regionally and interregionally. The only exception is Sachsen-Anhalt, where the intra-regional impacts decrease slightly. In the other three regions, the intra-regional impacts become about 3 (Bayern) to 7 (Sachsen) times larger compared to the case where only fixed technical allocation ratios are added. Regarding the interregional indirect impacts on the rest of Germany our outcomes show that positive indirect impacts vanish almost completely across all regions, while, at the same time, negative indirect impacts become 2.8 (Sachsen) to 3.4 (Thüringen) times larger than before. As in the cases before, adding fixed spatial allocation ratios again leads to a further increase in the drop of imports from foreign countries across all four regions and again this further increase is larger than before. However, the rank-order of regions changes, as the by far largest increase can now be observed for Thüringen (48%) followed by Bayern and Sachsen-Anhalt (both about 37%) and Sachsen (32%).

Comparing the indirect impacts across all of Germany shows that the total indirect impacts are relatively close to each other, ranging between about 13% to 18% of the direct impact. However, the extent to which these indirect impacts occur intra-regionally and interregionally is very different across the regions. The largest share of intra-regional impacts in nation-wide impacts of 20% can be observed for Bayern, whereas the lowest share of only 0.35% is observed for Sachsen-Anhalt.

References

Albala-Bertrand JM (2013) Disasters and the networked economy. Routledge, Oxon

Anderson CW, Santos JR, Haimes YY (2007) A risk-based input-output methodology for measuring the effects of the August 2003 Northeast blackout. Econ Syst Res 19(2):183–204

Carerra L, Standardi G, Bosello F, Mysiak J (2015) Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling. Environ Model Softw 63:109–122

Chenery HB (1953) Regional analysis. In: Chenery HB, Clark PG, Vera VC (eds) The structure and growth of the Italian economy. U.S. Mutual Security Agency, Rome, pp 97–129

Crowther KG, Haimes YY (2005) Application of the inoperability input-output model (IIM) for systemic risk assessment and management of interdependent infrastructures. Syst Eng 8 (4):323–341

DeMesnard L (2009) Is the Ghosh model interesting? J Reg Sci 49(2):361–372

Dietzenbacher E (1997) In vindication of the Ghosh model: a reinterpretation as a price model. J Reg Sci 37(4):629–651

Dietzenbacher E, Miller RE (2015) Reflections on the inoperability input-output model. Econ Syst Res 27(4):478–486

Ghosh A (1958) Input-output approach in an allocation system. Economica 25(4):58–64

Hallegate S (2008) An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. Risk Anal 28(3):779–799

Isard W (1951) Interregional and regional input-output analysis, a model of the space economy. Rev Econ Stat 33(4):318–328

Koks EE, Thissen M (2016) A multiregional impact assessment model for disaster analysis. Econ Syst Res 28(4):429–449

Koks EE, Carrerra L, Jonkeren O, Aerts J, Husby JCJH, Thissen M, Standardi G, Mysiak J (2015) Regional disaster impact analysis: comparing input-output and computable general equilibrium models. Nat Hazard Earth Syst Sci Discuss 3(11):7053–7088

Leontief WW (1951) The structure of the American economy: 1919–1939, 2nd edn. Oxford University Press, New York

Miller RE, Blair PD (2009) Input-output analysis: foundations and extensions. Cambridge University Press, New York

Moses LN (1955) The stability of interregional trading pattern and input-output analysis. Am Econ Rev 45(5):803–832

Oosterhaven J (1984) A family of square and rectangular interregional input-output tables and models. Reg Sci Urban Econ 14(4):565–582

Oosterhaven J (1988) On the plausibility of the supply-driven input-output model. J Reg Sci 28 (2):203–217

Oosterhaven J (1996) Leontief versus Ghoshian price and quantity models. South Econ J 62 (3):750–759
Oosterhaven J (2012) Adding supply-driven consumption makes the Ghosh model even more implausible. Econ Syst Res 24(1):101–111
Oosterhaven J (2017) On the limited usability of the inoperability IO model. Econ Syst Res 29:452–461
Oosterhaven J, Bouwmeester MC (2016) A new approach to modelling the impact of disruptive events. J Reg Sci 56(4):583–595
Oosterhaven J, Polenske KR (2009) Modern regional input-output and impact analyses. In: Capello R, Nijkamp P (eds) Handbook of regional growth and development theories. Edward Elgar, Cheltenham, pp 423–439
Oosterhaven J, Többen J (2017) Regional economic impacts of heavy flooding in Germany: a non-linear programming approach. Spat Econ Anal 12(4):404–428
Rose A, Guha G-S (2004) Computable general equilibrium modelling of electric utility lifeline losses from earthquakes. In: Okuyama Y, Chang SE (eds) Modeling spatial and economic impacts of disasters. Springer, Berlin, pp 119–141
Santos JR (2006) Inoperability input-output modeling of disruptions to interdependent economic systems. Syst Eng 9:20–34
Santos JR, Haimes YY (2004) Modelling the demand reduction input-output (I-O) inoperability due to terrorism of connected infrastructures. Risk Anal 24:1437–1451
Schulte in den Bäumen H, Többen J, Lenzen M (2015) Labour forced impacts and production losses due to the 2013 flood in Germany. J Hydrol 527:142–150
Standardi G, Bosello F, Eboli F (2014) A sub-national version of the GTAP model for Italy. Working Papers of the Fondatione Eni Enrico Mattei
Többen J (2017a) Effects of energy and climate policy in Germany: a multiregional analysis. PhD, Faculty of Economics and Business, University of Groningen
Többen J (2017b) Regional net impacts and social distribution effects of promoting renewable energies in Germany. Ecol Econ 135:195–208
Tsuchiya S, Tatana H, Okada N (2007) Economic loss assessment due to railroad and highway disruptions. Econ Syst Res 19(2):147–162

Johannes Többen is researcher at GWS Osnabrück and Potsdam Institute for Climate Impact Research. Before, he was Postdoctoral Fellow at the Industrial Ecology Programme (Indecol) at the Norwegian University of Science and Technology in Trondheim from 2017 to 2019. Johannes holds a PhD in Economics from the University of Groningen for his thesis on regional economic of the national energy-and climate policy in Germany. From 2012 to 2016, he worked as a researcher in the group for Systems' Analysis and Technology Evaluation of the Institute of Energy- and Climate Research at Forschungszentrum Jülich in Germany. His research interest is in the intersection of spatial economics, ecological economics and econometrics. Since 2015, Johannes has published 10 scientific articles covering economic impacts of the energy transition in Germany, spatial economic impacts of natural disasters, spatial ecological footprints and maximum entropy models.

Jan Oosterhaven is emeritus professor of Spatial Economics at the University of Groningen, where he started working in 1970. As a visiting professor he taught urban economics in 1985–1986 at the University of California, Los Angeles, and as a senior consultant he worked for TNO in 1998–1999. His research focuses on interregional input-output analysis, demo-economic modeling, indirect economic effects of supply shocks, and integral cost-benefit analyses of all kind of spatial policy measures. Besides about 75 research reports mostly for government agencies, he has written and edited 10 books and some 150 scientific articles on a wide range of subjects, such as sectoral, regional and urban (economic) policy, housing, impacts of social security, high speed rail, road infrastructure, tourism and agricultural projects.

Chapter 10
Transportation Disruptions and Regional Supply Chains: A Modeling Framework with Application to Coastal Shipping

Stephanie E. Chang and Hadi Dowlatabadi

Abstract Transportation system disruption is widely recognized as a major source of spatial and economic impact in disasters, yet modeling these effects remains a challenge. This chapter develops a framework for modeling transport system disruption that is designed to support decision-making for disaster resilience. It focuses on a relatively simple yet vital transport system, coastal shipping, and its role in regional supply chains, particularly in the delivery of essential commodities to coastal communities in the aftermath of a disaster. Disruption to this system can quickly cause shortages of critical needs such as fuel, as modern supply chains have increasingly adopted just-in-time delivery models entailing little slack. To develop the framework, this chapter first reviews the empirical and modeling literature on the vulnerability of maritime transportation systems and supply chains to hazards such as earthquakes, storm surge, oil spills, and labor strikes. Findings indicate a need for integrated models of transportation, critical supply chains, and community demand. Such models should capture not only the physical vulnerability of key transportation assets, but also disruption modes, duration, and effects of planning and preparedness. The study further grounds the discussion in a case study region on the Pacific coast of Canada. Data, local knowledge, and contextualized insights are developed through expert interviews and stakeholder interactions. Findings indicate the importance of accounting for cargo type, directionality of flows, reserves, regulations, and other critical aspects when modeling potential disruptions to transportation systems and supply chains. The chapter proposes a modeling framework that is spatially explicit, functionally specified, and operationally oriented. The framework helps address a general need for disaster impact models that capture critical risk reduction

S. E. Chang (✉)
School of Community and Regional Planning (SCARP), Institute for Resources, Environment and Sustainability (IRES), University of British Columbia, Vancouver, BC, Canada
e-mail: stephanie.chang@ubc.ca

H. Dowlatabadi
Institute for Resources, Environment and Sustainability (IRES), University of British Columbia, Vancouver, BC, Canada
e-mail: hadi.d@ubc.ca

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_10

and resilience-building strategies in ways that can support decision-makers in practice.

10.1 Introduction

Transportation disruption has long been recognized as a major source of spatial and economic impact in disasters. In the 1994 Northridge (Los Angeles) earthquake, for example, some $1.5 billion of the total $6.5 billion in business interruption losses have been ascribed to transportation system damage (Gordon et al. 1998). Moreover, the continuous and efficient functioning of transportation systems is becoming ever more critical to economic activity as financial pressures have led firms to implement just-in-time (JIT) inventory systems that retain little storage, redundancy, or slack at points of consumption, in order to streamline supply chains. While such initiatives are advantageous in a stable environment, they have led to increasingly complex global supply chains that render business continuity more vulnerable to disruptions in the transportation network (Tang 2006). Local and global supply chain vulnerability was acutely evident after the 2011 Great East Japan earthquake, tsunami, and nuclear disaster, when automobile manufacturers in Japan were operating at 50% capacity due primarily to a shortage of parts, and disruptions rippled to manufacturing facilities in the U.S. and Europe (Kagawa and Yamagishi 2011; Park et al. 2013; Watanabe 2013).

Transportation disruption nonetheless remains a challenge to model in ways that support reducing risk and building resilience. Several studies have adapted methods of urban and regional economic analysis such as input-output or computable general equilibrium modeling, sometimes linked with transportation network models, to assess the magnitude of economic losses arising from transportation system disruption in disasters (Cho et al. 2001, 2015; Ham et al. 2005; Tatano and Tsuchiya 2008; Rose and Wei 2013) or the potential time to economic recovery (Li et al. 2013). These approaches provide quantified insights into the impact of disasters but were not designed to assess how such impacts can be most effectively reduced through pre-disaster planning, mitigation investments, or post-disaster response. In part, this relates to the temporal structure of most economic models, where changes are assumed to be gradual and incremental over time, and where time steps are typically annual or, at most, monthly (Okuyama 2007). Methodological refinements have been proposed to more explicitly model temporal effects, such as the ability of firms to make up lost production after an event (Park et al. 2011).

Similar gaps have been identified in related literatures where the role of transportation in disasters is gaining attention. In the transportation field, while earlier literature focused on risk of individual assets such as bridges or ports, systems analyses of transportation performance in disasters are becoming more common. Issues such as passengers' risk perceptions and inter-modal substitution are beginning to be considered (Cox et al. 2011). The emphasis remains, however, on assessing vulnerability rather than risk reduction strategies (Faturechi and Miller-

Hooks 2015; Mattson and Jenelius 2015). Within the field of operations research, where disaster relief logistics is emerging as a research area, studies generally seek optimization strategies for the distribution of humanitarian aid (e.g., Barbarosoglu and Arda 2004; Berkoune et al. 2012). The literature on supply chain management has largely approached disaster risk from the perspective of the firm (e.g., Tang 2006). Disaster-affected communities are largely missing from analyses, and transportation vulnerability is only beginning to be included in supply chain risk analysis (Berle et al. 2011b).

There thus remains a critical need for methods that not only clarify transportation system vulnerability in disasters but also enable exploration of practical strategies for enhancing the resilience of these systems and the communities dependent upon them. Such methods should assess transportation performance in terms of system functionality, approach the problem from the perspective of communities, and enable examination of strategies for rapid and flexible system restoration (Chang et al. 2017). This chapter seeks to develop a framework for such analysis. It focuses on one type of transportation, coastal shipping.

Systems for moving freight by seas and waterways, while essential to global and local economies, are often taken for granted; yet their operations are vulnerable to disruption in many ways. Natural hazards such as storm surges, tsunamis, and earthquakes can damage port facilities and navigation channels. Human-induced hazards such as marine oil spills and terrorism threats can necessitate shipping system shutdowns. One extensive study of Asian ports found that disruptions since 1900 have been increasing, with natural disasters causing the most severe impacts (responsible for 83% of cargo affected) and labor strikes also representing a major source of disruption (accounting for 75% of man-made disruptions) (Lam and Su 2015). Risk of port damage from storms is anticipated to increase in future due to rising sea levels in combination with coastal flooding and storm surge (West et al. 2001; Nursey-Bray et al. 2013). In the shipping industry, trends toward consolidation, privatization, and logistics optimization have caused maritime transportation systems to become more vulnerable to disruption (Berle et al. 2011b).

If maritime transportation systems are disrupted, the cities and populations dependent upon them can suffer severe impacts. Besides the economic impacts of global supply chain disruptions, at the local scale, maritime transportation disruption can also have major impacts on coastal communities (Laska et al. 2005; Rose and Wei 2013). In some regions of the world, coastal communities are extremely dependent on maritime transportation for the movement of people and goods. Examples include islands and remote coastal areas, such as in the Arctic. Interruptions in delivery of supplies such as fuel, food, and medicines can be especially critical in the aftermath of natural disasters.

Systems-level methods for analyzing maritime transportation risk and disruption impacts are emerging but not commonplace (Faturechi and Miller-Hooks 2015). A few studies have examined spatial patterns and risk quantification for shipping accidents (Soares and Teixeira 2001; Pelot and Plummer 2008; Dobbins and Jenkins 2011). Studies are needed that approach port disruptions from the perspective of supply chain management (Loh and Thai 2015). As a practical matter, seismic design at ports focuses on how individual wharfs and crane structures would perform in earthquakes, rather than on how structural damage could disrupt overall port operations and the associated economic consequences (Ivey et al. 2010). While some studies have considered shipping and supply chain risk from a global perspective (Berle et al. 2011a; Gurning et al. 2011; Omer et al. 2012), analyses of coastal shipping and local or regional supply chains are especially lacking from both vulnerability and resilience perspectives.

10.2 Objective and Approach

This chapter develops a framework for modeling transport system disruption for purposes of supporting decision-making for disaster resilience, focusing on the case of coastal shipping. Coastal shipping (e.g., ferry systems) poses several advantages for understanding transportation vulnerability and resilience opportunities. From a physical standpoint, coastal shipping is a relatively simple type of transportation system to describe and model, with a sparse network configuration and few transportation service providers. This physical simplicity allows greater opportunity and transparency in capturing operational dimensions of system functionality. Furthermore, for many island and coastal communities, coastal shipping is critically important, accounting for nearly all the transportation of goods and people. Yet its associated risks remain poorly understood, as very few studies have examined its role in disaster contexts.

This chapter emphasizes an important need for improving communities' disaster resilience: understanding and reducing the vulnerability of critical supply chains during emergency response. We focus on the period of emergency response immediately after a major disaster. During the early response phase, the nature of transportation disruption, societal impacts, and response options is different from the long-term recovery phase. For example, because of just-in-time delivery supply chains, economic systems will be in considerable disequilibrium, production activities may not have options for adjusting to shortages [e.g., to implement adaptive resilience actions (Rose and Liao 2005)], and all members of society will be making emergency rather than normal operating decisions. Moreover, in the emergency period, disruption consequences will be acute and pre-planning will be especially important. There is thus a need for models that are sensitive to the conditions, decisions, and impacts that occur in the short term after a disaster. Similarly, this chapter emphasizes the transportation of critical commodities, especially fuel, whose disruption can cause disproportionately severe impacts because fuel availability underpins virtually all interventions hastening return to normal social economic activity in a region.

In order to develop the modeling framework, the methodological approach draws on two main sources of information. First, the relevant literature is reviewed to identify critical aspects of maritime transportation vulnerability and resilience in disasters, the effects on supply chains, and disaster risk (Sect. 10.3). Second, an in-depth empirical study is conducted to characterize coastal shipping risk in a case study region, based on expert interviews and stakeholder interactions (Sect. 10.4). Findings from the literature review and empirical study are then synthesized in an integrated modeling framework that characterizes the vulnerability of maritime transportation systems, potential hazards, and resilience strategies (Sect. 10.5). The chapter concludes with a discussion of modeling issues and areas for further research (Sect. 10.6).

10.3 Transport Systems and Supply Chains in Disasters: The Case of Coastal Shipping

A literature review was conducted of published sources related to maritime transportation systems, supply chains, and disasters, in order to determine requirements for a decision-support modeling framework. Four requirements were identified for a transportation impact model; specifically that it should be able to account for:

1. The physical vulnerability of key assets such as ports;
2. The different modes by which hazards can cause system disruption;
3. The duration of disruption;
4. The effects of planning and preparedness on system disruption.

These requirements are discussed below in the context of coastal shipping; however, the same overall methodology pertains to modeling spatial and economic impacts of road and other transportation modes.

10.3.1 Vulnerable Transportation Assets

A transportation impact model should be able to account for the vulnerability of critical assets to damage and loss of functionality in disasters. That is, a model should be sensitive to weak links in the system and to their importance for network functionality. This capacity is important both for assessing how transport disruption would affect a region and for identifying specific, practical strategies for reducing risk.

In maritime transportation systems, port infrastructure is susceptible to damage from a range of hazards (ATC 2016). Earthquakes and earthquake-induced tsunamis have caused substantial damage to ports around the world (Werner, ed. 1998). In addition to ground shaking, ground failure (e.g., liquefaction and lateral spreading) often causes substantial damage to wharves, cranes, yards, and connecting rail and highway infrastructure. Tsunamis inflict structural damage, scouring, and debris impacts, such as from ships washed ashore; there is also risk of conflagration and hazardous materials releases because of oil and other combustibles stored in port areas. Recent examples of earthquake and/or tsunami damage to ports include Lyttelton in the 2011 Christchurch (New Zealand) earthquake, numerous Chilean ports in the 2010 Maule earthquake, and ports throughout northeastern Japan in the 2011 earthquake and tsunami (Chalmers et al. 2013; Tomita et al. 2013; Robertson 2015).

Accounting for vulnerable assets in a transportation system requires not just identification of weak links, but recognizing the criticality of individual assets within the system. Redundancy is a central concept in system resilience (e.g., Bruneau et al. 2003), and the low redundancy in maritime transportation networks represents a source of system vulnerability. It is important to note that redundancy has economic as well as physical dimensions. A case in point is the 1995 earthquake that destroyed the Port of Kobe, Japan (Chang 2000, 2010). In terms of container throughput, Kobe's global ranking dropped from 6th before the earthquake (in 1994) to 17th when it fully reopened (in 1997) and continued to decline thereafter. While local and domestic cargo traffic largely recovered, severe and permanent losses were sustained in the international transshipment sector, for which the Port's international competitors provided viable network redundancy.

10.3.2 Hazard-Specific Modes of Impact

The literature further indicates the importance of recognizing key differences between types of hazards that can disrupt transportation in disasters. Similarly to capturing the vulnerability of critical assets, the capacity to represent hazard-specific modes of impact is critical for investigating the benefits of specific risk reduction and resilience-building strategies.

Maritime transportation systems can be disrupted in different ways, or through different failure modes (Berle et al. 2011b). As noted previously, earthquakes can cause substantial damage to a port that may require months or even years to repair. Ports are also vulnerable in coastal storms and tsunamis. If boats and ships do not evacuate from the harbor, they may become unmoored and inflict damage as floating debris (Tomita et al. 2013; Robertson 2015). This suggests that warning systems for vessels to evacuate a harbor can reduce damage in such events. Hurricane Sandy in 2012 sent a 14-foot storm surge into the Port of New York and New Jersey, which contained not only transportation infrastructure but also a petro-chemical industrial complex. Waterfront infrastructure and facilities were damaged, oil and hazardous materials were released into the environment, debris was swept into shipping channels, and corrosive saltwater from the storm surge destroyed operational equipment at marine terminals and backup power generators (Sturgis et al. 2014). Earthquake-induced tsunamis represent a distinct failure mode because of their potentially extensive spatial reach. The 2011 tsunami in Japan damaged 10 major ports and over 300 fishing ports along a coastline hundreds of kilometers long (Tohoku Bureau of Economy, Trade and Industry 2012).

Human-induced or technological disasters can disrupt shipping without necessarily damaging port infrastructure. In a 2006 oil spill event in Louisiana caused by heavy rains overwhelming a refinery treatment system, a major shipping channel was shut down for 6 days to enable oil spill cleanup (Berle et al. 2011b). A 2010 ship collision in Port Arthur, Texas, caused an oil spill that closed a navigation waterway for 5 days (Berle et al. 2011b).

Other hazards disrupt shipping operations without entailing any physical or environmental damage at all. Labor strikes by longshoremen, truck drivers, etc. (e.g., the 10-day, 2002 West Coast port lockout in the U.S.) have caused substantial economic losses to ports, diversions of cargo flows, and regional economic impacts. Such impacts are difficult to quantify reliably, as traditional methods do not adequately account for flexible responses by shippers and other agents in the supply chain (Hall 2004). Other unplanned operational disruptions can also be consequential. In August 2015, the province of Nova Scotia in Canada, which is almost entirely reliant on fuel deliveries by tanker ships, experienced a gasoline shortage due to a non-disaster shipping disruption. When one scheduled tanker was delayed and the next tanker was found to be carrying a fuel load that did not meet environmental standards, bulk gasoline deliveries were disrupted for 3 days, leading to rapidly depleted stocks and shortages at the fuel pump (MacNeil and Keefe 2015)—yet another example of the vulnerability borne of just-in-time delivery systems.

10.3.3 Duration of Disruption

Closely related to the concept of different impact modes is the observation that capturing the duration of system disruption is essential for modeling impacts on communities and strategies for building resilience. Duration is influenced by factors such as the severity of physical damage, the type of damage, the requirements of cleanup, and the effectiveness of pre-disaster planning and emergency response. As demonstrated in previous disasters, shipping disruptions can range from days to months or even years. In Hurricane Sandy, underwater surveys, which were required for navigational safety before shipping channels could be reopened, required 3–5 days (Sturgis et al. 2014). Damage at the port and associated refineries, together with electric power outage, led to a fuel crisis in the region that lasted for some 10 days and severely hampered emergency response (Smythe 2013). In the 2011 tsunami in Japan, emergency restoration enabled partial functionality at almost all of the damaged ports within weeks or months (Tohoku Bureau of Economy, Trade and Industry 2012). Sunken tsunami debris, such as shipping containers and cars, impeded navigation in harbor areas during response and recovery; clearing this debris required some 80 days (Tomita et al. 2013). Rerouting traffic, which is a loss to an individual port, is also illustrative of adaptive capacity and resilience from the perspective of system functionality and the communities reliant on the maritime transport system.

10.3.4 Planning and Preparedness

Finally, previous studies indicate the importance of considering planning and preparedness in understanding how and how severely hazards can disrupt transportation systems. Resilience of maritime systems can be enhanced by reducing vulnerability or by increasing adaptive capacity (Omer et al. 2012). Reducing vulnerability might seek to harden the system, add redundancy, increase diversity, expand capacity, or increase modularity. Enhancing adaptive capacity could involve improving resource allocation, response policies, collaboration, and situational awareness.

Lack of planning for transportation and supply chain disruption has been demonstrated to impede disaster response and recovery. In the 2011 Great East Japan triple disaster, prefectural and local governments were overwhelmed with the task of humanitarian logistics, which they had largely neglected in their disaster planning (Holguín-Veras et al. 2014). They did not have the institutional expertise, private sector ties, or experience to mount an effective logistics response. The private sector—in particular, construction, transportation, and retail companies—were instrumental in the response, as they brought expertise and assets in logistics management. Their participation was improvised, however, and hampered by lack of planning. For example, private companies criticized the government for failing to consider how to phase out private sector volunteering and transition to a for-pay model of service provision. Fuel logistics was another bottleneck: many trucking companies that had volunteered were unable to participate in the humanitarian logistics due to lack of fuel for their return trips. Efforts to organize an emergency fuel delivery by rail were stymied by lack of planning for logistics and permits (Watanabe 2013).

By the same token, preparedness and planning by port authorities and maritime transportation providers have been found to significantly shorten disruption times, as demonstrated in Hurricane Sandy (Smythe 2013; Burke and Sipe 2014). New York City's ferry systems were well-prepared and operational within 2 days after Sandy; in contrast, an unprepared ferry system in Brisbane, Australia, was disrupted for over 4 weeks following a 2011 flood. Prior to a disaster, it is essential for system operators to address not only infrastructure design, but also emergency response planning, insurance and legal requirements, management of staff, and coordination during reconstruction.

While ill-prepared maritime transportation imposes vulnerability on coastal communities, with pre-disaster actions, a resilient maritime system can also provide valuable mobility in the aftermath of a disaster. Ferry systems have proven useful for evacuation and emergency supply transportation (Scanlon 2003). In the 1989 Loma Prieta earthquake that struck the San Francisco region, the Bay Bridge, which serves as a vital transportation link across the bay, was damaged and shut down for one month. Within hours of the earthquake, emergency ferry service was established to shuttle 15,000 stranded people between the East Bay and San Francisco; continuing after the emergency, expanded ferry service became one of the positive legacies of the disaster (Hansen and Weinstein 1991). In the aftermath of the 9/11 2001 terrorist attacks in New York City, a boatlift operations occurred spontaneously, with an improvised fleet of various harbor craft providing a "load and go" service that evacuated about 500,000 people from Manhattan. Ferries became waterborne ambulances, and for about 2 years, ferries absorbed much of the passenger flow that was displaced by closure of the PATH subway to New Jersey (Kendra and Wachtendorf 2006; Bruzzone 2012). Ferries were vital in resupplying areas hit by the 2004 Indian Ocean tsunami in Indonesia (Burke and Sipe 2014). Temporary ferry services were also utilized for several months in the New York metro region after Hurricane Sandy (Smythe 2013).

Prior studies thus establish the need for models of transportation impact in disasters to consider the spatial and temporal attributes of physical damage, functional disruption, and operational preparedness and planning. These considerations are crucial for assessing both system vulnerability and alternative strategies to reduce this vulnerability. Findings from the literature review are complemented by an in-depth empirical investigation of one case study region, described next.

10.4 Regional Case Study

10.4.1 Study Region

The southern coast of British Columbia, Canada, is a diverse region that is highly dependent on coastal shipping (Fig. 10.1). The 50 largest communities range in population from about 600,000 (City of Vancouver) down to some 4000 residents. In terms of transportation connectivity, at one extreme, the municipalities of the Metro Vancouver region in the Lower Mainland are highly connected by a redundant network of land and marine (ferry) transport links. At the other end of the spectrum are small islands that can only be accessed by water. Many municipalities on Vancouver Island, including the provincial capital of Victoria, are moderately connected to other communities but still highly dependent on ferries for the transport of people and goods.

The importance of coastal shipping and the reliance on just-in-time delivery contribute to the region's vulnerability to maritime transport disruption. For example, Victoria's municipal government acknowledges that "Vancouver Island is dependent on ferry services for an estimated 90% of its food and food supply in Victoria is estimated to be sufficient for 3 days" (City of Victoria 2012, p. 121). There is very little warehousing on the island and little spare capacity in the supply chain. Anecdotally, milk that is produced on Island dairy farms is shipped to the mainland for pasteurization before being returned to Island grocery stores for sale. Cargo is transported around the region by a small number of shipping companies, including BC Ferries and several small and medium sized private operators. BC Ferries was transformed from a Crown corporation to a regulated commercial organization in 2003 and has been cutting back service on less trafficked routes to improve its financial performance.

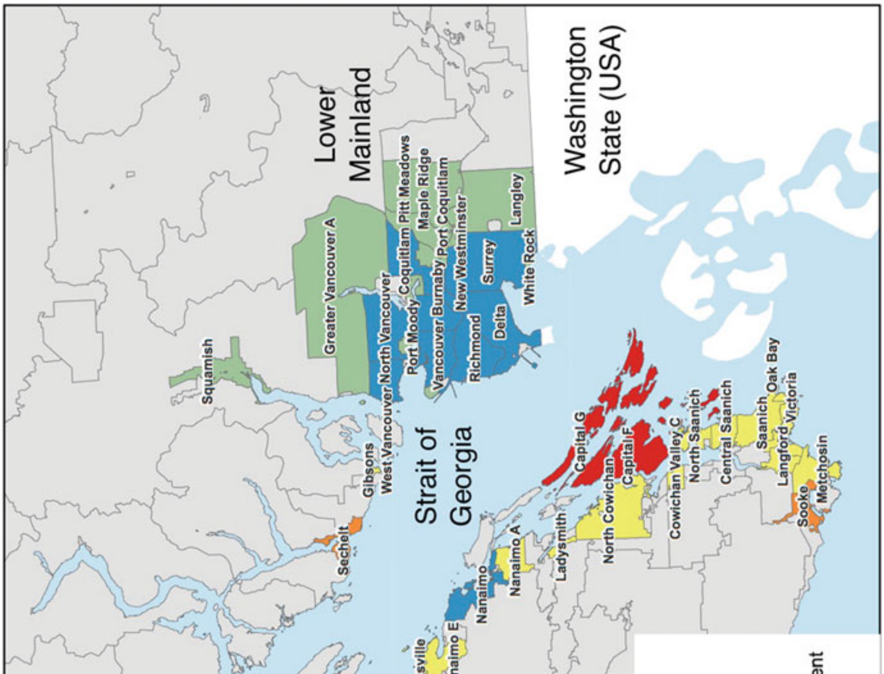


Fig. 10.1 Transportation Connectivity of Coastal Communities in Study Region

Vulnerability of communities in relation to transportation and supply chain disruptions is, however, complex. Ironically, regions with less frequent service are more likely to have higher local stocks in anticipation of potential service interruptions. Smaller communities do not attract large commercial retailers and remain the domain of small family owned shops. Family owned shops do not have access to sophisticated JIT logistics and have larger stock on hand in order to meet their clients' needs.

Although the region has not experienced major incidents of maritime transport disruption, such disruption could potentially arise from many sources. For example, the region is vulnerable to catastrophic earthquakes. Furthermore, provincial emergency management is under-resourced and unprepared for such an event (AIR 2013; Auditor General of British Columbia 2014). Some potential disruption scenarios are described further below.

For disasters involving maritime transportation, the emergency response system remains untested. That is, the lack of major disruption experience itself can be viewed as a vulnerability, since neither the transport industry nor emergency managers—not to mention potentially affected communities—have firsthand understanding of the potential effects of maritime transport disruption and ways to reduce the impacts. Efforts to establish multi-sectoral marine coordination are only just beginning. Notably in Canada, when disasters involve maritime transportation, all layers of government up to the Coast Guard, and Federal Departments of Environment, Transport and Fisheries are legally involved, adding administrative complexity to managing any emergency response. Moreover, in maritime transportation, the private sector provides critical services but has no emergency response obligations.

10.4.2 Data Collection

Extensive data collection was conducted with regional stakeholders to inform a model of maritime transportation disruption suitable for vulnerability analysis and resilience decision-making. Some 19 interviews were conducted, involving 27 representatives from a broad range of public and private sector organizations involved in maritime transportation and/or emergency management. These included shipping companies, trucking companies, port authorities, transportation regulatory authorities, emergency management units at the local and provincial government level, and other relevant organizations. In addition, several focus group sessions were conducted: two in a remote coastal community (Powell River) and two at a regional workshop on marine environmental hazards (in Vancouver). The focus groups involved some of the interviewees as well as other types of stakeholders such as municipal planners, government environmental scientists, and researchers. An online survey ($n = 31$ respondents) was also conducted to gather comparable information across the study participants. This primary data collection was supplemented by review of secondary information sources such as organizations' websites and relevant reports, planning documents, and prior studies. The data collection focused on general aspects of vulnerability and resilience of maritime transportation systems as well as specifics of the system, prior disruption experiences, risk reduction strategies, and resilience-building opportunities in the region. Information from these multiple data sources, including in particular the stakeholder interviews, provided the basis for developing foundational insights (Sect. 10.4.3) for the modeling framework described in Sect. 10.5 below.

10.4.3 Findings

The regional case study yielded several key insights that inform the development of a modeling framework for maritime transportation disruption and decision-support. While based on the particularities of the study region, these insights are framed here in terms of generalized considerations that are also applicable to other regions.

First, the *cargo* being considered is important for defining the relevant network. At the global level, Ducruet's (2013) study of maritime commodity flows found that liquid bulk networks do not exhibit much overlap with those of other commodities (i.e., containers, general cargo, and solid bulk cargo), and passenger traffic shows little correlation with goods movement. This is confirmed at the local level by the case study interviews. Under normal conditions, safety regulations preclude dangerous goods transport on passenger ferries; and, market segmentation leads to other goods being shipped by other means. Thus, to get from City A to City B via marine transportation, passengers normally travel on a different ship along a different route than bulk fuels. Cargo ships for some types of commodities (e.g., bulk products, vehicles) are specialized, and port facilities for handling them may be segregated.

In other words, the maritime transportation network for fuel is likely to be different than the network for food or for passengers. In the B.C. case study, for example, BC Ferries accounts for all the marine transportation of people but only some of the cargo movement. Most goods are transported by other companies, which use different docking facilities and different shipping routes. Even in an emergency, there would only be partial interoperability within the system; for example, BC Ferries ships cannot utilize another major company's terminals because its ships are not compatible with the physical docking mechanism.

Second, the marine transportation network entails particular forms of *flexibility and constraints* that differ from road networks. Redundancy is important for network resilience in the event of disruptions. In principle, new marine routes can be readily created by adding new sailings, adapting port terminals to handle different types of goods, changing regulations, etc. In this sense, the marine network is more flexible than a road network where adding a link between two towns may entail time-consuming new construction. However, marine routes are constrained by the technical requirements of ships, docking facilities, and equipment for loading and unloading cargo. Because of the capital investments required, the number of ship operators and vessels that serve a local area are typically limited. Competing cargo shippers may have assets (e.g., ships, loading/unloading equipment, docks) that are not interchangeable. Substitutability may therefore be operationally constrained.

Third, because the problem is framed as how to ensure commodity supply to a particular destination community, there is *directionality* in the network. That is, while vessels may travel both directions on a route, the flow of commodities for consumption is uni-directional from the supply side to the demand side. The supply side includes the port of origin and landside delivery (e.g., fuel tankers, access roads). Similarly, the demand side includes the port of destination as well as the local distribution system that transports the commodity to the end users, as well as the end users themselves.

Fourth, storage capacity and *reserves* on both the supply and demand sides are important. From the perspective of the end user, a temporary disruption in the supply chain may be easily weathered if sufficient reserves are on hand. Reserves can be held by any entity along the supply chain. In the case of gasoline, for example, reserves could be stored along the supply system, in tank farms at ports, or at retail gas stations. Food can be stored in warehouses, in stores, or at people's homes. As noted earlier, however, just-in-time delivery systems entail minimal on-site storage and rely on continuous flows where commodities are, in effect, stored on the vehicles or vessels that are transporting them.

It should be noted that *demand* itself is a variable quantity. In a disaster situation, people's behaviors can change, leading to shifting commodity needs. Conservation behavior can lead to reduced demand, while conversely, "panic buying" and hoarding behavior can aggravate shortages. Furthermore, people themselves can relocate, leading to spatial changes in demand patterns.

From a functional perspective, the transport system includes not only physical infrastructure and assets but also the *labor* to operate it. Crews are needed to operate ships, cranes, trucks, and the like in sufficient numbers at any point in time. They must also have the requisite qualifications, which may include training, certifications, licensing, etc. They also need to be able to travel to where their services are needed. Therefore, availability of personnel is a likely bottleneck in times of crisis even if the physical transport infrastructure is available.

Finally, the operations of all elements in the transport system are subject to *regulations* by various authorities. These include regulations imposed for reasons of health, safety, and environmental protection. Examples include separating hazardous materials from passengers, limiting hours that ships crews can work, and licensing requirements for vessels. Some ports require local pilots and tug boats to be used for large vessels to enter and leave the harbor. These regulations pose important oversight and constraints on maritime transport operations, and can play a key role in understanding how the system would respond to a disaster as well as how it can become more flexible in responding to one.

10.5 Modeling Framework

The literature review and case study yielded several recommendations for modeling transportation disruption in disasters for purposes of supporting risk reduction and regional resilience decision-making. As discussed above, these include having the capacity to account for: physical vulnerability of key assets, different modes of system disruption, duration of disruption, effects of planning and preparedness, cargo-relevant network attributes, flexibility and constraints of the transport mode, directionality of transport, storage and reserves, demand, labor, and regulations. These recommendations suggest that an effective model should account for spatial as well as functional and operational characteristics of the transportation system in relation to supply chains.

A spatially explicit model incorporates geographic locations, spatial correlations, and network relationships. This is essential for capturing the spatial damage patterns of hazards such as earthquakes and tsunamis (including physical vulnerability of transportation assets and hazard-specific modes of transportation disruption), as well as characteristics of the network (e.g., shipping routes) and flows (e.g., directionality).

A functionally specified model depicts flows across the system. This focuses attention on networks and network attributes relevant to a particular commodity (e.g., the fuel transport network as opposed to container shipping, commodity reserves, labor requirements, relevant regulations, and characteristics of demand for the commodity). Furthermore, it enables directional analysis (i.e., from sources of supply to locations of demand) and direct treatment of the duration of flow disruption.

An operationally oriented model is sensitive to the decisions and decision-makers that can affect risk and resilience. It enables exploration of practical actions within the flexibility and constraints of the system (e.g., for adding new shipping routes in an emergency) and reflects preparedness and planning efforts that can reduce immediate disruption in a disaster or hasten restoration (e.g., planning fuel stocks and distribution priorities during the early phase of response). There are subtle tradeoffs in such disaster pre-planning, such as recognizing that a full fuel storage tank is more likely to collapse in the event of a local earthquake and trading off such a risk against the integrated risk of loss of functionality in supply chain for fuel to that community (Costa et al. 2017). It also requires an understanding of how to operate and protect refueling stations until normal supply is restored.

With these considerations in mind, a modeling framework is proposed below. It is comprised of three parts that respectively characterize the system at risk, the potential disruption from hazards, and potential solutions for reducing risk.

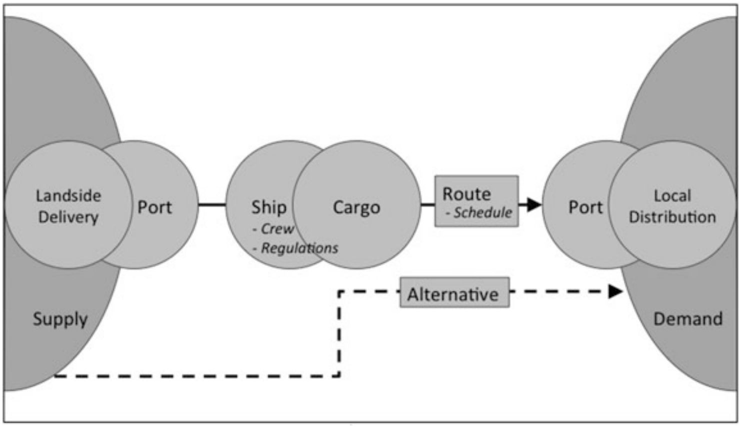


Fig. 10.2 Elements of local maritime transportation system

10.5.1 System at Risk

The maritime transport system in defined here in terms of key elements that affect its functionality and operations. This includes a topological characterization of origin and destination nodes of each marine transportation link, or route. Other elements of the system—ships, cargo, crew requirements, regulations, etc.—are also represented to adequately capture factors that can influence cargo flows (Fig. 10.2).

10.5.2 Hazards

Hazards, or the potential sources of disruption, are distinguished in terms of how they would operationally affect the transportation system. Hazards are categorized according to which elements of the system they primarily affect, as well as whether they are spatially localized or affect a broad geographic area and, hence, the regional supply chain (Table 10.1). Most hazards primarily affect one type of system element. For example, a shipboard fire or other mishap may put a single ship out of commission. A hurricane could cause storm surge damage at multiple ports along a coast. Earthquakes and tsunamis are notably different, however, in that they affect multiple types of system elements—the supply side (e.g., damage at production centers), ports, routes (e.g., undersea slumping in dredged shipping channels), ships (e.g., tsunamis sweeping ships inland), and the demand side (e.g., damage to homes, businesses).

From an economic perspective, hazards also differ in whether they primarily affect capital or labor inputs, or both. Storm surge flooding may cause substantial property damage but, with adequate warning, cause minimal human casualties. A strike by port workers, in contrast, could severely disrupt labor supply without any

Table 10.1 A typology and examples of maritime transportation hazards

Element disrupted	Spatial extent of hazard: Single location (local event)	Multiple locations (supply chain event)
Land side	• Terrorism incident at single location • Industrial accident • Local earthquake[a]	• Terrorism at multiple locations • Regional earthquake[a]
Port	• Fire at port • Riverine flooding • Labor strike (port) • Terrorism (or threat) • Local earthquake[a]	• Storm surge flooding • Tsunami • Regional earthquake[a]
Route (incl. navigation)	• Navigation channel blockage (e.g., from rail bridge accident, ship sinking, oil spill cleanup)	• Undersea slumping in navigation channel • Outage of navigational telecommunications system
Ship	• Shipboard fire	• Labor strike (ships) • Tsunami

[a]In the case study region, a crustal ("local") earthquake would likely damage only one major port, whereas a subduction zone ("regional") megaquake and tsunami would likely destroy infrastructure of many ports along the entire coastal region

accompanying capital losses. Some hazards such as earthquakes typically disrupt both capital and labor inputs. The economic mode of disruption is important because of limitations in substitutability between capital and labor, especially in the short term, and differences in planning for such disruptions.

In addition to spatial extent and system elements affected, several other considerations are important when understanding potential hazards. The duration of disruption can vary substantially between such hazards as shipboard fires (hours to days) and tsunami damage (months to years). The type of emergency response required also differs in terms of expertise required, resources, equipment, and entities involved. Similarly, regulations and regulatory environments can differ greatly. For example, in Canada, the response regime for an oil spill in a harbor involves four Federal entities, the Coast Guard, Department of Fisheries, the Ministry of Environment and the Department of Transportation—none of which would play a major role in responding to a port labor strike or an earthquake. Furthermore, some hazards affect demand (e.g., fear of shortages that trigger hoarding behavior).

10.5.3 Solutions

The third part of the framework characterizes potential strategies for reducing risk and enhancing resilience. Some actions strengthen system elements to minimize initial disruption while other strategies improve the capacity to handle the disruption

Table 10.2 A typology and examples of solutions in maritime transportation risk

System element	Objective	
	Minimize initial disruption	Develop capacity to handle disruption
Supply and land side	• Capital investments • Storage/warehousing	• Protocols for prioritizing cargo
Port	• Capital investments • Protocols for harbor evacuation of ships (tsunami) • Warning systems	• Mobile harbor cranes • Resource inventories (docks) • Backup electric power • Emergency repurposing of facilities • Emergency sharing of facilities • Underwater surveillance capacity • Sister ports strategy of mutual aid, port strategic alliances • Operating longer hours
Route (incl. navigation)		• Emergency alternate routes
Ship	• Warning systems	• Resource inventories (ships) • Reserve ships • Emergency staffing
Regulations		• Emergency “rule-breaking”
Demand and local distribution		• Household stockpiling • Understanding requirements, response planning with suppliers/distributors, rationing, prioritizing, conserving, ensuring security and safety • Government communication strategy

(Table 10.2). Actions can minimize damage, increase storage, increase redundancy, and increase resources available for emergency response.

Resilience measures are envisioned here broadly. They range from capital investments (e.g., mobile cranes for unloading ships, seismically strengthening port facilities and grounds) to increasing storage (e.g., commercial warehouses or household stockpiling), developing resource inventories, certifying extra staff for emergency roles, developing protocols for prioritizing cargo, repurposing port terminals for non-routine use, and “rule-breaking” measures such as relaxing safety requirements in emergencies. Resilience measures also include obtaining better warning systems and real-time information about marine conditions. Thus, resilience measures can entail preparedness planning and investments related to not only physical infrastructure and assets, but also training personnel and developing protocols, rules, and regulations.

10.6 Conclusions

The approach adopted in this study focuses on the flow of goods through transportation systems. The system is defined to include the communities (e.g., towns and cities) that are connected by transportation infrastructure and that benefit from the flow of goods, both as producers and consumers. For coastal communities, the transportation of goods by maritime modes is often critical. When these flows are disrupted, in the short term, communities may be affected by shortages in the supply of consumed goods, especially necessities such as food and fuel. (If disruptions are lengthy, communities can also be affected by decline in the demand for their produced goods.) The severity of the disruption depends on the capacity of the remaining network and the speed with which capacity is restored. Transport disruptions do not necessarily lead to severe impacts to communities, as they can be mitigated if communities have sufficient reserves on hand, are able to produce the goods locally, or are able to adapt consumption behaviors. Self-sufficiency and connectedness thus have a dynamic interaction that affects vulnerability to disruptions. Just-in-time delivery systems increase vulnerability by minimizing reserves, especially if there is no local capacity for producing and distributing the goods. In sum, the supply chain is a multi-sectoral system with many points of vulnerability, as well as many opportunities for increasing resilience.

To support decision-making for disaster resilience, models of spatial and economic impact need to be able to capture decision opportunities. An important strategy for regional resilience is to minimize transportation disruption of essential commodity supply chains; however, current modeling approaches are limited in their capacity to investigate this problem. This chapter has developed a framework outlining important attributes for such a decision-support model, particularly the need for sufficient spatial, functional, and operational specificity. Focusing on the case of coastal shipping, it has highlighted the importance of introducing new dimensions to impact models such as attention to critical commodity flows, storage capacity, preparedness planning, operational protocols, regulations, and different decision-making entities (e.g., port authorities, ferry operators, local governments) in the system.

Implementing this modeling framework can take different forms, and is an area for further research. Due to the complexity and data demands of fully specifying an operational model, it may be advantageous to adopt a modular approach wherein only certain aspects are modeled in detail. For example, to investigate resilience strategies that can be undertaken by a local government, modeling the transportation system in spatial and operational detail may be unnecessary; rather, functional transportation disruption can be handled exogenously, with model development focused on local conditions such as storage reserves and strategies such as demand management. Similarly, to investigate approaches such as increasing redundancy in the transport system, detailed modeling of network flows will be required while the demand side can be simplified. Since the purpose would be to model effects of resilience strategies, simulation rather than optimization approaches would be advantageous.

Finally, it should be noted that the findings and framework are not limited to the case study region or to coastal shipping. Rather, the conclusions pertain to a general need for disaster impact models that capture critical risk reduction and resilience-building strategies in ways that can support decision-makers in practice.

Acknowledgments The authors are grateful to the emergency managers, maritime commerce representatives, and other experts who participated in this project. This study was funded by the Marine Environmental Observation Prediction and Response (MEOPAR) Network of Centres of Excellence (NCE). Bethany Dobson, Allanah Brown, Xuesi Shen, and Rodrigo Costa assisted with this study. Findings and opinions are the authors' own.

References

AIR Worldwide (2013) Study of impact and the insurance and economic cost of a major earthquake in British Columbia and Ontario/Québec. Report commissioned by the Insurance Bureau of Canada, AIR Worldwide, Boston, MA

Applied Technology Council (ATC) (2016) Critical assessment of lifeline system performance: understanding societal needs in disaster recovery. Report no. NIST GCR 16r-917-39, National Institute of Standards and Technology, Gaithersburg, MD

Auditor General of British Columbia (2014) Catastrophic earthquake preparedness. p 44. www.bcauditor.com. Accessed 6 March 2016

Barbarosoglu G, Arda Y (2004) A two-stage stochastic programming framework for transportation planning in disaster response. J Oper Res Soc 55:43–53

Berkoune D, Renaud J, Rekik M, Ruiz A (2012) Transportation in disaster response operations. Socio Econ Plan Sci 46:23–32

Berle O, Asbjornslett BE, Rice JB (2011a) Formal vulnerability assessment of a maritime transportation system. Reliab Eng Syst Saf 96(6):696–705

Berle O, Rice JB Jr, Asbjornslett BE (2011b) Failure modes in the maritime transportation system: a functional approach to throughput vulnerability. Marit Policy Manag 38(6):605–632

Bruneau M, Chang SE, Eguchi RT, Lee GC, O'Rourke TD, Reinhorn AM, Shinozuka M, Tierney K, Wallace WA, von Winterfeldt D (2003) A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake Spectra 19(4):733–752

Bruzzone A (2012) Guidelines for ferry transportation services. Transportation Research Board, TCRP Report 152, Washington, DC

Burke MI, Sipe N (2014) Urban ferries and catastrophic floods: experiences and lessons learned in Brisbane, Australia, and New York City. Transp Res Rec 2459:127–132

Chalmers G, McLennan N, Barsanti L (2013) Lyttelton port of Christchurch seismic resiliance from an owner's perspective. In: Ostbo BI, Oates D (eds) Ports 2013: success through diversification, Proceedings of Ports'13: 13th triennial international conference. Seattle, Washington, pp 1405–1414

Chang SE (2000) Disasters and transport systems: loss, recovery, and competition at the port of Kobe after the 1995 earthquake. J Transp Geogr 8(1):53–65

Chang SE (2010) Urban disaster recovery: a measurement framework with application to the 1995 Kobe earthquake. Disasters 34(2):303–327

Chang SE, Brown AJ, Costa R, Dobson B, Dowlatabadi H, Haukaas T (2017) A community resilience approach to assessing transportation risk in disasters. Proceeding of 16th world conference on earthquake engineering, Santiago, Chile. Paper no 3431

Cho S, Gordon P, Moore JE II, Richardson HW, Shinozuka M, Chang S (2001) Integrating transportation network and regional economic models to estimate the costs of a large urban earthquake. J Reg Sci 41(1):39–65

Cho JK, Gordon P, Moore JE II, Pan Q, Park JY, Richardson HW (2015) TransNIEMO: economic impact analysis using a model of consistent inter-regional economic and network equilibria. Transp Plan Technol 38(5):483–502

City of Victoria (2012) Official community plan, Section 18: emergency management, pp 120–124. http://www.victoria.ca/EN/main/departments/planning-development/community-planning/official-community-plan.html. Accessed 9 March 2016
Costa R, Haukaas T, Chang S, Dowlatabadi H (2017) Network model to assess the probability of fuel shortage in coastal British Columbia. Proceeding of 12th international conference on structural safety and reliability (ICOSSAR)
Cox A, Prager F, Rose A (2011) Transportation security and the role of resilience: a foundation for operational metrics. Transp Policy 18:307–317
Dobbins JP, Jenkins LM (2011) Geographic information systems for estimating coastal maritime risk. Transp Res Rec 2222:17–24
Ducruet C (2013) Network diversity and maritime flows. J Transp Geogr 30:77–88
Faturechi R, Miller-Hooks E (2015) Measuring the performance of transportation infrastructure systems in disasters: a comprehensive review. J Infrastruct Syst 21(1):04014025
Gordon P, Richardson HW, Davis B (1998) Transport-related impacts of the northridge earthquake. J Transp Stat 1(2):21–36
Gurning R, Cahoon S, Nguyen HO, Achmadi T (2011) Mitigating maritime disruptions: evidence from the Australian-Indonesian wheat supply chain. Int J Shipp Transp Logist 3(4):406–429
Hall PV (2004) We'd have to sink the ships': impact studies and the 2002 west coast port lockout. Econ Dev Q 18(4):354–367
Ham H, Kim TJ, Boyce D (2005) Assessment of economic impacts from unexpected events with an interregional commodity flow and multimodal transportation network model. Transp Res A 39:849–860
Hansen M, Weinstein S (1991) East Bay ferry service and the Loma Prieta earthquake. University of California Transportation Center, Berkeley, CA. Report no 162
Holguín-Veras J, Taniguchi E, Jaller M, Aros-Vera F, Ferreira F, Thompson RG (2014) The Tohoku disasters: chief lessons concerning the post-disaster humanitarian logistics response and policy implications. Transp Res A 69:86–104
Ivey LM, Rix GJ, Werner SD, Erera AL (2010) Framework for earthquake risk assessment for container ports. Transp Res Rec 2166:116–123
Kagawa Y, Yamagishi H (2011) Domestic auto factories running at 50%. The Daily Yomiuri Online, April 27
Kendra J, Wachtendorf T (2006) The waterborne evacuation of lower Manhattan on September 11: a case of distributed sensemaking. University of Delaware, Disaster Research Center, Newark, DE. Preliminary Paper #355
Lam JSL, Su S (2015) Disruption risks and mitigation strategies: an analysis of Asian ports. Marit Policy Manag 42(5):415–435
Laska S, Wooddell G, Hagelman R, Gramlings R, Teets Farris M (2005) At risk: the human, community, and infrastructure resources of coastal Louisiana. J Coast Res 44:90–111
Li J, Crawford-Brown D, Syddall M, Guan D (2013) Modeling imbalanced economic recovery following a natural disaster using input-output analysis. Risk Anal 33(10):1908–1923
Loh HS, Thai VV (2015) Managing port-related supply chain disruptions (PSCDs): a management model and empirical evidence. Marit Policy Manag 43(4):436–455. https://doi.org/10.1080/03088839.2015.1107921
MacNeil A, Keefe DJ (2015) The Nova Scotia fuel shortage: report of the independent review panel. December. http://novascotia.ca/dma/fuel-supply.asp. Accessed 2 March 2016
Mattson L-G, Jenelius E (2015) Vulnerability and resilience of transport systems - a discussion of recent research. Transp Res A 81:16–34
Nursey-Bray M, Blackwell B, Brooks B, Campbell ML, Goldsworthy L, Pateman H, Rodrigues I, Roome M, Wright JT, Francis J, Hewitt CL (2013) Vulnerabilities and adaptation of ports to climate change. J Environ Plan Manag 56(7):1021–1045
Okuyama Y (2007) Economic modeling for disaster impact analysis: past, present, and future. Econ Syst Res 19(2):115–124

Omer M, Mastashari A, Nilchiani R, Mansouri M (2012) A framework for assessing resiliency of maritime transportation systems. Marit Policy Manag 39(7):685–703
Park JY, Cho J, Rose A (2011) Modeling a major source of economic resilience to disasters: recapturing lost production. Nat Hazards 58:163–182
Park Y, Hong P, Roh JJ (2013) Supply chain lessons from the catastrophic natural disaster in Japan. Bus Horiz 56:75–85
Pelot R, Plummer L (2008) Spatial analysis of traffic and risks in the coastal zone. J Coast Conserv 11:201–207
Robertson I (2015) Vulnerability of Hawaii commercial port and harbor facilities to tsunamis and Hurricane storm surge and wave action. University of Hawaii at Manoa, Department of Civil and Environmental Engineering, Research report UHM/CEE/15-01
Rose A, Liao SY (2005) Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. J Reg Sci 45:75–112
Rose A, Wei D (2013) Consequences of a port shutdown: the special role of resilience. Econ Syst Res 25(3):212–232
Scanlon J (2003) Transportation in emergencies: an often neglected story. Disaster Prev Manag 12 (5):428–437
Smythe TC (2013) Assessing the impacts of Hurricane Sandy on the Port of New York and New Jersey's maritime responders and response infrastructure. University of Colorado Natural Hazards Center, Quick Response Report No. 238
Soares CG, Teixeira AP (2001) Risk assessment in maritime transportation. Reliab Eng Syst Saf 74:299–309
Sturgis LA, Smythe TC, Tucci AE (2014) Port recovery in the aftermath of Hurricane Sandy: improving port resiliency in the era of climate change. Center for a New American Security, Washington, DC
Tang CS (2006) Robust strategies for mitigating supply chain disruptions. Int J Log Res Appl 9 (1):33–45
Tatano H, Tsuchiya S (2008) A framework for economic loss estimation due to seismic transportation network disruption: a spatial computable general equilibrium approach. Nat Hazards 44:253–265
Tohoku Bureau of Economy, Trade and Industry (2012) The reconstruction of the Tohoku region. September. http://www.tohoku.meti.go.jp/s_kokusai/index_kokusai2.html. Accessed 29 February 2016
Tomita T, Arikawa T, Asai T (2013) Damage in ports due to the 2011 off the Pacific Coast of Tohoku earthquake tsunami. J Disaster Res 8(4):594–604
Watanabe K (2013) Ideal interoperability of logistics that enhance resilience of supply chains based on PPP (Public-Private Partnership). J Disaster Res 7(4):344–348
Werner SD (ed) (1998) Seismic guidelines for ports. Technical Council on Lifeline Earthquake Engineering (TCLEE) Monograph No. 12, American Society of Civil Engineers, Reston, VA
West JJ, Small MJ, Dowlatabadi H (2001) Storms, investor decisions, and the economic impacts of sea level rise. Clim Chang 48:317–342

Stephanie E. Chang is a professor with the School of Community and Regional Planning (SCARP) and the Institute for Resources, Environment and Sustainability (IRES) at the University of British Columbia, Canada. Her research addresses issues of natural hazard risk and resilience, including socioeconomic impacts, urban risk dynamics, disaster recovery, and critical infrastructure systems. Her current research focuses on planning for multi-hazard risks faced by coastal communities. Dr. Chang received her B.S.E. in Civil Engineering from Princeton University (1989) and M.S. and Ph.D. in Regional Science from Cornell University (1994).

Hadi Dowlatabadi is a professor with the Institute for Resources, Environment and Sustainability (IRES) at the University of British Columbia, Canada. His research involves characterization of systems—especially, quantitative models of the interstices among resource development, environmental and human health and public policy. Hadi received his BSc from the University of Edinburgh (1980) and his PhD in physics from Cambridge University (1984). He holds a Canada Research Chair in Applied Mathematics, is a University Fellow with Resources for the Future, and an adjunct professor with the Department of Engineering and Public Policy at Carnegie Mellon University.

Chapter 11
Concatenated Disruptions with Resilience

Sam Cole

Abstract This chapter presents a method for modelling resilience in economic systems confronted by multiple irregular shocks. For this, investment portfolio theory is reformulated as a protected production function. This function determines the share of output that is dedicated to protection as economic agents attempt to maintain their preferred level of consumption and safety in the face of exogenous hazards. With this, resilience becomes the ability of production to withstand and recover from the repeated shocks. This mechanism is illustrated via model comprising aggregated domestic sector and a single export sector trading with a larger regional system. Solving the model, first as a comparative static system gives multiple stable and unstable equilibrium solutions for the level of economic activity. Equating these solutions gives the level of protection that offers greatest well-being. This production–protection relationship is then incorporated into a time-step simulation showing how the economy evolves in response to random shocks and concatenated disturbances, including irregular collapses beyond the desired resilience regime. Within this dynamic model, solutions to the static model appear as weak attractors. Thus, a further contribution of the paper is that it bridges between equilibrium and evolutionary economics, and comparable challenges in other disciplines. The method is advanced as a closure for a social accounting-event matrix based approach.

S. Cole (✉)
University at Buffalo, The State University of New York, Buffalo, NY, USA
e-mail: samcole@buffalo.edu

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_11

11.1 Introduction

Disaster resilience is the ability of individuals, communities, organizations and states to adapt to and recover from hazards, shocks or stresses without compromising long-term prospects for development (see e.g. UNISDR 2005; OECD 2013). Working with this appreciation, this chapter addresses the issue of how to incorporate chronic shocks and catastrophic disruptions in a macro-economic system. It employs a functional description of the embodied resilience against shocks in all economic and social sectors. This formulation allows relationships between the size of shocks, levels of protection, and the consequent disruption to be explored. The approach is presented here as a simplified regional economic model with an aggregate domestic economy driven by exogenous shocks. The key components are the available technology (represented by a production-protection function), societal risk propensity, and the openness and growth potential of the economy. The formulation refines the portfolio of protection approach presented in earlier papers (Cole 2004a, 2010). The goal has been to incorporate the resulting resilience relationships as variable coefficients in multi-sectoral, multi-regional models using the event-insurance matrix approach, again described in previous papers (Cole 1997, 2004b, 2012b).

The starting point for analysis is the simple-minded truism that, in order to assure the benefits of productive activity, we must protect it against shocks and disruptions. For this reason, all economic actors: businesses, households, and governments, whether as consumers or producers, protect the performance of their activities against the hazards they confront. This protection takes place across a wide spectrum of shocks and disruptions, and the means of protection varies accordingly. Present-day systems of protection have evolved over time so that, within the means available to them, actors must, in some sense, have learned to balance their array of protection measures, at a individual, kinship, societal, and ultimately global levels, in both commercial and informal ways. As best they are able, actors and activities develop a portfolio of protection that maximizes the net performance of their portfolio of acquisitions. They balance economic loss against other losses—such as mortality and heritage—and they adapt this portfolio as novel threats and information become apparent, or perceptions and priorities change, or new resources and new protections become available.

Individual and societal goals with respect to levels of protection are similar, but complementary. For an individual activity and shock, protection should be sufficient to mitigate these events so that they do not become major disruptions or disasters, bankrupt them, or trap them in poverty. For society at large, protection must be sufficient to avoid progressive collapse due to a concatenation of events cascading through the economic system, or failing this, sufficient to ensure the possibility of recovery. It should be resilient so that disaster does not lead to a permanent crippling of livelihoods or economies.

Section 11.2 provides a short review that positions the paper within the relevant literature. Discussion then falls into three topics: the core production–protection function, macroeconomic equilibrium solutions, and time-step simulation. Section 11.3, after outlining the modeling framework to be used, discusses the protection–performance function. This function is integrated into the secular production and consumption functions by allocating inputs between protection and performance-enhancing expenditures. The utility maximizing allocation of inputs, as an adaptation of financial portfolio theory that responds to the prevailing level of disruption (and hence uncertainty). This is used to define a potentially optimal short-run or "risk neutral" level of protection, and a definition of safety factors and risk propensity in relation to the exceptional larger shocks.

In Sect. 11.4, the production–protection function is integrated into an aggregate transaction model. This is a two-sector social accounting framework comprising an export sector and a domestic sector with a general equilibrium closure (Arrow and Hahn 1971). The model is first solved as a comparative static model to demonstrate the existence of multiple equilibria solutions. Section 11.5 argues that these solutions are, in effect, "weak attractors" for the system. When upper-level solutions are unstable, the low-level solutions become a temporary income floor or "trap". These solutions respectively represent the production and protection capabilities of the economy and are used to determine the size of safety factors required to maintain stability against day-to-day shocks, and to ensure recovery from major transient disruptions. This result, in turn, illustrates how, for a given ambient shock, there can be a level of import dependence that offers resiliency and maximizes net utility.

Sections 11.6 and 11.7 describe time-step simulations. For this, multi-period solutions are computed to illustrate the implications of systematically including shocks, protections, and systemic feedbacks, including replacement investment. For this, multi-period solutions are computed as a round-by round cycling of income (see e.g. Dorfman et al. 1958) including the (negative) contributions from disruptions. This simulation illustrates how the findings from the comparative static equilibrium income model carry over to the disequilibrium dynamic case with a tendency to jump between states when large exogenous shocks are applied. Section 11.8 summarizes the findings and suggests possibilities for estimation, extensions, and applications.

11.2 Literature Review

At the outset it is observed that research on the economics of disasters is somewhat balkanized within sub-fields in regional economics, economic anthropology, risk analysis, finance, and insurance. Even in the context of natural disasters researchers struggle to find satisfactory comprehensive definitions of key concepts such as vulnerability, loss, or resilience, and more especially the relationships between them (see e.g. Neubert and Caswell 1997; Okuyama and Sahin 2009; Caschili et al. 2015; Modical and Zoboli 2016). According to the Hyogo Framework for Action (UNISDR 2005), disaster resilience is determined by the degree to which individuals, communities and public and private institutions are capable of organizing themselves to learn from past disasters and reduce their risks to future ones, at international, regional, national and local levels. The OECD (2013) study observes that disaster resilience is part of the broader concept of resilience—'the ability of individuals, communities and states and their institutions to absorb and recover from shocks, whilst positively adapting and transforming their structures and means for living in the face of long-term changes and uncertainty.'

Several authors have advocated a Markowitz portfolio approach to stabilize the regional economic base by diversifying products, components, or markets, or by rebalancing the mix of exports or timing of investments; see e.g. Barth et al. (1973), Board and Sutcliffe (1991), Siegel et al. (1995), and Awerbuch and Berger (2003). Bostrom and Cirkovic (2008) characterize the severity of risks in terms of their scope: numbers impacted, intensity, and likelihood of occurrence. Kunreuther et al. (2011) have formalized elements of disaster impacts from catastrophe of an asset portfolio as an exceedance probability curve. This model described in this paper uses a similar device.

Other authors (Biggs et al. 2011; Toyama and Sagara 2012; Shreve and Kelman 2014) emphasize accounting for the real-world performance of mitigation, reiterating that, when shocks are concatenated, and unpredictable, preventive expenditures reduce but do not eliminate risk. The analytic challenge is exacerbated because many phenomena are essentially non-linear with multiple potentially-likely outcomes (Kehoe 1988; Kay 1993). In a recent article, "The Strange Economics of Scylla and Charybdis", Martin and Pindynk (2015) again reiterate that large projects change total consumption and marginal utility, causing the usual intuition (of conventional cost-benefit analysis) to break down because of the "essential interdependence among the projects that must be taken into account when formulating policy."

Protection, as interpreted in this paper, includes financial instruments, primarily insurance and savings. Various approaches have been advocated for insuring major events and catastrophes have been suggested, such as catastrophe bundles (Chichilnisky and Heal 1998) and economic catastrophe bonds (Lakdawalla and Zanjani 2006). Coval et al. (2007a, b) suggest the higher returns from these bonds are due rating agencies and investors treating events with a low default likelihood as "safe." Similarly, Burnecki and Nicoló (2017) conclude that the currently competing theories for valuation of catastrophe bonds are very dependent on assumptions about the distribution of shocks and responses. Chichilnisky (2009) asserts that since conventional expected utility analysis anticipates average responses to average risks, it also anticipates average responses to extreme risks, and so underestimates "extremal responses to extreme risks." She advocates enhanced sensitivity to rare events. For present purposes, a similar precautionary principle is incorporated into our equations via a safety factor that is used to explore the consequences of varying expenditures on protection.

The case studies of protection and its failures, cited below, cover a wide range of geographic, secular, and socio-economic situations, Others focus on the broader geophysical, technological, institutional, and philosophical dilemmas, such as acceptable risk; see, in particular, Fischhoff et al. (1981), Cuny (1983), Morton (1991), Cutter (1993), Adams (1995), Tobin and Montz (1997). There are many studies of specific domains and disaster mitigation techniques; see e.g. medicine, Humber and Almeder (1987); earthquakes, Berke and Beatley (1992); transport, construction and utilities, Shinozuka et al. (1998); engineering and consumer products, Hood and Jones (1996); environment, Smith (1996); insurance-type services, Kunreuther and Pauly (2003); sustainable livelihoods, Twigg (2001) and Skoufias and Quisumbing (2003); floods, Green (2004) and van der Veen (2003); tourism, Mansfield and Pizam (2006); border protection, McPherson et al. (2006), or homeland security Sternberg and Lee (2006). Protection may be formal or informal (Halperin 1990, 1994; Landa 1994; Cole 1995). Formally, this includes locally and globally incorporated and socialized insurance; see Arrow (1965), Kunreuther and Rose (2004) and Louberge and Schlesinger (1999). It includes price and policy adjustments designed to increase overall yields (see e.g. Rose and Laio 2005). Informal and often non-monetized protection through kin and faith-based organizations (as social-safety nets) is discussed in the economic anthropology, development, and institutional literatures; see e.g. Smith (1996), Halperin (1990, 1994), Hoff et al. (1993), Landa (1994), Elias (1995), Elliott (1997), and Sen (2000).

There are several partially cross-referenced related literatures that address and contrast real-world complexity with analytically-tractable equilibrium economics. Nelson (1995: 49), citing a broad literature, not least Marshall (whose Principles of Economics was first published in 1890), says "Most [economists] readily acknowledge that . . . at least in some situations . . . frequent or continuing shocks, generated internally as well as externally may make it hazardous to assume that the system will ever get to equilibrium: thus the fixed or moving equilibrium in the theory must be understood as an "attractor" rather than a characteristic of where the system is."

The stylized model proposed in this paper attempts to capture such systemic perceptions drawing on a range of inter-related literatures. Studies of the economy-wide impacts of disasters—discussed in this section—primarily deal with singular large events utilizing input-output, statistical modeling and simulation, and computable general equilibrium. Specifically, the model draws on previous studies using lagged social accounting models to estimate the impact of natural disasters, plant shut-downs, and mitigation (see e.g. Cole 1988, 1997, 1995, 1999, 2004a). With its focus on chronic and concatenated disturbances this paper simplifies the secular structure and time-lagged transaction and focuses on the stability of economies faced with large irregular shocks. The formal core of the paper, that a production and utility functions may be specified as a trade-off between the performance of an activity and its level of protection, is related to discussion of "insurance" in several strands of economics. These include utility theory (again, see e.g. Arrow 1965; Ehrlich and Becker 1972); the earnings-variability frontier of financial portfolio theory (Markowitz 1959); and the realization that stock option prices embody their risk premium (Merton 1973; Black and Scholes 1973). The underlying idea is that risk-averse investors construct their portfolios so as to optimize or maximize their expected return in the face of a given level of market risk, recognizing here that securing higher rewards entails greater risk. Recognizing that "protection" reduces risk provides the starting point for our production-protection function and utility maximization. In a dynamic model these static equilibrium solutions behave as attractors for complex trajectories, including structured and quasi-cyclical behavior such as those as described Anderson et al. (1988), Freeman and Louca (2001), and others (see e.g. Mandelbrot 1982, 1999), and a bridge from disaster research to theories of evolutionary economic change (see, e.g. Nelson 1995; Batty and Longley 1994).

11.3 Performance–Protection Function

There are two inter-related considerations for our treatment of protection (see Cole 2004a, b, 2010). The first is the relationship between the shock to an economic activity and the resulting disruption, as muted by the prevailing degree of protection. Shocks to exogenous or domestic income are measured relative to a specified steady level of demand and disruptions are measured relative to past or expected output. For clarity, a shock is the period-to-period change in income prior to protection, while a disruption is the residual shift after protection. Thus, shocks in the domestic economy are the net impact of new shocks to export income, together with domestic shocks, and indirect concatenated disruptions initiated in previous time periods. Hazards are substantively predictable disruptions, averted or diminished through adequate protection. As noted, there are several functional definitions across the literature cited.

The second consideration is the selection of the level of protection and the choice of safety factors. The key assertion here is that all choices reflect a distribution of inputs between performance (or use value) and its protection. The appropriate allocation of expenditures between these two goals for a given production (or consumption) activity may be determined from the relationship between the technologies, costs, variability, and welfare objectives involved. Protection, as defined here, is the intrinsic quality that provides resilience, flexibility, longevity, and robustness. Protection therefore encompasses all *practical* material and financial means whereby economic actors enhance their net utility. It follows that, without protection, there would be no utility: in the limiting case, for example, an infinitely light vehicle would have infinite acceleration, but only instantaneous survivability. Thus, it important to recognize differences between structural (e.g. input-output) models dealing with annualized accounts and impacts, and simulation models.

In contrast to input-output models and associated macro-models, for a time-step simulation model, the steps are not necessarily years, but some appropriate time scale relevant to the events studied. For example, this may be daily, seasonal or annual, or, in the limit, instantaneous. Schematically, Lim $x \to 0$, $(1 - x).x \to 0$, so when there is no protection x, there is no output, even though the residual performance, $(1 - x) \to 1$. In time step δ, with output T, the utility $= x(1 - x)\delta T$ with safety expenditure $x\delta T$ and performance $(1 - x)\delta T$. When there is no protection, i.e. when $x = 0$, the performance is maximized. However, this implies that the system lifetime given *any* disruption and planning horizon are also zero. In general, the choice of time-step in simulations is based on the magnitude and duration of the shock relative to the level of economic activity, and the processes whereby the downstream shocks are concatenated. Computationally, these are treated as subtractions from the undisrupted round-by-round multiplier process.

Performance, as defined here, is simply an indicator of prevailing level of well-being, the value of the functional share of output (for example, a vehicle's speed). Protection provides safety and longevity in the face of regular and irregular shocks and are the ingredients of survival. While survival is an essential aspect of welfare, it is traded against utility, taken to be *current* value output net of the cost of protection. The level of protection adjusts so as to maximize the short-run use value of production given prevailing shocks and imposed safety factor. In practice, the latter depends on safety margins, including risk tolerance, and perceived potential losses, according to various criteria such as 100-year flood, discounted returns, expected lifetime. The safety margin determines how long an actor might hope to avoid a major disaster, in other words how forward-looking the actor is. Thus, a discounted current utility flow ultimately provides an appropriate measure of welfare.

The relationship between performance and protection is argued here from theories of portfolio management, now widely accepted as the basis for financial and other forms of management whereby earnings from an assemblage of assets are traded off against their inherent variability. Risk is reduced or the expected rate of return improved when assets having dissimilar price movements are combined. In Markowitz's (1959) original theory an investor has a choice of a very wide range of investments, but has no control over either the performance or the variability of the individual components (stocks, bonds, real estate, and so on). In contrast, with designed systems (such as motor vehicles, hotels, power stations) and also planning systems (transportation networks, retail chains, regional economic development, even homeland security) there might be fewer options in terms of components but there is significant control over the level of protection afforded by each component, and hence the system as a whole. For individuals and households, possibilities depend on their occupation, social network, and related circumstances.

A further assertion here is that actors independently maximize their utility by adjusting their portfolio of protective measures. Although we are dealing with an aggregate economy, for the moment it is useful to consider individual activities (such as infrastructure, agriculture, households, or other meaningful categories). Protection against the consequences of shocks and disruptions are achieved in many ways depending on the type of activity and disruption, and the technological means available. In Fig. 11.1 the protection–performance relationship is characterized as three overlapping regimes. For frequent and intermediate shocks performance–protection characteristics may be extracted from testing and statistical analysis (Busch et al. 1987). For intermediate shocks the situation is less clear-cut but is addressed statistically via insurance, portfolio management, and mutualization of risks. For the larger shocks—those generally referred to as disasters, even "Acts of God"—the situation is more uncertain, even ambiguous, and often uncompensated, or subject to "non-market" humanitarian disaster relief. But, while larger shocks are infrequent, unknowable, and even marginally calculable, protection against smaller average-sized shocks will reduce the damage from larger or unusual shocks.

Costs of protection therefore may include provision of safety margins in engineered and social systems, costs of insurance and yield management, public

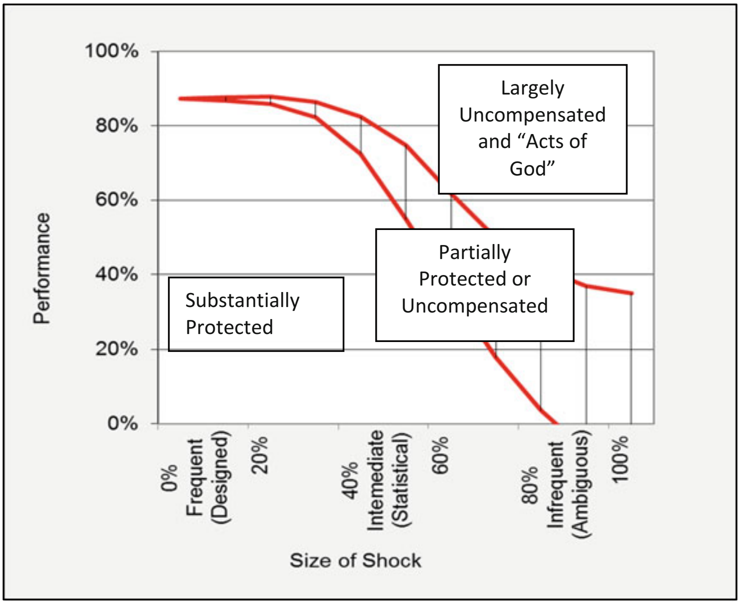


Fig. 11.1 Performance level and uncertainty versus shock

and private compensation, and reconstruction. This therefore includes both pre- and post-event resilience expenditures. Net utility is the residual, after the "costs" of protection are subtracted from the total output. As indicated above, the dividing line is diffuse, but the distinction is reasonable. This device, in effect, transforms the Markowitz earnings-variability frontier into a production function where "protection" becomes an explicit factor of production. The frontier becomes a convex (inverted "U" shaped) curve, implying that there is a protection portfolio that offers greatest net utility. This production/utility function may be constructed in several ways: the form given below has convenient analytic and (potentially) empirical properties. Utility U varies through time and between activities in response to shocks and changing demand. Temporarily, activity and time indicators are omitted from all variables. For any given singular activity

$$U = T(1 - e) \tag{11.1}$$

where T is the current value expenditure of value of output and $e < 1$ is protection expenditures as a share of output.[1] The proportion of output protected from a shock s by protection expenditure e is given by

[1]The cost of protecting utility $O(1 - e)$ is Oe, so the ratio Cost of Protection/Utility Protected = 1/(1 − 1/e) is constant for all magnitude of shocks for a given level of protection. This is consistent with the assertion that the function represents an optimal protection portfolio. Again, the imperfections of this approximation are recognized.

$$p = (1 - b/e) \text{ where } b = (s/h)^{\alpha} < e \tag{11.2}$$

The shock s is defined as the share of output that would be lost in absence of protection. Parameters h and α describe the protection technology: h measures the effectiveness of the protection, and α determines the criticality of protection and whether there is a potential "tipping point." While this equation is an approximation in terms of translating distributed shocks to average impacts, it is sufficient to illustrate a wide variety of shock-performance profiles.

Protection against shocks of increasing magnitude varies across types of protection technology (as measured by their criticality). For higher values of α, the profile is convex, even step-like. Step-like protection is characteristic of engineered systems with a tipping point or critical limit (such as a dam). For $\alpha < 1$ the curve is concave reflecting an informal system of defense. With $\alpha = 1$ the relationship is linear and, arguably, approximates the protection of an aggregate economy combining disparate entities and modes of protection. For this reason, and to simplify analysis and show that the findings are due to the properties of the performance–protection system rather than non-linearity from scale economies or similar characteristics, we adopt this profile for discussion of the macro-economic response to shocks. The performance of an activity (use value per unit output) is

$$P = (1 - e)(1 - b/e). \tag{11.3}$$

For a given s, h, and α, performance is maximized when $\partial P/\partial e = 0$ and $\partial^2 P/\partial e^2 < 0$, at

$$e = (b)^{\alpha/2} \tag{11.4}$$

We discuss now the relationship between shocks and safety factors. The former are manifest in all shapes and sizes. For some activities, the underlying pattern appears quite random with occasional spikes. In most cases, fluctuations are superimposed on a seasonal amplitude and periodicity. Even if underlying causes of these chronic fluctuations cannot be well explained, generally, some statistical description is forthcoming, and appropriate precautions assessed. Most activities also experience atypical shocks with novel causes (such as terrorism) or exceptional magnitude (such as Force 5 hurricanes). There are also atypical events due to spillover and concatenations between activities. Greatest vulnerability arises when the atypical events across activities combine to create a truly exceptional event sufficient to push one or more activity beyond its tipping point.

In the analysis that follows, the approximation is made that activities experience an averaged background variability of direct and indirect origins with infrequent major shocks. Since there is, in reality, considerable variability in the magnitude of shocks and also the possibility of occasional major shocks, or simply a high level of risk adversity, actors generally elect to protect themselves against a "target" shock that is considerably higher than the average shock. To represent this, we assume that activities seek protection against a target shock fv where f is the safety factor. We examine first the "equilibrium" situation with this safety factor facing average shocks, v. In this case, the optimal expenditure is

$$e_f = (vf/h)^{\alpha/2} \tag{11.5}$$

The parameter h measures the relative efficiency of protection technology and also serves to normalize expenditures relative to the magnitude of shocks in the above equations. A plausible working assumption here is that the smaller the average shock, the better we have become over time at dealing with it. At a minimum, from Eq. (11.3), $h > vf$, since if $h < vf$ then $U < 0$. As an analytic simplification, and because we wish to focus on the importance of the safety factor, f, we shall set $h = 1/v$. Nonetheless, the productivity of protection technology could be treated as an independent variable with, for example, short run improvements facilitating a reduction in protection expenditures.

A final, but central, issue with regard to shocks and disruptions is how they might be best measured; whether to assume constant or adaptive referencing, or safety to be constant or adaptive. In practice, shocks are measured in a variety of ways, relative to some previous level, day, month, year, century, etc., or even relative to some wished-for forecast level. Thus, the magnitude of "shocks" depends on how they are defined. Since ambient conditions—levels of exogenous demand and shocks, domestic economic activities and disruptions, production and protection technologies, and risk tolerance—change over time, shocks necessarily must be measured relative to some objectively or subjectively identified more stable or "reference" state of affairs. For the following, shocks will be measured relative to the expected level of output as determined from Eq. (11.1) and protection based on established trends. Safety factors are treated as exogenous.

11.4 Equilibrium Solutions

The simplified macro-economic system we are dealing with is shown Fig. 11.2. This is essentially a fully aggregated input-output or social accounting framework (see e.g. Stone 1961; Cole 1995; Kunreuther and Rose 2004; Okuyama and Santos 2014). The three principal components are exogenous demand, domestic production and demand, and protection. The economy is driven by an exogenous demand that is subject to various fluctuations and occasional major shocks. These shocks are transmitted to the domestic economy and combine with local disruptions, which determine the proportion of income required to protect production and consumption against shocks. The round-by-round multiplier process circulates and thereby amplifies income and disruptions. The economic system may be represented formally such that the total income provided by this economic activity is

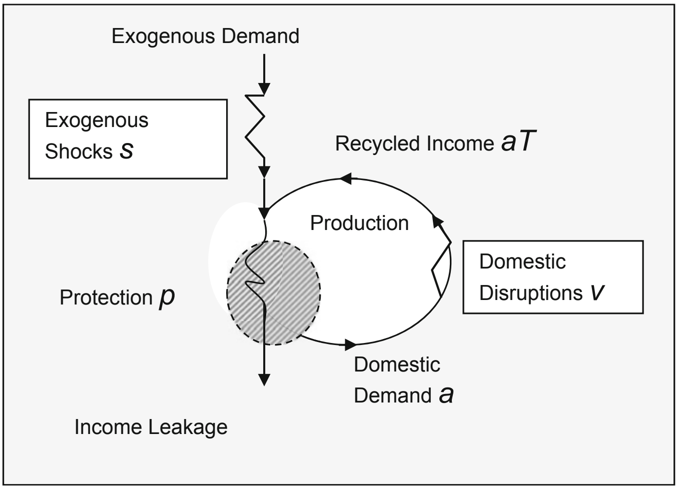


Fig. 11.2 The protected economic system

$$T(t) = \{(1 - s(t))X(t) + a(t)T(t - 1)\}p(v(t), h(t), f(t)) \tag{11.6}$$

The total income $T(t)$ at time t has both direct and indirect contributions. The first contribution $(1 - s(t))X$ arises from an exogenous demand $X(t)$ as attenuated by shocks $s(t)$. The second contribution $a(t)T(t - 1)$ is the indirect income circulated from the previous year through the economy, where a is the domestic purchase coefficient (or DPC). These terms require little explanation, at this point. The last factor $p(v, h, f)$ is the level of protection afforded to protect against net local disruptions $v(t)$, using protection technology $h(t)$ and a safety factor $f(t)$. This is the core of the model and will now be explained. While any or all of these parameters may vary with time we focus initially on the secular behavior of T as a function of the parameters s, a, v, h, and especially f.

To determine the equilibrium solutions the shock to exogenous demand s is set to zero except for perturbations (considered later). The domestic shock in each time period is measured relative to the reference level of income T_V that prevails in absence of exceptional shocks but is affected by a background shock v_0. Thus, the total shock to the domestic economy is a combination of the background shock and irregular shocks from changes due to unusual events, including changes in exogenous demand or increased or reduced production capacity. On a period-to-period basis, the combined shock $v(t)$ experienced in the domestic economy becomes

$$v(t) = v_0 + \mid T(t) - T_V \mid / T_V \tag{11.7}$$

For simplicity, the efficacy of protection is assumed to be symmetrical in that both positive and negative deviations from the reference level (since $v(t) > v_0$) imply an increase in protection costs that, in the latter case, will generally be more than that offset by increases in income. The shock $v(t)$ affects all sources of income processed within the domestic economy—new export demand, induced and circulated income. This concatenation of shocks arises because successive impacts attenuate the income cycled through the domestic economy via the round-by-round multiplier processes. Although Eq. (11.6) describes income levels across successive time periods, we may use it to calculate the equilibrium level of income in absence of additional shocks. In this case, $v(t) = 0$ so which implies that $T(t) = T(t + 1) = T_V$. Thus, for the moment, for consideration of static equilibria we again omit the time variable from the equations. From Eq. (11.7) we have

$$T_V = X(1 - s)p_V/(1 - ap_V) \tag{11.8}$$

Here $p_V = 1 - v_0/b_V$ is the level of protection arising from, and protecting against, the average shock, while $b_V = (v_0 fh)^{1/2}$ since $e_f = (v_0 f/h)^{1/2}$ is the share of expenditures required to protect against an average shock with a safety factor f. With no disruptions or protection, Eq. (11.9) becomes an aggregate Leontief output equation (see e.g. Dorfman et al. 1958). As such it provides a plausible reference against which to measure disruptions, although, as noted earlier, without protection, there is no net production, i.e. when $p_V = 0$, $T_V = 0$. The level of protection with income level T and reference level T_V is

$$p(T) = p_V - \mid 1 - (T/T_V) \mid /b_V \tag{11.9}$$

From Eqs. (11.7) and (11.8) we observe that the model is quadratic in T so there must be a second solution. (Indeed, with other reference levels or specifications of protection and disruption, there may be many solutions). To obtain the other solution we substitute (11.8) into (11.7)

$$\begin{aligned} &T^2 - T\{1 - ap_V + a/b_V + X(1 - s)/(b_V T_V)\}(T_V b_V/a) \\ &\quad + X(1 - s)\{p_V - 1/b_V\}(T_V b_V/a) \\ &\quad = 0 \end{aligned} \tag{11.10}$$

Comparing this with the equation $(T - T_L)(T - T_V) = 0$ shows that the second solution T_L is given by[2]

$$T_L = X(b_V p_V - 1)/a \tag{11.11}$$

After substitution for b_V and p_V,

[2]The solution to the quadratic equation may be obtained by substitution of (11.7) into (11.6) and obtain the standard solutions $x = \{-B \pm \sqrt{(A^2 + 4AC)}\}/2A$ to the quadratic $Ax^2 + Bx + C = 0$. These expressions are, however, less easy to decipher.

$$T_L = X\left(\left(v_0 hf\right)^{1/2} - v_0 - 1\right)/a \tag{11.12}$$

For the situations we are primarily interested in, when shocks are positive (and tend to reduce income), this second equilibrium lies below the reference level. From Eq. (11.12) it is seen that $T_L > 0$ when $p_V > 1/b_V$, and with $h = 1/v_0, f = (1 + v_0)^2$ is the minimum safety factor for any activity to proceed. At the lower level, the circulated income aT_L is barely sustained. This lower solution represents the economic underpinning of the economy—the limited amount of economic activity that is well-protected.

11.5 Weak Attractors

The relationship between the solutions to Eq. (11.10) is next be demonstrated for both their static and dynamic properties. Figure 11.3, for example, illustrates the static equilibrium by comparing the computed levels of supply [the LHS of Eq. (11.10)] versus levels of demand (the RHS). For purposes of illustration, we take $X = 1$, $s = 0$, $a = 0.5, f = 2$, $v_0 = 20\%$, $h = 1/v_0$, and $\alpha = 1$, plausible values for a mid-sized regional economy. The intersection of the two curves corresponds

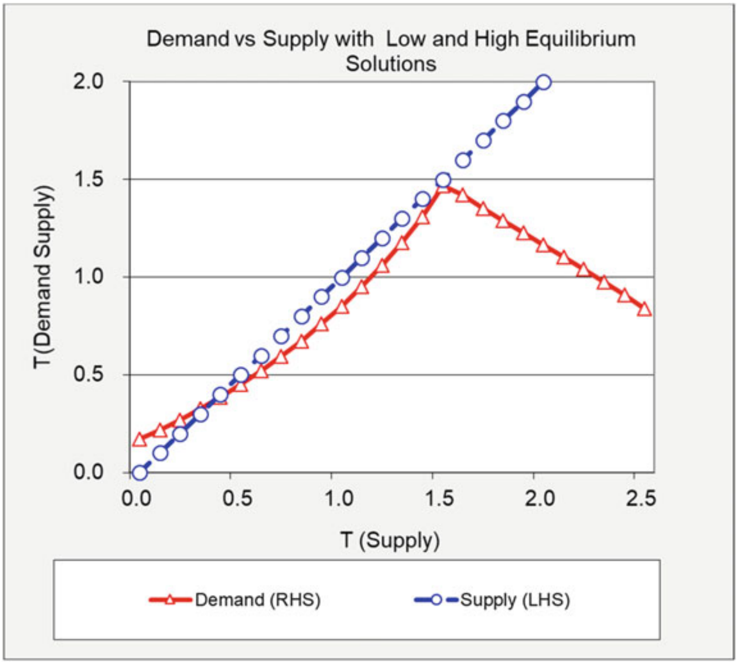


Fig. 11.3 Equilibrium solutions from supply versus demand curves with linear protection

to the two solutions T_V and T_L derived above. If the economy is operating at the upper level, but experiences a small additional shock, then the RHS is reduced, which lowers the LHS, and so on, potentially in a progressive decline until the lower equilibrium T_L is reached. Thus, the solution T_V is meta-stable. Moreover, depending again on the parameters adopted, the demand curve may merely graze (i.e. is tangential to) the supply curve at the higher solution. This, and the closeness of the supply and demand curves between the two solutions, means that in some circumstances even a small perturbation can trigger a progressive collapse. For levels below T_L this stepwise tatonnement is reversed so this provides a floor below which income may not fall (in absence of other shocks). Thus, the upper and lower bounds might best be described as "weak attractors" with trajectories appearing to be "chaotic", driven by the concatenation of exogenous shocks as opposed to, for example, an endogenous cluster-enhanced growth potential (see Cole 2009, 2012a, b). The latter is "deterministic" in that it arises directly from endogenous agency (such as over-rapid investment) as opposed to a failure to well-address events arising from exogenous agency.

Again, a plausible interpretation of these results is that, in a protected system, there are two conditions for stability. The first is the familiar Say's Law condition that supply and demand in an economy must be in balance (and, in a fixed price model that income and expenditure are equal). This condition is recognized by the solution T_V. The second condition is that there also must be a balance of between the cost of disruptions and protection expenditures, recognized by the second solution for T_L. A general static equilibrium requires that both production and protection should be in balance. Protection is an intrinsic requirement for a stable balanced economy.

The above results come about, in part, because of the way that shocks are referenced. Since the disrupted state is chronic, rather than temporary, costs for protection are incurred as long as the economy remains disrupted. Moreover, the costs of protection are sufficiently high that, in the event of an unusual disruption, they progressively drain the economy of income that might otherwise restore its previous level of performance. Obviously, such a production-protection imbalance cannot continue indefinitely.

The two solutions for production and protection balance may be satisfied simultaneously by adopting an appropriate safety factor. The necessary level protection for $T_V = T_L$ is

$$p_V = \left[(v_0 + 1) - \sqrt{\left\{(v_0 + 1)^2 - 4v_0 a\right\}}\right]/2av_0 \qquad (11.13)$$

This equation prescribes the safety factor required for an economy to be resilient (described only by a and v_0, with $h = 1/v_0$). The requirement that $T_V = T_L$ also preserves the credibility of the measurement and referencing of disruptions since the implied "goal" of the economy is to restore and maintain income to its historic level.

Equation (11.13) provides some insight into the relationship between the stability of an economy and its dependence on the rest of the world. In the economic system described, reducing imports increases gains from exports by increasing the income multiplier. However, even though the upper-level solution increases with the DPC, a, the lower solution decreases, so if stability is to be achieved, some balance must be found. Further, from Eq. (11.12) we see that f increases approximately as the square of aT_L, and so the additional cost of protection offsets any gains from protectionism, and vice versa. All actors as producers or consumers are constantly involved in a similar adjustment process within their own domain. Thus, all activities are in permanent disequilibrium. Nonetheless, the above comparative equilibrium results inform interpretation of dynamic disequilibrium, considered next.

11.6 Dynamic Equilibrium and Dissipative States

We now discuss some of the dynamic properties of Eq. (11.1). The main goal here is to demonstrate that even though the system we are describing has characteristics of a "complex" system (see e.g. Anderson et al. 1988; Arthur 1988; Allen 1994), and is certainly not in equilibrium. Thus, the earlier results remain relevant. The supply-demand intersection shown in Fig. 11.3 suggested that the upper-level equilibrium solution to Eq. (11.6) is unstable to small disruptions. The corresponding result for the dynamic equilibrium may be demonstrated by calculating the RHS of Eq. (11.6) for successive time periods so that $T(t + 1)$ is derived from $T(t)$, and so on. In order to facilitate derivation of the earlier analytic results it was useful to separate background shocks from occasional major events. This device is employed temporarily to confirm asymptotic equilibria and stability properties in the presence of perturbations.

Figure 11.4 shows the trajectories from two simulations of the impacts when a steady (20%) background shock is applied. For the first, a relatively low safety factor, $f = 2$ (about half that required for $T_L = T_V$) is adopted. Initially, income is maintained at the higher equilibrium T_V. However, it is destabilized by a small shock, falls to the lower level T_L, and remains there. This situation may be compared to the "poverty trap" (Nelson 1956). Whilst greater protection might enable actors to avoid the trap, they simply cannot afford it; see e.g. Taylor and Lysy (1979), Smith (1990), Halperin (1990), Hoff et al. (1993), Twigg (2001). Instability of the upper level equilibrium may be understood from Eq. (11.6) by considering the consequences of a small perturbation, $\delta v > 0$, at time t when the economy is operating at the upper equilibrium (so that $T(t - 1) = T_V$ and $p = 1$). This will reduce the level of income $T(t)$ below T_V since

$$T(t) = (X + aT_V)(p_V + \delta p) = T_V(1 + \delta p) < T_V \text{ since } \delta p = -\delta v/bT_V. \quad (11.14)$$

Similarly, $T(t + 1) < T(t)$, and so on.

In the second trajectory, with a larger safety factor, $f = 3$, there is a major event with temporary total loss of export demand. In this case, the shock is sufficient to cause the income to fall below T_L, and then rise back to this lower equilibrium level.

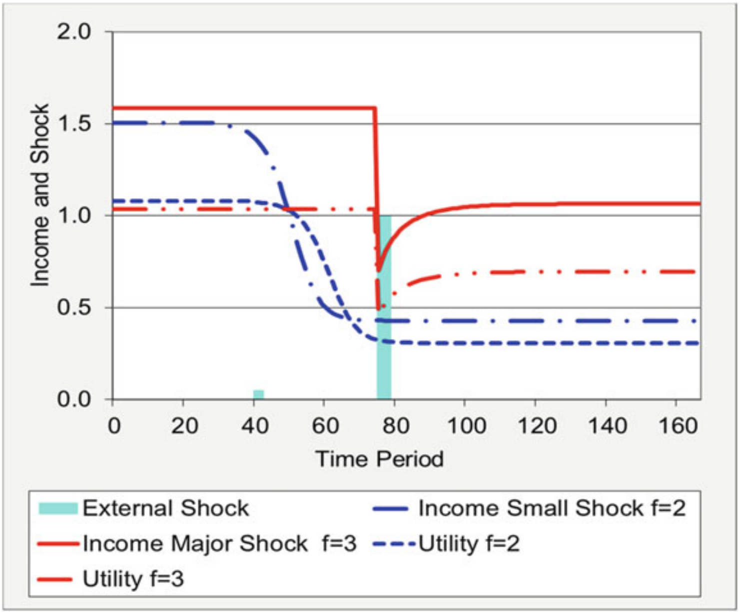


Fig. 11.4 Asymptotic solutions for impact of shocks and protection on income

This will occur only when the income loss $Xp_V < T_V - T_L$. If the safety factor is sufficiently large [as prescribed by Eq. (11.13)], income returns to the upper equilibrium level.

11.7 Time-Step Simulations of Exogenous and Concatenated Shocks

We now explore the situation when variability of exogenous shocks, $s(t)$, in each time period is made explicit. The domestic background shock v_0 in Eq. (11.7) is now set to zero, so that domestic disturbances are due only to variability in external demand. Domestically generated shocks arising, for example from lumpy investments as well as other causes, may be incorporated using the same procedure. The resulting time-averaged domestic shock for the simulation now determines the level of protection. An exogenous random shock varying between zero and 40% is applied to exogenous demand. A single 100% loss of export demand within one time-step is included for purpose of comparison with the previous results.

Figure 11.5 shows a "typical" segment of a simulation using a safety factor $f = 2$, about half the level prescribed by Eq. (11.13). The system is clearly rather sensitive to all shocks, but there is a tendency for income to fluctuate around the upper equilibrium, at least until the economy is destabilized by the temporary loss of

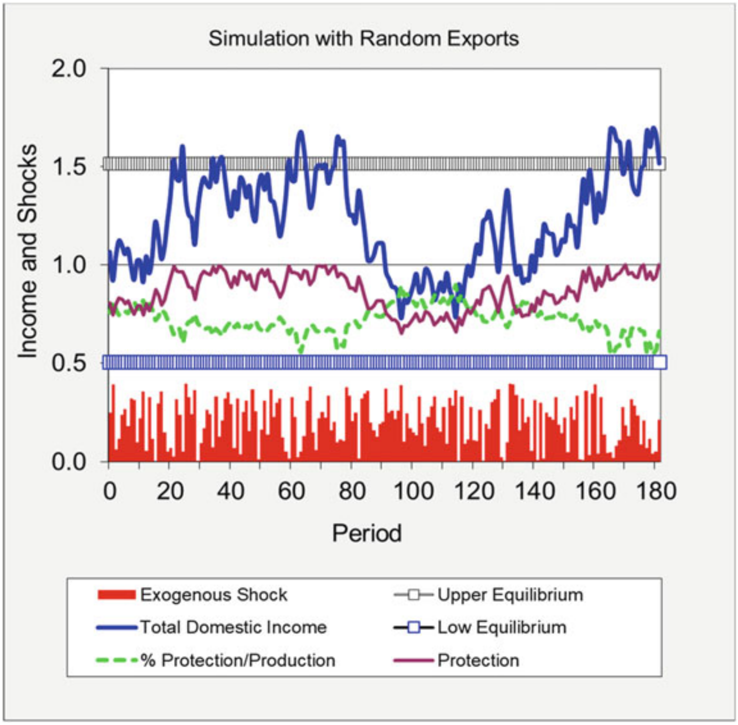


Fig. 11.5 Frequency of shocks and residual disruptions

export earnings or for other reasons discussed below. Generally, trajectory fluctuates below the higher equilibrium. Significant loss of exogenous demand leads to a rapid collapse of income towards the lower equilibrium followed by a slower stepped recovery back to the previous level.

The substantial jumps in income seen in Fig. 11.5 might be explained as the result of clusters of above or below average shocks. Statistically, such clusters are not unusual, especially when the exogenous shocks are themselves the outcome of complicated processes (such as competitive markets, natural events, and political cycles).[3] That such clusters might, in themselves, lead to rapid and significant "jump" in income over *n* time periods is seen from the time series expansion of Eq. (11.1). We note here that both shocks and protection hold relatively steady so

[3]Goldenfeld and Kadanoff (1999) say that many biological, physical, and social, and economic systems are dominated by big events and "intermediacy." Empirically, the probability Ω of a jump j is found to be $\Omega(j) = \exp(-|j|/\delta|)$ where δ is the standard deviation, rather than the usual Gaussian form $\Omega = \exp(|j^2|/2\delta^2)/(2\delta^2)$. Thus, such events are far more likely than suggested by Gaussian statistics; see also Mandelbrot (1999).

long as the economy remains at the given level with the major contributions to the multiplier series comes from the first few terms,

$$| T(t) - T(t-n) | \approx Xsp\left\{1 + ap + (ap)^2 + (ap)^3 + (ap)^3 \ldots\ldots\right\} \tag{11.15}$$

Thus, depending on the pattern of exogenous shocks in terms of magnitude, frequency, after-shocks, and concatenations, the combined shock $c(t)$ defined in Eq. (11.7) experienced within the domestic economy can be large, relative to the target shock, vf. As income is circulated, given a more or less steady exogenous demand, income is substantially restored after relatively few time periods. (For example, $a = 0.5$ and $p = 0.8$, income reaches 99% of potential after 5 periods. Similarly, a succession of average shocks of 20% would accumulate very rapidly to the target level).

The combined (direct and indirect) shock experienced by the domestic economy is the net result of the random exogenous shock and downstream disruptions from previous time periods, and the level of protection at any given time is a response to this shock. The way in which the exogenous random shocks "trickle down" to determine the level or distribution of protection is indicated by Fig. 11.6. Thus, the initial random shock (biased towards lower values), when combined with concatenated shocks, transforms into skewed distribution (with a higher mean value), damped by the protection to give the final distribution of disruptions. The net performance of the economy—also shown—mirrors this distribution.

This coincidental accumulation of disruptions alone does not explain the phenomenon exhibited in Fig. 11.5 that income remains at the upper or lower level for extended periods but also rapidly transitions between them. This behavior is characteristic of self-organizing dissipative complex systems.[4] This in turn suggests that *both* the income levels T_V and T_L are "strange attractors."[5] At the upper level, T_V represents a dissipative state—far from equilibrium. Although the overall level is sustained by the exogenous demand X, its potential for disruption is driven by the exogenous shocks registered by $v(t)$. Dissipation arises through unprotected losses and extra-regional income leakages.

Figure 11.7, which graphs the level of income versus exogenous shock, supports this interpretation. The upper level around T_V is the operational level for the

---

[4]Definitions of "complexity" vary: the most concise is from Goldenfeld and Kadanoff (1999) is "structure with variations". They distinguish this from "chaos", which they describe as sensitivity to initial conditions with outcomes difficult to predict and growing exponentially with time; see also Gardener and Ashby (1970), Prigogine (1976), Feigenbaum (1978), Anderson et al. (1988) and Ledesdorf and van der Besselaar (1994).

[5]This term was introduced by Lorentz (1963). Attempting to understand turbulence in weather systems, but unable to solve the seemingly-simple 3-dimensional equations, Lorentz simulated trajectories similar to the 2 dimensional equations and trajectories shown here. Similar behavior is observed in the extended Lotka-Volterra (1920) predator-prey model (see Chen and Cohen 2001; Neubert and Caswell 1997) observe that, despite local stability, a perturbation may be temporarily amplified and DeAngelis and Waterhouse (1987) showed that frequent perturbations might maintain ecological systems far from equilibrium.

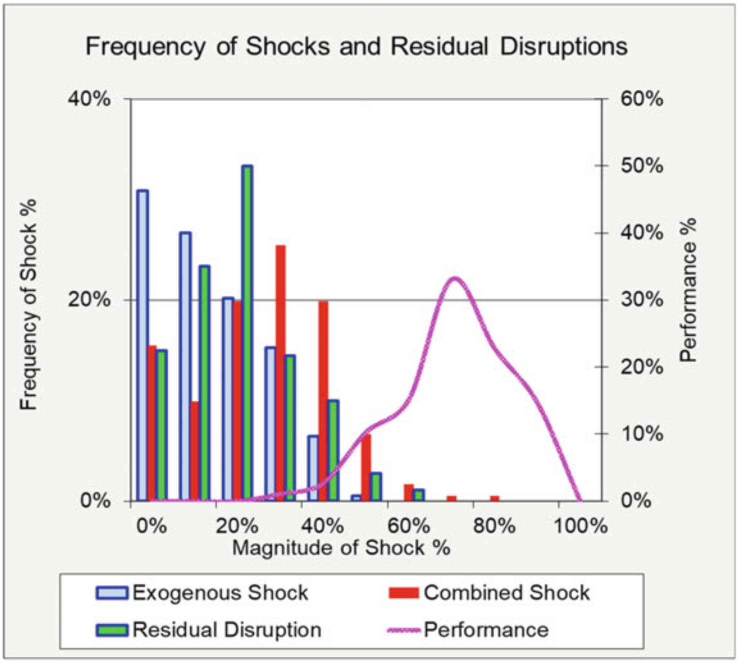


Fig. 11.6 Typical simulation results: exogenous shocks, income, and performance

economy and dominates in terms of the number of periods. For much of the time income slides back and forth along an inclined path in the direction shown. The slope of this path, $\partial T_V/\partial p_V$, measures the effectiveness of protection in this mode (generally on the upper side of the distribution shown in Fig. 11.7). Given a transient accumulation of shocks, the system rapidly transitions to the lower level T_L that represents the amount of activity protected. This typically less visited level may be viewed as somewhat steadier since $\partial T_L/\partial p_L$, is lower than at the higher level. Given a succession of smaller shocks the system returns somewhat more slowly to the higher level. The overall progression induced in the economy is indicated by the arrows—short-term (typically several periods) precession at the upper and lower levels, with less frequent passage between the two levels.

This picture may be related directly to the static equilibrium solutions by rewriting Eqs. (11.8) and (11.10) in order to obtain expressions for the accumulated disruption, c_V and c_L respectively, in terms of the income T in the vicinity of the upper and lower equilibria from the approximations, $T \approx (X + aT)\ \{1 - |v_0 + c_V|/b_V\}$ and $T \approx X/a\{b(1 - |v_0 + c_L|/b_V) - 1\}$. Thus,

$$| \, v_0 + c_V \, | \approx b_V\{1 - T/(X + aT)\} \text{ and } | \, v_0 + c_L \, | \approx b_V - 1 - aT/X \qquad (11.16)$$

As explained above, these amounts may be interpreted as the potential for disruption in the economy, including the tendency to jump between the upper and

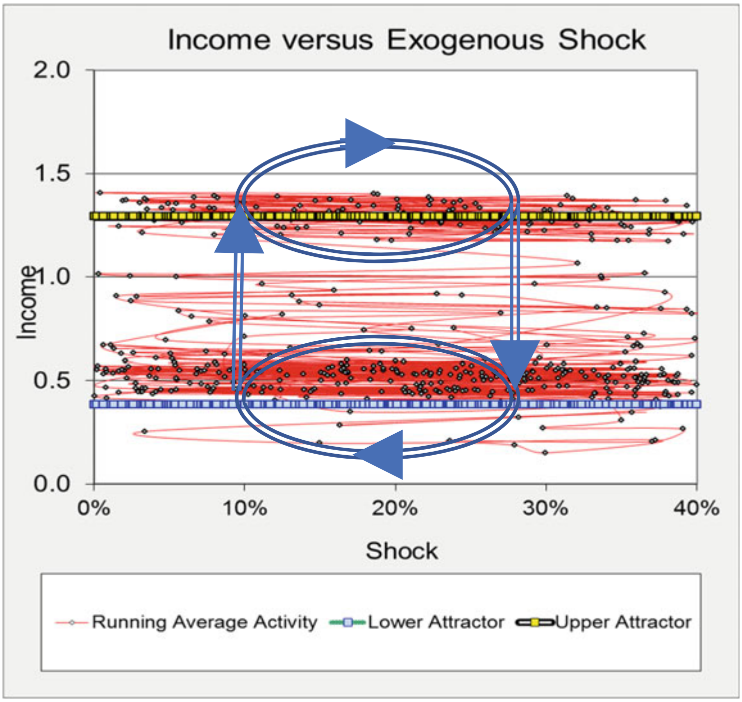


Fig. 11.7 Transitions between upper and lower income regimes

lower states. Thus, the system is in (or primarily in) one or other state as long as the accumulated shock [as indicated by Eq. (11.16)] remains less than the target shock.

This short explanation necessarily simplifies transitions and outcomes. Given that the behavior is induced by random shocks every simulation is different. For example, in some cases intermittent modes are observed when the trajectory stalls as it climbs from the lower to the upper mode. With linear protection profiles this is simply "accident": with non-linear and more critical protection profiles this is an embodied characteristic. In absence of a major extra shock, the system may remain at the upper level for several hundred periods or fall spontaneously several times to the lower level. In other cases, there is quasi-periodic behavior over several medium run cycles (100 cycles). The pattern changes according to the level of protection and exogenous shocks but is typically a bimodal distribution of income. This is illustrated in Fig. 11.8 for three levels of protection ($f = 2$, 4, and 6) based on the random distribution of shocks described above. This shows that the least protected system exhibits least variation at the upper income level but is more likely to transition to the lower level. Thus, as shown in Fig. 11.9, when the safety factor is increased, utility shows a weak maximum at about half the prescribed safety level and declines with higher safety factors. Income is higher because of the greater protection, but this gain is more than offset by its cost. Thus, the major benefit from higher levels of protection lies in the reduced variability in income—as measured by the standard

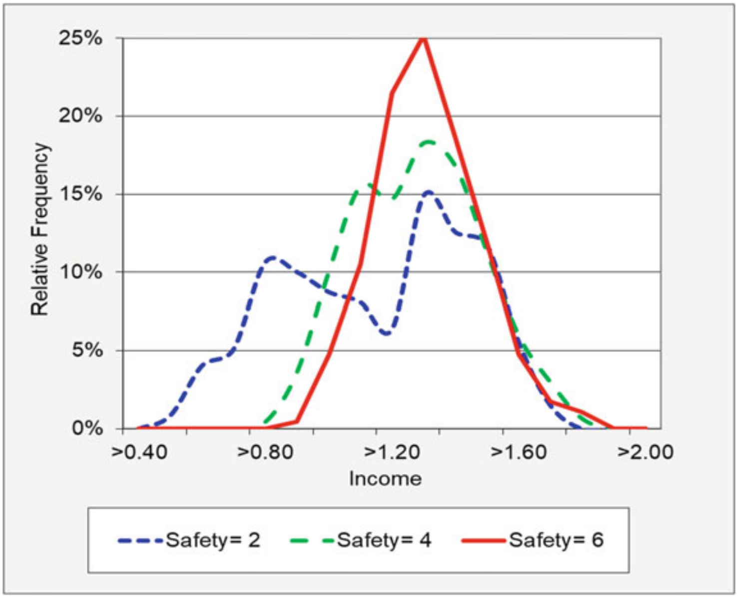


Fig. 11.8 Distribution of income versus safety factor

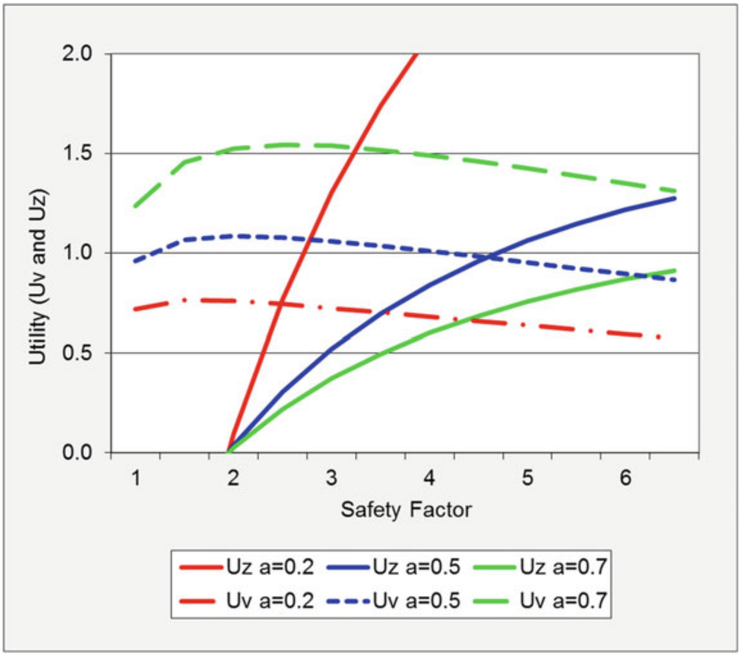


Fig. 11.9 Utility and disruptions versus safety factor

deviation of utility from average, the size of the largest disruption, and the percentage of time periods spent in a "critical" state (for purposes of comparison, taken to be at less than half the average utility).

11.8 Conclusions: Estimation and Extensions

This paper has addressed a topical and universal question of how to balance the protection of a system against the well-being it provides, asserting that all systems balance performance and survival in an intuitive even instinctive evolved manner. Although this idea is explicit in some of the economic literature cited, the starting point here has been studies of the impact of disasters and disaster management, and the "ultimate question" of "How safe is safe enough?" (see Kunrether and Slovic 1978). Making the connection between this literature and the portfolio and insurance literature allows a link back into production function, macro-economic structural and general equilibrium analysis, the results of which, in turn, establish a link to chaos and complexity theory, and possibly to evolutionary theories. To this extent the paper possibly goes some way to addressing some of the concerns of Anderson (1995), Nelson (1995), Freeman and Louca (2001) as to the utility of equilibrium analysis in dynamic economic systems.

The paper has developed an approach that integrates portfolio theory into a dynamic macroeconomic framework. The re-characterization of the Markowitz portfolio as a production function allows us to determine an optimal level of protection for individual activities and sub-systems, in terms of their operating conditions, technology and risk tolerance. The latter, is introduced via a "safety factor" that relates day-to-day disruptions to perceptions (or more rational assessments) of the likelihood of exceptional shocks and their consequences. Incorporating this result into a macro-economic framework, allows us to derive a comparative static "general equilibrium" for production and protection that provides unique solutions, again in terms of the technologies of production and protection, the variability of imports or domestic production, and the safety factor or risk tolerance.

Although the high-level equilibrium is potentially unstable, and the lower equilibrium characterized as a "poverty trap", together, these solutions provide conditions for resilience (the ability to mitigate and recover from shocks). The results illustrate how, for an economy with a given pattern of exogenous shocks, production technology, and a protection regime that adapts to these conditions, there can also be an optimal level of import dependence. The computed dynamic trajectories of the macro-model exhibit multiple characteristics associated with "complexity" including chronic instability, erratic switching and medium-run (several cycles) periodic behavior. The conjecture here was that equilibrium solutions to the static model are equivalent to the "strange attractors" and govern many of the trajectories exhibited by the model. The importance of this finding is that policy-related information, in particular, the level of protection required to negate spontaneous switching, can be deduced from a comparatively straightforward static model, even though we may not fully comprehend the dynamic trajectories. In this sense, the attractors are no longer "strange" Similar explanations for other systems might provide ground rules for protection that can enhance their stability and resilience.

The paper has adopted a stylized specification, partly for analytic tractability, but also to show that the results come from particular features of the model (rather than, say, from non-linearity, or multiple-agency). Referring back to Fig. 11.1, these essential components are a forcing factor (in our model, this is exports) and variability (in exports or domestic production), an accumulator or amplifier process (via domestic cycling of income and disruptions), a dissipative process (unprotected losses and leakages), and a regulatory process (protection and safety factor). Given this similarity in structure, the trajectories generated by the model are also recognizable.

The hypothesized performance-protection relationships in Fig. 11.2, characterize regimes across in several fields, such as construction, public utilities, transport safety and homeland security, flood and earthquake, environmental protection, and sustainable livelihoods, and many elaborations in the insurance, risk management, insurance, and actuarial literatures that deal with the interfaces between the protection regimes. The stylized profile (with relationships varying from linear to critical) reflects the observation that generally we are better adapted to everyday shocks than major shocks, and that disruptions and ways of dealing with them vary across activities. As with all algebraic expressions adopted in the economic and other social sciences, the choice of function is somewhat artificial, chosen for theoretical tractability, and with an eye to available data. As Lloyd (2001) explains, most established production functions such as the "von Thunen-Mill-Pareto-Wicksell-Cobb-Douglas" function have been devised to obtain specific properties. With respect to the form of the function used here there are competing views. Arrow (1965), for example, argued that since insurance—as an exchange of money-for-money—should be treated differently from other desires. Subsequent authors argued that it should be considered in the same way as contributions to ordinary production and utility functions; see Ehrlich and Becker (1972). While the specification of the production function here favors the idea that protection supports well-being, rather than being a part of it, depending on the actors involved, other alternatives may be more appropriate.

With regard to the regulatory process, in our simple model, we have focused primarily on the role of an exogenous safety factor used to demonstrate specific policies. Other regulatory variables are implicit. For example, some aspects of "markets" have been subsumed into the portfolio of protection (implying that this represents optimal protection–performance choices by activities), others have been thwarted (the use of Leontief fixed coefficients), while the level of protection, which adjusts endogenously assumes an equilibrating role (similar to price in a CGE model). In similar manner, the technologies of production (import dependence) and protection (efficacy and criticality) have been fixed or adjusted exogenously. These variables may each be treated as endogenous, which mutes, exacerbates, or otherwise transforms the model trajectories. Although it is not easy (maybe impossible) to solve Eq. (11.7) for the multiple static equilibrium algebraically, it is straightforward to compute Fig. 11.5 and its variants and hence determine the properties of the system in terms of familiar variables (level of exports, domestic purchase coefficient, magnitude of shock, and so on) and common-sense definitions of protection and risk tolerance. For this reason, it is extremely useful that the static equilibrium results may be related so directly the simulations. Thus, analytic solutions to multiple-equilibria systems such as those discussed by Kehoe (1988), see also Debreu (1972), Deiker (1972), Shapely and Shubik (1977) may be explored.

The macro-model uses the example of single sector with a random exogenous shock to demonstrate the relationship between risk-tolerance, import dependence, and stability and makes use of average variability as a statistical convenience. Nonetheless, the shocks experienced by most activities have a distinctive structure (seasonal cycles, oil peaks, business cycles) even when they are not explicable, or have multiple explanations. Even with the present model the internal processes appear to transform the "random" distribution so that the trajectories exhibit reinforced "cyclical" behavior. This might be apparent in systems with multiple sectors or regions with contrasting performance-protection profiles, or technologies with lumpy characteristics, or patterns of investment with differing characteristics, or multiple producers of a single product with competing technologies (Nirei 2004). Shocks, and cycles, and jumps concatenate and reinforce each other through a variety of accumulator processes, whilst being by a variety of protective and adaptive processes, to reveal systematic structuring of levels and variability of income.

The performance-protection function has been conceptualized to provide closure for a more detailed structural framework for disaster impact research (Cole 1995). In the same sense that social accounts might be used to describe the transactions within a small community, a city region, or a cluster of national economies, the relevant parameters for households and the public sector might be estimated from a variety of data, included as an "event" and "insurance" matrices mapped—as data allows—onto the underlying transaction matrix. At the cross-national level, recent data such as the OECD Social Expenditure Database (SOCX) or similar World Bank Social Expenditure Indicators (ASPIRE) that includes, for example, comparative national data on public expenditure on social programs (cash transfers, pensions, public works, and other social assistance). Similar data are available for many regions and cities, even smaller communities, at least in OECD economies. While this may be sufficient to differentiate nations and some categories of households, it may be less useful for major disasters and diverse communities, especially where both production and protection combine both formal and informal components—overseas bank accounts, public patronage, extended family, and so on—depending on one's status within a society (see e.g. Cole 1995). Beyond this, the appropriate metric for evaluating strategies for households (as opposed to production activities) may be time-spent socializing and establishing family and other networks, as much as monetary expenditures. (e.g. Landa 1994; Halperin 1994; Gershuny 2011), accumulating the social capital to be relied upon during critical situations, thus maintaining and protecting individual and collective life satisfactions. Following this line of thinking, it may be worthwhile to reframe the core variable "protection" as one of "survival". With this, each activity and expenditure—whether nutrition, shelter, education, or innovation (spanning, for example, the Maslow hierarchy of needs)—become actions or expenditures with impacts delayed to corresponding time horizons. Similarly, with the role of family resilience in addressing mental health and other adversity whereby the crises concatenate through the immediate fragile family, but potentially muted by support from extended family, physicians, and community groups (Walsh 2012). Of special relevance to our wider issue here is the idea of "strengths forged through adversity", the lifelong individual and collective learning and adaptation, corresponding (at least) algebraically to the time-varying technological, communication, and organizational improvements assumed here for disaster management and catastrophe planning.

In their review of the "Costs and Benefits of Catastrophes and Their Aftermath", Greenberg et al. (2007) explain why modeling insurance impacts is "challenging". They review an earlier formulation of the present approach, Cole (2010). These authors advocate that, borrowing from this approach, modelers could prepare well-prepared and not-prepared scenarios for regions, thus merging of risk assessment and economic cost models. Moving forward, and still within the framework of an IO or SAM-type transaction matrix and Markowitz portfolio analysis, there are several possible approaches. One, fully incorporating the algorithm explored in this paper, is to map every account (or even every transaction) with a functionally determined degree of protection. An alternative, is to use the resulting model as a means to determine the portfolio of output, similar to allocation within an investment portfolio. A third approach, favored by this author, is to combine autonomous protection functions for independent actors (primarily business and households) with a multi-criteria optimization model (e.g. van der Veen et al. 1994) for public sector allocations along this line in Cole (2002). For the multi-criteria optimization, the growth of each prioritized variable (relative to the base level) is weighted and lagged appropriately, and the sum-product of weights and growth is adopted as the target variable to be maximized. Within a selection of potential policy scenarios, favorable outcomes such output or employment are weighted positively, and unfavorable items, not least variability, are given a negative weight. Unweighted items (primarily those governed by an autonomous protected-production function) play a passive role. In this case, one should expect multiple attractors corresponding to the putative equilibria. Overall, this sub-optimal outcome indicates the direction required—for example, to take more account of resilience concerns.

References

Adams J (1995) Risk. UCL Press, London

Allen P (1994) In: Ledesdorf L, van der Besselaar P (eds) Evolutionary complex systems: models of technology change. Pinter, London

Anderson P (17th Mar 1995) Science: 1617 cited by Freeman and Louca (2001:122) op cit

Anderson P, Arrow K, Pines D (1988) The economy as an evolving complex system. Addison-Wesley, Boston, MA
Arrow K (1965) Aspects of the theory of risk bearing. Helsinki. Yrgo Jahnnonin Saatio. Cited in Erhlich and Becker (1972 op cit)
Arrow K, Hahn F (1971) General competitive equilibrium. Holden Day, San Francisco
Arthur W (1988) Self-reinforcing mechanisms in economics. In Anderson, Arrow, and Pines (op cit)
Awerbuch S, Berger M (2003) Applying portfolio theory to EU electricity planning and policy-making. International Energy Agency, EET/2003/03, Paris
Barth J, Kraft J, Weist P (1973) A portfolio theoretic approach to industrial diversification and regional employment. J Reg Sci 15(1):9–15
Batty M, Longley P (1994) Fractal cities. Academic, London
Berke B, Beatley T (1992) Planning for earthquakes: risk, politics, and policy. Johns Hopkins Press, London
Biggs D, Biggs R, Dakos V, Scholes R, Schoon M (2011) Are we entering an era of concatenated global crises? Ecol Soc 16(2):27
Black F, Scholes M (1973) The pricing of options and corporate liabilities. J Polit Econ 81:637–654
Board J, Sutcliffe C (1991) Risk and income tradeoffs in regional policy: a portfolio theoretic approach. J Reg Sci 31(2):191–210
Bostrom N, Cirkovic M (2008) Global catastrophic risks. OUP, Oxford
Burnecki K, Nicoló M (2017) Stable weak approximation at work in index-linked catastrophe bond pricing. Giuricich Risks 5:64. https://doi.org/10.3390/risks5040064
Busch K, Meinhardt T, Ballew M (1987) Statistical approach to quantitative risk assessment. In Humber and Almeder (op cit)
Caschili S, Reggiani A, Medda F (2015) Resilience and vulnerability of spatial economic networks. Netw Spat Econ 15:205–210. https://doi.org/10.1007/s11067-015-9283-9
Chatterji M, Arlosoroff S, Guha G (2002) Conflict management of water resources. Ashgate, Aldershot
Chen X, Cohen J (2001) Transient dynamics and food-web-complexity in the Lotka-Volterra cascade model. Proc R Soc Lond B 268:868–877
Chichilnisky G (2009) Catastrophic risks. Int J Green Econ 3(2):130–141
Chichilnisky G, Heal G (1998) Managing unknown risks: the future of global reinsurance. J Portf Manag 24(4):1–8
Cole S (1988) The delayed impacts of plant closures in a reformulated Leontief model. Papers of the Regional Science Association 65: 135–149
Cole S (1995) Lifelines and livelihood: a social accounting matrix approach to calamity preparedness. J Conting Crisis Manag 3:4. Reprinted in Kunreuther and Rose (2004) op cit
Cole S (1997) Decision support for calamity preparedness. In Shinozuka M, Rose A, Eguchi R (op cit), Engineering and socio-economic analysis of electricity lifelines in Memphis, Tennessee, National Center for Earthquake Engineering Research, University at Buffalo
Cole S (1999) In the spirit of Miyazawa: multipliers and the metropolis. In Hewings, Sonis, Madden, and Kimura (op cit)
Cole S (2002) Water resources in China's Yellow River Delta: an application of social–environmental accounting, and multi-criteria scenario analysis. In: Chatterji M et al (op cit)
Cole S (2004a) Performance and protection in an adaptive transaction model. Disaster Prev Manag 13(3):4
Cole S (2004b) Geohazards in social systems: an insurance matrix approach. In: Okuyama Y, Chang S (eds) Modeling spatial impacts of disasters. Springer, Heidelberg. (op cit)
Cole S (2009) A logistic tourism model: resort cycles, globalization, and chaos. Ann Tour Res 36(4):689–714
Cole S (2010) The regional portfolio of disruptions, protection, and disasters. Ann Reg Sci 44(2): 251–272

Cole S (2012a) Creative chaos? Globalization, agglomeration and the metropolis. J Econ Geogr 2012:1–22

Cole S (2012b) Managing chaos in nonlinear economic systems: globalization and destination tourism. In: Banerjee S (ed) Chaos and complexity theory for business management: nonlinear dynamics. ISI Global, Claybrooke Parva, UK

Coval J, Jurek J, Stafford E (2007a) Economic catastrophe bonds. Harvard Business School, Working Paper, June

Coval J, Jurek J, Stafford E (2007b) Economic catastrophe bonds. Harvard Business School, www.hbs.edu/faculty/Publication%20Files/07-102.pdf

Cuny F (1983) Disasters and development. Oxford University Press, Oxford

Cutter S (1993) Living with risk. Arnold, London

DeAngelis D, Waterhouse J (1987) Equilibrium and non-equilibrium concepts in ecological models. For Ecol Manag 57:1–21

Debreu G (1972) Smooth preferences. Econometrica 40:603–612

Dierker E (1972) Two remarks on the number of equilibria of an economy. Econometrica 40:951–953

Dorfman R, Samuelson P, Solow R (1958) Linear programming in economic analysis. McGraw-Hill, New York

Ehrlich I, Becker G (1972) Market insurance, self insurance, and self protection. J Polit Econ 80(4):623–648

Elias P (1995) Northern aboriginal communities: economies and development. Captus University Publications, Ontario

Elliott A (1997) Corruption and the global economy. Institute for International Economics, Washington

Feigenbaum M (1978) Quantitative universality for a class of non-linear transformations. J Stat Phys 19:25–52

Fischhoff B, Lichtenstein S, Slovic P, Derby S, Keeny R (1981) Acceptable risk. Cambridge University Press, Cambridge

Freeman C, Louca F (2001) As time goes by: from the industrial revolutions to the information revolution. Oxford University Press, Oxford

Gardener MR, Ashby WR (1970) Connectance of large dynamic (cybernetic) systems: critical values for stability. Nature 228(5273):784

Gershuny J (2011) Time-use surveys and the measurement of national well-being. Centre for Time-use Research, Department of Sociology, University of Oxford, Oxford

Goldenfeld N, Kadanoff L (1999) Simple lessons from complexity. Science 284:87–89

Green G (2004) The evaluation of vulnerability to flooding. Disaster Prev Manag 13(4):323–329

Greenberg M, Lahr M, Mantel N (2007) Understanding the economic costs and benefits of catastrophes and their aftermath: a review and suggestions for the U.S. Federal Government. Risk Anal 27(1):83–96

Halperin R (1990) The livelihood of Kin: making ends meet the Kentucky way. University of Texas Press, Austin

Halperin R (1994) Cultural economies past and present. Univeristy of Texas Press, Austin

Hewings G, Sonis M, Madden M, Kimura Y (1999) Understanding and interpreting economic structure: advances in spatial science. Springer, Berlin

Hoff K, Braverman A, Stiglitz J (1993) The economics of rural organization. Oxford University Press/World Bank, Oxford

Hood C, Jones D (1996) Accident and design: contemporary debates in risk management. University of London Press, London

Humber J, Almeder R (1987) Quantitative risk assessment: biomedical ethics reviews. Humana Press, Clifton, NJ

Jansch E, Waddington C (1976) Evolution and consciousness. Addison-Wesley, Boston, MA

Kay B (1993) Chaos and complexity. VCH Publishers, New York

Kehoe T (1988) Computation and multiplicity of equilibria. In Anderson, Arrow, and Pines (op cit)

Kunrether H, Slovic P (1978) Economics, psychology, and protective behavior. Am Econ Rev 68(2):64–69
Kunreuther H, Pauly M (2003) Neglecting disaster: why don't people insure against large losses. Wharton School, March
Kunreuther H, Rose A (eds) (2004) The economics of natural hazards, international library of critical writings in economics. Elgar, Cheltenham
Kunreuther H et al (2011) The costs and benefits of reducing risk from natural hazards to residential structures in developing countries. IIASA, Vienna
Lakdawalla D, Zanjani G (2006) Catastrophe bonds, reinsurance, and the optimal collateralization of risk-transfer. NBER Working Paper No. 12742, December 2006, JEL No. G11, G22
Landa J (1994) Trust, ethnicity, and identity. Unversity of Michigan Press, Ann Arbor, MI
Ledesdorf L, van der Besselaar P (eds) (1994) Evolutionary economics and chaos theory: new directions in technology studies. Pinter, London
Lloyd P (2001) The origins of the von Thunen-Mill-Pareto-Wicksell-Cobb-Douglas function. Hist Polit Econ 33(1):1–6
Lorentz EN (1963) Deterministic nonperiodic flow. J Atmos Sci 20:130–141
Lotka A (1920) Analytic notes on certain rhythmic relations in organic systems. Proc Natl Acad Sci U S A 6:410–415
Louberge H, Schlesinger H (1999) Optimal catastrophe insurance with multiple catastrophes. International Center for Financial Asset Management and Engineering, Research Paper 7, University of Alabama
MacPherson A, McConnell J, Vance A, Vanchan V (2006) The impact of U.S. Government anti-terrorism policies on Canada-U.S. cross-border commerce. Canada-United States Trade Center, University at Buffalo
Mandelbrot B (1982) Fractal geometry of nature. W.H. Freeman, New York
Mandelbrot B (1999) Fractals and scaling in finance: discontinuity, concentration, and risk. Springer, New York
Mansfield Y, Pizam A (2006) Tourism, security, and safety. Butterworth Heinemann, London
Markowitz H (1959) Portfolio selection: the efficient diversification of investments. Wiley, New York
Martin I, Pindyck R (2015) Averting catastrophes: the strange economics of Scylla and Charybdis. Am Econ Rev 105(10):2947–2985
Merton RC (1973) Theory of rational option pricing. Bell J Econ Manag Sci 4:141–183
Modical M, Zoboli R (2016) Vulnerability, resilience, hazard, risk, damage, and loss: a socio-ecological framework for natural disaster analysis. Web Ecol 16:59–62. www.web-ecol.net/16/59/2016/. https://doi.org/10.5194/we-16-59-2016
Morton A (1991) Disasters and dilemmas: strategies for real-life decision making. Basil Blackwell, Oxford
Nelson R (1956) Theory of low-level equilibrium trap in underdeveloped economies. Am Econ Rev 46(5):894–908
Nelson R (1995) Recent evolutionary theorizing about economic change. J Econ Lit 33:48–90
Neubert M, Caswell H (1997) Alternatives to resilience for measuring the response of ecological systems to perturbations. Ecology 78:653–665
Nirei M (2004) Lumpy investment, sectoral propagation, and business cycles. Working Paper, Santa Fe Institute, New Mexico
OECD (2013) Risk and resilience: from good idea to good practice. WP 13/2013
Okuyama Y, Chang S (eds) (2004) Modeling spatial and economic impacts of disasters, Advances in science. Springer, Heidelberg
Okuyama Y, Sahin S (2009) Impact estimation of disasters: a global aggregate for 1960 to 2007. World Bank, Policy Research Working Paper 4963
Okuyama Y, Santos J (2014) Disaster impact and input-output analysis. Econ Syst Res 26(1):1–12. https://doi.org/10.1080/09535314.2013.871505
Prigogine I (1976) Order through fluctuations: self-organization and social systems. In Jansch E, Waddington C. (op cit)

Rose A, Laio S (2005) Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. J Reg Sci 45(1):75–112
Rose A, Benavides J, Chang S, Szczesniak P, Lim D (2004) In: Shinozuka M, Rose A, Eguchi R (eds) The regional economic impacts of an earthquake. Wiley, Hoboken, NJ
Sen A (2000) Development as freedom. Random House, New York
Shapely L, Shubik M (1977) An example of a trading economy with three competing equilibria. J Polit Econ 85:873–875
Shinozuka M, Rose A, Eguchi R (1998) Engineering and socioeconomic impacts of earthquakes. MCEER, Buffalo
Shreve C, Kelman I (2014) Does mitigation save? Reviewing cost-benefit analyses of disaster risk reduction. Int J Disaster Risk Reduct 10:213–235
Siegel P, Johnson T, Alwang J (1995) Regional economic diversity and diversification: seeking a framework for analysis. Growth Chang 26(2):261–284
Skoufias E, Quisumbing A (2003) Consumption insurance and vulnerability to poverty: a synthesis of evidence for Bangladesh, Ethiopia, Mali, Mexico, and Russia. Inter-American Development Bank, Washington
Smith E (1990) Perspectives on the informal economy. University Press of America, New York
Smith K (1996) Environmental disaster: assessing risk and reducing disaster. Routledge, New York
Sternberg E, Lee G (2006) Meeting the challenge of facility protection for homeland security. J Homel Secur Emerg Manag 3(1):1–19
Stone R (1961) Input-output and national accounts. Organization for Economic Cooperation and Development, Paris. System for National Accounts, United Nations, New York
Taylor L, Lysy F (1979) Vanishing income redistributions: Keynesian clues about model surprises in the short run. J Dev Econ 6:1
Tobin G, Montz B (1997) Natural hazards: explanation and integration. Guildford Press, New York
Toyama M, Sagara J (2012) CTI engineering measuring the cost-effectiveness of various DRM measures 3 measuring the cost-effectiveness of various DRM measures World Bank 2012 knowledge note. pp 6–1
Twigg J (2001) Sustainable livelihoods and vulnerability to disasters. Disaster Mitigation Unit, Working Paper, 2/2001
UNISDR (2005) World conference on disaster reduction. 18–22 January 2005, Kobe, Hyogo, Japan
van der Veen A (2003) In search of a common methodology on damage estimation. In: van der Veen A (ed). EUR 20997 EN, Joint Research Center, Ispra, European Commission
van der Veen A et al (1994) Cost-benefit analysis and multi-criteria analysis. J Coast Eng. University of Twente, Netherlands
Walsh F (2012) Developmental perspectives on family functioning (Ch 17). Family resilience: strengths forged through adversity in normal family processes. Guildford Press, New York, pp 399–427

Professor Emeritus Sam Cole joined the Department of Regional Planning at the University at Buffalo in 1983. Educated in theoretical physics at Imperial College, London, and Sussex University with post-doctoral fellowship at the Cavendish Laboratory Cambridge, Professor Cole joined the UK Department of Environment Urban Planning Division and the Science Policy Research Unit at Sussex University. He has consulted with international and regional development agencies and private organizations in many countries in Africa, Asia and the South Pacific, and the Americas. He has prepared policy documents and models, for several international agencies including the Commission on Culture and Development, the UN Population Division, UNITAR, DEASA, and the UNESCO Medium Term Plan, and the economic plan for the independence of the island nation of Aruba. Professor Cole continues to research global-local interactions and structures, disaster management, tourism, chaos and public policy issues in the Caribbean and elsewhere.

Chapter 12
Vulnerability, Resilience and Exposure: Methodological Aspects

Marco Modica, Aura Reggiani, and Peter Nijkamp

Abstract The economic recession which followed the 2008 financial crisis has raised important issues on differences in the impact, especially from a spatial perspective, of the socio-economic shocks—at both the regional and the community level, especially in the European Union Member States. These differences may be due to the different levels of vulnerability, resilience and exposure, and may arise because of dissimilarities in the intrinsic characteristics of regions or communities (e.g. the pre-crisis economic characteristics of regions, ageing, household income, and so on). While, in the scientific literature, a great deal of attention has been paid to the concept of resilience (e.g. the capacity to bounce back or to resist a given shock) and vulnerability (e.g. the inherent characteristics that create the potential for harm), less attention has been paid to the full set of measures of socio-economic exposure (e.g. the things affected by a shock), as well as to both the relationship between vulnerability, resilience and exposure and the losses which ensue as a result of different external shocks and exposure.

The objective of this chapter is the exploration of the above-mentioned links, since a closer analysis of these complex interrelations might produce different outcomes. This study aims to review systematically the existing literature on vulnerability, resilience and exposure, in order to understand the connections between these concepts, with reference not only to economic shocks but also to other catastrophic events, such as natural disasters, man-made disasters, and so on.

M. Modica (✉)
Gran Sasso Science Institute (GSSI), L'Aquila, Italy
e-mail: marco.modica@gssi.it

A. Reggiani
Department of Economics, University of Bologna, Bologna, Italy
e-mail: aura.reggiani@unibo.it

P. Nijkamp
Tinbergen Institute, Amsterdam, The Netherlands

Adam Mickiewicz University, Poznań, Poland

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_12

12.1 Introduction

In recent years, a number of events have dramatically increased the perception of instability, insecurity and uncertainty across the world (Christopherson et al. 2010). To mention but a few of these events, we may refer to, economic crises (e.g. the great economic recession after the crisis of 2008); natural and man-made disasters or even compound events (e.g. the earthquake, tsunami and nuclear power plant accident because of the Tōhoku earthquake and tsunami in 2011); political instability (e.g. the coup attempt in Turkey in 2016); and terrorist attacks (e.g. the terrorist attacks in Paris in 2015). The combination of all these crises has most likely played a significant role in generating a general sense of insecurity (Hudson 2010).

However, it is possible to recognise differences of shocks—at both the regional and the community level (Modica 2014; Modica et al. 2017a, b). These differences are relevant, since the shock might occur as a result of dissimilarities in the intrinsic characteristics of regions or communities (e.g. the pre-crisis economic characteristics of regions, ageing, household income, etc.) that are able to influence the capacity of areas to recover from or resist a shock. While a great deal of attention has been paid, in the scientific literature, to the concept of vulnerability (e.g. inherent characteristics that create the potential for harm; Modica and Zoboli 2016) and resilience (e.g. the capacity to bounce back, or to resist a given shock, or the ability to adapt after a shock and to develop new growth paths; Martin 2012), less attention has been devoted to full measures of exposure (e.g. all the objects that are potentially affected by a shock, such as buildings and infrastructure when considering physical exposure, or population when considering socio-economic exposure), as well as to the relationships between vulnerability, resilience and exposure, in relation to different external shocks.

The objective of this chapter is the exploration of the above-mentioned links, since these interrelations might produce different outcomes. To this purpose, we first aim to review the existing literature on vulnerability and resilience in order to understand the connections between these concepts, with reference not only to economic shocks, but also to other catastrophic events, such as natural disasters, man-made disasters, and so on. Next, we focus on the concept of exposure, by concentrating on objects or areas exposed to a shock.

Given the wide coverage of these concepts and the wide array of disciplines relevant to these issues, it is becoming common in the literature to focus vulnerability/resilience on the following elements: (a) what?, (b) when?, (c) where?, and (d) for whom? (Faggian et al. 2017; Meerow and Newell 2015; Modica and Reggiani 2014, 2015). Using this framework, we may identify from the literature on vulnerability and resilience three main topics, for which it is possible to apply these concepts ('what'), at least in the social sciences: economic shocks; natural and man-made disasters; and terrorist attacks. These events are all exogenous shocks that can be considered as the trigger of a response for a given object or area ('for whom') that defines an ex-ante and an ex-post period ('when'). From an analysis of the literature, we distinguish four main classes of objects or entities: firms;

infrastructures; communities and regions/areas. The ‘where’ question is mostly related to the location of shocks; indeed with regard to natural and man-made disasters, we may recognise different places such as urban or rural areas, whereas states, (sub)regions or municipalities are typically analysed in the presence of economic shocks.

The chapter is organised as follows. In the next section we review the available literature in relation to the socio-economic vulnerability issue. Next, in Sect. 12.3 we review the resilience literature. Section 12.4 considers the exposure concept on the basis of the preceding two sections. Section 12.5 provides a discussion on the connections between the two concepts of vulnerability and resilience, in relation to the notion of exposure. Finally, Sect. 12.6 concludes with some retrospective and prospective remarks.

12.2 Vulnerability

As indicated in the previous section, a wide range of different disciplines uses the term ‘vulnerability’, producing a multi-faceted meaning that differs according to the different objectives and points of view of the analysts. On the basis of the work by Sarewitz et al. (2003), a rough and general definition that encompasses several aspects of vulnerability is as follows: an inherent characteristic of individuals, communities, networks, infrastructure, and systems that is able to produce the potential (negative) effects, regardless of the risk of occurrence of any particular shock such as economic crises, natural and man-made disasters or, even terrorist attacks.

Given these premises, it is evident that a vulnerability approach may analyse this concept from several points of view. One way to review the literature on vulnerability is to focus on the variables that are commonly used to define and analyse vulnerability. Through a Scopus search concerning the key terms of ‘vulnerability’, ‘economic vulnerability’, and ‘social vulnerability’ as keywords, in the economics area, initially 596 articles were selected; among these, only 32 were in line with our analysis in terms of the specific type of shock under analysis (e.g. recession or natural and man-made disaster) and we discharged articles addressing issues such as food security, ecology or very specific business (e.g. small scale fishermen).

This review shows that most studies analyse vulnerability in particular by means of composite indicators that include several aspects of the object of analysis. Vulnerability indicators are more or less complex, varying from only one variable to other more complex indicators which may include as many as 28 variables. In addition, all the adopted variables can be encoded to ten ‘domains’: economic (e.g. measures of wealth, inequality, employment and so on); institutional (e.g. corruption, institutional capacity, etc.); social (e.g. education, human health, etc.); business (e.g. business density, productivity, etc.); demographic (e.g. age structure, gender); natural (e.g. air pollution, quality of water, etc.); land (e.g. land use, urbanization); agricultural (e.g. presence of arable land, dependency on agriculture, etc.); material (e.g. infrastructures, buildings, etc.); and risk (e.g. exposure to hazard).

Table 12.3, in Annex 1, contains a review of the selected papers that analyse vulnerability by means of composite indicators. In Table 12.3, the papers are ordered according to the number of variables included in the composite indicator, without considering duplicate variables from the papers in the above rows. The identification of the variables as described above (i.e. according to the ten domains) is also included.

As a key finding we note here that most analyses refer to natural disasters (21 papers), while only a few papers focus on economic measures of vulnerability (5 papers), even though the economic and social environment are fundamental aspects evaluated in all studies concerned.

For an in-depth discussion on the composition of the variables included in the vulnerability analysis, we refer to Sect. 12.5 which provides a comparison with the aspects of resilience. We now proceed in the next section with a first look at the analysis of resilience.

12.3 Resilience

Given the broad extent of the disciplinary fields where the resilience concept can be applied, it is necessary to treat resilience according to its definition, context,[1] and measurement. Much of resilience has been 'imported' in the social sciences from other disciplines such as ecology (Holling 1973; Pimm 1984) and engineering (Bruneau et al. 2003; Haimes 2009). For this reason, the interpretation and the definition of resilience changes according to the context of the analysis, though Rose (2007) contends that there are more commonalities than differences in the definitions. For instance, when looking at resilience to economic shocks, Duval et al. (2007) define economic resilience as the ability to maintain the economic outcome close to the potential growth path in the aftermath of a shock. Rose (2007), on the other hand, defines resilience as the ability of a system to maintain its function after the shock (static resilience) or to hasten the speed of recovery (dynamic resilience, see also Rose and Krausmann 2013). When the context pertains to address natural and man-made disasters, even the interpretation of resilience may be slightly different: for instance, Rose and Liao (2005) and Rose (2007) mainly focus on the both inherent and adaptive ability of firms and regions to reduce the potential losses of a shock (e.g. maintaining function and speeding recovery).[2] Similarly, Bruneau et al. (2003) address four dimensions of resilience, extending beyond engineering to also

[1]Context includes features such as scale, as for example the micro (individual business), meso (sector or market) or macro (entire economy or system) levels.

[2]Inherent resilience pertains to resilience that is already ingrained in the system, while adaptive resilience pertains to improvisations in reaction to the shock. Rose (2007, 2017) emphasizes that resilience is actually a process, whereby resilience capacity can be enhanced prior to the shock (e.g., stockpiling critical materials, purchasing backup electricity generators lining up alternative suppliers, making the system more flexible in general), though most of the enhanced capacity is not applied until after the disaster strikes.

include the reduction of the economic and social disruptions caused by a natural disaster on the social units concerned.

Interestingly, in the large number of definitions of resilience identified in our review, two major characteristics of resilience can be recognised: (1) the capacity to recover from shocks; and (2) the degree of preparedness. These characteristics lead to three main definitions of resilience: (1) the capacity to recover from a shock (known as ecological resilience; Holling 1973; Pimm 1984); (2) the capacity to resist a shock (known as 'engineering resilience'; Bruneau et al. 2003; Haimes 2009)[3]; and (3) the ability to adapt after a shock (known as 'adaptive resilience'; Martin 2012) or to develop new growth paths (Boschma 2015).[4] All the aspects mentioned above are clearly useful for a better comprehension of the works considered in the literature review.

After a Scopus, in the economic area, search on the terms 'resilience', 'economic resilience' and 'community resilience', initially 311 papers were identified; however, only 31 papers were finally selected as being consistent with the aim of our study in terms of the specific type of shock under analysis (e.g. recession or natural and man-made disaster). Furthermore, we discharged articles addressing very specific business (e.g. firms of a given industrial sector) because we keep our analysis more general as possible.

From our review, large differences in the analysis of economic resilience and resilience to natural disasters appear to emerge. Economic resilience is typically addressed by means of empirical analysis selecting one key factor (e.g. employment, sales revenue GDP, etc.) as the dependent variable, while resilience to natural disasters is mainly expressed by means of composite indicators that include several aspects of the object of analysis. This difference is to a great extent due to the fact that economic impacts can be more readily reduced to a single common denominator, such as dollars or jobs.[5]

Table 12.4, in Annex 2, contains a review of the papers which analyse resilience. Analogously to Table 12.3, in Table 12.4 the papers are ordered according to the number of variables included in the composite indicator without considering duplicate variables. The identification of the variables as described above (i.e. according to the ten domains) is also included.

Our main finding is that most analyses of economic resilience refer to the resilience of regions to financial crises (21 papers), while only a few papers provide an economic evaluation of resilience to natural disasters (4 papers).[6] In addition, in the light of natural disasters, 6 papers evaluate the social response of communities to

[3]This is often referred to as 'robustness'.

[4]We note that ecologists overlap their definition of recovery sometimes with the concept of adapting; however, for explanatory reasons we prefer to separate the two concepts.

[5]We thank one of the editors for this noteworthy suggestion.

[6]This outcome arises because our identification strategy is based on reviewing primarily economics journals (see for instance, Kajitani and Tatano 2009 and Wein and Rose 2011). It should be noted that, in this phase of the analysis, we did not consider papers written by economists and social scientists in 'hazards' journals (see e.g. Rose 2017 and Rose et al. 2016).

extreme weather conditions. Before going in-depth in these two latter sections, we move in defining some basic issues related to the exposure.

12.4 Exposure

Given the similarities and differences in the concepts of vulnerability and resilience, and in the light of multi-faceted meaning of these two concepts, it is important to define now appropriately, the essence and relevance of the concept of exposure. Exposure is a state of a phenomenon that may be affected by an external force. In the context of vulnerability and resilience, exposure relates to all the elements at risk from the shock under analysis; in particular, according to Cardona et al. (2012, p. 69), exposed elements comprise '*human beings, their livelihoods, and assets*'. A correct definition of exposed variables may be important for two reasons. First, a good description is needed for a proper definition of the relevant research framework as well for developing the appropriate research questions. Second, many studies aim to analyse vulnerability and resilience for policy-relevant issues, for instance, to develop mitigation plans in reducing the vulnerability to hazards (Berry et al. 2006; Godschalk et al. 1998; Kythreotis and Bristow 2017; Modica et al. 2017b) or to draw a resilient policy and adaptive strategy so as to face economic crises (MacKinnon and Derickson 2013; Modica et al. 2018; Somers 2009).

However, for a proper evaluation of recovery policies it is necessary to know the precise number and nature of exposed entities (e.g. in some cases, the exposure might be too small to justify a policy action). Given the difficulties of addressing all relevant exposed variables considered in the literature, we offer a discussion of exposure variables in the next paragraph, by assuming that the choice of a proxy for exposure mostly depends on the sequence of effects which are expected to occur when a shock affects the object under analysis (Modica and Zoboli 2016; Pelling 2003).

As we have previously indicated, exposure is usually characterised by three main dimensions that are all related to human being, namely, human life, their livelihoods, and their assets. In addition, according to different types of analysis, many differences in the exposure variables used can be observed. For example, the density of the built environment (asset) is used as the exposure variable in case of flood risk assessment (e.g. Jongman et al. 2012; Koks et al. 2014, 2015: Sterlacchini et al. 2016); Gross Domestic Product (livelihoods), population density (human life), and the value of real estate assets are used in earthquake loss assessment (Field et al. 2005; Meroni et al. 2016). As a last step, it may be necessary to mention briefly the potential losses caused by a shock. It turns out that, in the case of economic crises, potential losses are estimated by looking at macroeconomic variables that are able to synthesise the aggregate exposed value of the entire economic system (e.g. GDP, employment, Gross Value Added, GVA, etc.). When considering natural disasters, the assessment is much more complex; in this case, there is an extensive literature which focusses on what might be defined as losses due to extreme events (for more details see Marin and Modica 2017 and ECLAC 2003). In this regard, direct and indirect losses can be distinguished. Direct losses refer to direct damage to people (injuries and fatalities) and objects (e.g. goods, buildings, infrastructures; see ECLAC 2003) or even damage arising from the interruption of economic activities (see Rose and Lim 2002; Rose et al. 2007). The category of indirect losses is clearly broader, as this includes all losses caused by disasters through a sequence of actions or reactions that are not directly related to the extreme event but that started because of the shock. As an example, foregone production experienced because of the interruption of activities in relation to a disaster might affect the whole supply chain of the production activities including that of customers and suppliers (see e.g. Van Der Veen and Logtmeijer 2005). Other examples include fires caused by earthquakes due to gas line breaks or toxic material releases from several types of natural disasters due to breakage of containers (see Young et al. 2004 for a review).

In the next section, we will discuss the results from our review of the literature by considering the link between vulnerability, resilience and exposure. In particular, we summarise the results provided in Sects. 12.2 and 12.3, by underlining that the main variables typically used in a vulnerability and resilience framework can be conceived of as general measures of exposure.

12.5 Methodological Connections Between Vulnerability, Resilience and Exposure

As highlighted in the previous sections, vulnerability is an inherent characteristic of individuals, communities, networks, and systems that, when interacted with exposure, might induce potential (negative) effects, regardless of the risk of occurrence of any particular shock. Resilience, on the other hand, is the capacity to recover from a shock, the capacity to resist, or the ability to adapt after a shock and to develop new growth categories. Actually, the link between these two concepts is still debated (Cutter et al. 2008), but the two concepts share common characteristics, as is denoted in Tables 12.1 and 12.2. Indeed, both these concepts focus mainly on the economic 'environment' and, in particular, on the macroeconomic characteristics of the object of analysis. Economic aspects are therefore important issues for both vulnerability and resilience studies. One possible explanation is that socio-economic conditions influence both the inherent characteristics of individuals, communities, and network infrastructures (for instance, richer people live in dwellings which are better built in relation to the quality of materials used) and the capacity to recover from a shock.

But, when looking at vulnerability as a stand-alone concept, the literature focusses on other inherent characteristics that can influence the vulnerability of people or goods; for instance, the agricultural environment plays an important role in the vulnerability literature, because it is often related to the capacity of communities to deal with external shocks (especially natural disasters) in less developed countries. For this reason, agricultural issues are covered by almost 50% of the papers analysed in our review. Likewise, land use is an important aspect in vulnerability analysis, because the man-made environment of territories often creates a great source of vulnerability,

Table 12.1 Review of vulnerability characteristics, by number of papers and their percentage of the total

Environment	Total	Sub-environment	No. of papers	% of the total
Agricultural	12/32	Extension of agriculture (e.g. arable land)	11	34.4
		Dependency on agriculture (e.g. food import dependency	5	15.6
		Rural population	2	6.3
Business	6/32	Financial exposure (e.g. debt/equity)	1	3.13
		Density of business	3	9.4
Demographic	16/32	Age	14	43.8
		Gender	3	9.4
		Population growth	2	6.3
Economic	28/32	Macroeconomic performance (e.g. GDP, saving)	18	56.3
		Debt (e.g. sovereign debt rating)	3	9.4
		Total revenue	2	6.3
		Transportation costs	1	3.1
		Poverty	13	40.6
		Household debt	3	9.4
		Inequality	7	21.9
		Unemployment	8	25
		Productivity	1	3.1
		Sectorial dependence	4	12.5
Institutional	13/32	Corruption	2	6.3
		Dependence on external resource (e.g. energy imports)	3	9.4
		Emergency plans (e.g. failure to communicate knowledge)	4	12.5
		Government effectiveness (e.g. governance index)	2	6.3
		Institutional capacity	6	18.8
		Political rights	5	15.6
Land	18/32	Land use (e.g. relative urban entropy)	3	9.4
		Population pressure (crowding)	13	40.6
		Urbanisation (e.g. formation of slums)	5	15.6
Material	8/32	Infrastructure characteristics (e.g. road density)	3	9.4
		Building characteristics (e.g. number of buildings)	8	25
Natural	10/32	Air pollution	2	6.3
		Ecosystem conversion (e.g. % land unmanaged)	4	12.5
		Ecosystem service value	1	3.13
		Environmental sustainability	2	6.3
		Erosion	2	6.3
		Soil pollution	2	6.3
		Water pollution	5	15.63

(continued)

Table 12.1 (continued)

Environment	Total	Sub-environment	No. of papers	% of the total
Risk	11/32	Insurance	1	3.13
		Population at risk	4	12.5
		Previous disaster effects (e.g. number of people affected)	6	18.8
Social	17/32	Crime	2	6.3
		Disability	2	6.3
		Education (e.g. literacy rate)	14	43.8
		Family structure (e.g. % of single parents)	5	15.6
		Female condition (e.g. rate of female inactivity)	5	15.6
		Health conditions (e.g. child mortality)	12	37.5
		Ethnic minorities	4	12.5
		Social capital	3	9.4

especially when analysing natural disasters. Finally, socio-economic aspects are also of a great importance in the analysis of vulnerability.

When addressing resilience as a stand-alone concept, much scientific attention appears to be paid to institutional and business domains. The first of these aspects refers to the capacity to develop mitigation measures and to respond to a given shock (e.g., natural disasters or economic crises); the latter aspect focusses on the capacity of business activities to be prepared for or to innovate after a shock.

Vulnerability and resilience appear to have some common characteristics, mainly regarding the socio-economic conditions of the objects of the analysis. However, a certain ambiguity still exists between vulnerability and resilience concepts (see e.g. Gallopín 2006).

As already suggested by previous authors the concepts of vulnerability and resilience need thorough attention in order to shed light on the characteristics that determine the degree of vulnerability and resilience in a socio-economic and ecological system. In fact, in the previous sections we have shown the main variables that may be considered as synthetic indicators of these two concepts. However, following Cutter et al. (2008, p. 600), the statement that "*the literature is divided when it comes to explaining the causal structure of vulnerability*" is noteworthy (see also Cutter 1996 and Ribot 1995 for more details). This statement is even more appropriate when it comes to explain the causal structure of resilience. Moreover, without a solid underpinning of the conditions that characterize vulnerability and resilience, it will be difficult to point out a clear relationship between these two concepts. As an example of this ambiguity we refer to an earlier paper (Mustafa 1998, p. 294), which states that '*vulnerability to hazard is caused by lack of resilience against environmental stress, and resilience is a function of access to productive resources, health, education, and political empowerment*'. In a more recent publication (Cutter et al. 2008), the connection between vulnerability and

Table 12.2 Review of resilience characteristics by number of papers and percentage of the total

Environment	Total	Sub-environment	No. of papers	% of the total
Agricultural	1/31	Rural characteristics	1	3.2
Business	10/31	Financial exposure (e.g. debt/equity)	1	3.2
		Density of business	6	19.4
		Credit market	2	6.5
		Corporate Taxation	1	3.2
		Redditivity (e.g. return on equity)	4	12.9
Demographic	6/31	Age	3	9.7
		Gender	4	12.9
		Population growth	2	6.5
Economic	31/31	Macroeconomic performance (e.g. GDP, savings, gross domestic fixed investments, consumption, growth, trade, inflation)	22	71.0
		Debt (e.g. sovereign debt rating)	7	22.6
		Poverty	9	29
		Housing (e.g. home ownership)	6	19.4
		Inequality	4	12.9
		Unemployment	16	51.6
		Productivity	7	22.6
		Sectorial dependence	5	16.1
Institutional	14/31	Emergency plans (e.g. failure to communicate knowledge)	3	9.7
		Government effectiveness (e.g. governance index)	6	19.4
		Institutional and financial capacity	8	25.8
		Political fragmentation	3	9.7
		Political rights	1	3.2
Land	3/31	Land use (e.g. relative urban entropy)	3	9.7
		Population pressure (crowding)	3	9.7
		Urbanisation (e.g. formation of slums)	2	6.5
Material	7/31	Infrastructure characteristics (e.g. road density)	3	9.7
		Building characteristics (e.g. number of buildings)	4	12.9
Natural	7/31	Air pollution	1	3.2
		Ecosystem conversion (e.g. % land unmanaged)	4	12.9
		Ecosystem service value	1	3.2
		Environmental sustainability	1	3.2
		Erosion	1	3.2
		Soil pollution	2	6.5
		Water pollution	3	9.7
Risk	3/31	Insurance	2	6.5
		Previous disaster effects (e.g. number of people affected)	1	3.2

(continued)

Table 12.2 (continued)

Environment	Total	Sub-environment	No. of papers	% of the total
Social	13/31	Accessibility	4	12.9
		Crime	1	3.2
		Disability	2	6.5
		Education (e.g. literacy rate)	8	25.8
		Family structure (e.g. % of single parents)	1	3.2
		Female condition (e.g. rate of female inactivity)	2	6.5
		Health conditions (e.g. child mortality)	7	22.6
		Ethnic minorities	3	9.7
		Quality of life	1	3.2
		Social capital	8	25.8

resilience was visually presented in Venn diagrams (Fig. 12.1). More specifically, this figure addresses the question whether resilience is part of vulnerability or the other way round, or whether vulnerability and resilience show common characteristics but are two separate concepts.

To answer the above question we provide in Fig. 12.2 a comparison of vulnerability and resilience in terms of the ten 'domains' that we have emphasized in the previous sections and that stem from our review of the literature. As a preliminary finding we can affirm that—only with the exception of economic and social characteristics, which show up to be in the literature with almost the same frequency—all the other 'domains' are distributed in different ways regarding vulnerability and resilience. For instance, for the vulnerability indicators, agricultural, demographic, land and risk variables are appearing more frequently than for the resilience indicators. On the contrary, business, institutional and material variables appear more frequently for resilience indicators.

Clearly, both concepts seem to show common characteristics that are especially arising from underlying socio-economic conditions. A further aspect that deserves attention concerns the main variables that are typically used in a vulnerability and resilience framework. We have selected the five most recurring variables for both the vulnerability and the resilience indicators.

Figure 12.3 provides more details. First, among the first five indicators in order of appearance regarding vulnerability and resilience, three variables appear to be recurrent in the analysis of both concepts. They are: the macroeconomic performance of the area under analysis (e.g., GDP, which ranks first in both vulnerability and resilience analysis), the level of education (third in vulnerability and fifth in a resilience framework), and a poverty indicator (respectively fifth and third). All these variables fall in the sphere of the socio-economic 'domains'.

It is interesting to notice that while the top-5 variables are quite equally distributed in terms of frequency of appearance in the literature when looking at the vulnerability literature, this is not the case for the top-5 variables used in the

Fig. 12.1 Adaptation of the conceptual linkages between vulnerability and resilience provided by Cutter et al. (2008, p. 600, Fig. 1)

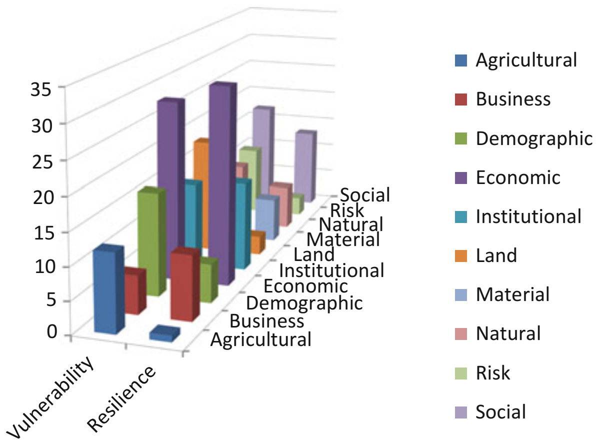


Fig. 12.2 Comparison of vulnerability and resilience characteristics by 'domains' (frequency of papers)

resilience framework, where wealth and (un)employment account for a greater part of the literature.

As a last step of this analysis, it is interesting to note that, as mentioned in Sect. 12.4, among the variables used to define 'components' of vulnerability and exposure, some are basically variables that are able to identify the exposure of a given area to a shock. Referring again to the more frequent variables used in the context of vulnerability and resilience (see Fig. 12.3), three variables can be interpreted as related to exposure, namely, macroeconomic performance (e.g. GDP), (un)employment and population (density). Even though the last two variables are not the top variables used for identifying resilience and vulnerability (respectively), they—jointly with the macroeconomic performance indicator—seem to capture well the exposure concept. In fact, the macroeconomic performance is an exposure measure *per se* that is able to summarize all exposed economic assets of an area in a synthetic value indicator (i.e., all assets). At the same way, (un)employment is a proxy that is able to characterise the livelihoods of a given area; it is typically used to evaluate, for

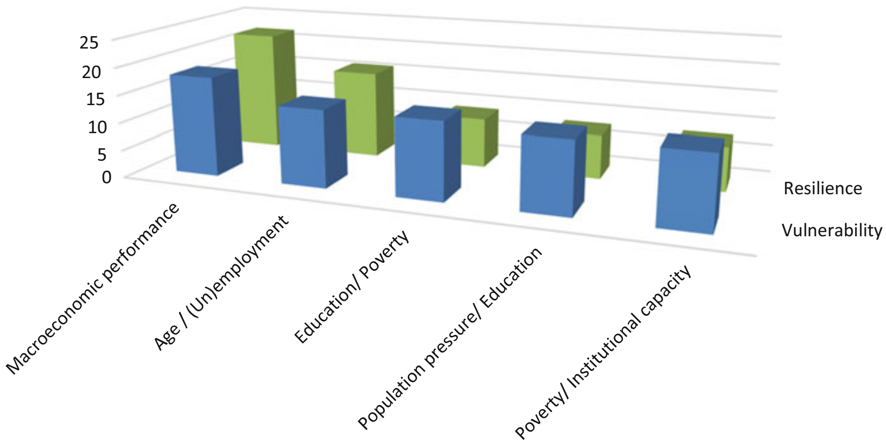


Fig. 12.3 Top-5 indicators of vulnerability and resilience (frequency of papers). When only one indicator is reported on the *x-axis*, it means that it is common between vulnerability and resilience. When two different indicators are reported, the first is related to vulnerability and the second to resilience (e.g. age/(un)employment are the second most frequent indicators used for vulnerability and resilience, respectively)

instance, the regional resilience (see Martin 2012). Population pressure, instead, provides a value for the exposure of human beings (the potential life loss when an area is affected by a natural disaster for example). At the extreme, even the level of education might be interpreted as a value of exposure, viz. as the potential loss of human capital due to an external shock.

All in all, this pattern indicates that even though vulnerability, resilience and exposure show some common characteristics especially regarding the socio-economic variables, these three concepts capture different meanings that are strongly interrelated though. In sum, vulnerability concerns the (degree of) susceptibility of the system, while resilience refers to the capacity of the system to react to shocks and finally exposure is the potential loss.

12.6 Conclusions

The aim of this chapter was to provide an in-depth investigation of the concepts of resilience, vulnerability and exposure, on the basis of the scientific literature. Consequently, we have reviewed several papers dealing with two relevant concepts, resilience and vulnerability; they provided evidence of the close link between these two concepts. Furthermore, attention was paid to another recent concept, i.e. exposure, which has been less analysed in the literature on economic and natural disasters. In this framework, a series of articles which adopt different measures of exposure in different contexts were analysed as well.

Our analysis here provided several novel insights. First, we denote that greater consensus is reached by the definition of the components that characterise the vulnerability concept with respect of those for resilience. Indeed, five variables are commonly used in a vulnerability index/analysis (e.g. macroeconomic performance, age, education, population pressure and poverty), while, looking at the resilience indicators/analyses, only two variables have received greater consensus (e.g. macroeconomic performance and unemployment). Second, we provide a discussion on the fact that relatively little interest is given to the concept of exposure, even though this is a main component in any analysis on evaluation of (natural or economic) risk. Finally, we highlight that, even though vulnerability and resilience share common characteristics, they need to be analysed as distinct but connected concepts.

Further analyses may be devoted in the future to the exploration of the connections between vulnerability, resilience and exposure, particularly with a view to building more sophisticated analyses able to take into account the multi-faceted aspects of external shocks.

Acknowledgment The authors wish to thank two anonymous referees, as well as the editors, for the valuable comments.

Annex 1

Table 12.3 Papers analysed for the vulnerability review

Paper, Year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Brooks et al. (2005)	Vulnerability to climate change	– Risk	1	– Number of people affected	–
Reggiani et al. (2016)	Economic vulnerability	– Economic	1	– Employment	Indicator
Flatø et al. (2017)	Vulnerability to climate change	– Economic	1	– Household income	Indicator
Wei et al. (2004)	Vulnerability to natural disasters in China	– Economic – Land – Risk	4	– GDP – Population density – Total cost of the damage	Data Envelopment Analysis (DEA)
UNDP (2015)	Social vulnerability to climate change	– Demographic – Economic – Social	4	– Expected years of schooling – GNI per capita – Life expectancy at birth – Mean years of schooling	Indicator
Briguglio (1995)	Vulnerability for small islands to climate change	– Economic – Risk – Natural – Demographic	6	– Ratio of imports and exports to GDP – Transport and freight costs – Index of disaster proneness – Environmental fragility – Dependence on foreign finance sources – Demographic changes	Indicator
Estoque and Murayama (2014)	Social-Ecological status	– Land – Risk	6	– Land use – National protected areas – Relative (urban) entropy – Ecosystem service values	Indicator
Haddad (2005)	Vulnerability to climate change	– Natural – Economic – Institutional – Social	7	– Gini coefficient – Low/middle income nation – % shared water basin – Political rights – PPP adjusted GDP – Sovereign debt rating – Water stressed countries	Indicator

(continued)

Table 12.3 (continued)

Paper, Year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Mustafa (1998)	Vulnerability to flood hazard	– Agricultural – Land – Economic – Social	8	– Landholdings – % of non-agricultural sources of income – Number of cattle heads – Market/community means of recovery (e.g. sales of livestock/loans from family)	Indicator
Zou and Wei (2009)	Vulnerability to coastal hazards in Southeast Asia	– Economic – Demographic	8	– External debt – GDP Annual change – Gross domestic saving – Ratio of agriculture – Ratio of consumption – Total revenue – Trade balance	Factor analysis over 41 variables
Ding et al. (2017)	Economic Vulnerability to climate change on marine fisheries	– Agriculture – Economic – Business – Institutional – Risk	8	– Gross indicator of climate change – Food security dependence – Employment dependency to marine resources – Economic dependency to marine sectors	Indicator
Vincent (2004)	Vulnerability to climate change in Africa	– Demographic – Economic – Institutional – Social	9	– Corruption – % of dependent population – Health expenditure – % HIV/AIDS – Poverty – Rural population – Urban population growth	Indicator
Graziano (2013)	Vulnerability of the economic dimension in Italy	– Business – Economic	9	– Bad loans to enterprise – Bad loans to households – Debt/equity – Production specialisation – Labour costs/value added – Net interest expenses – Protests/population – Rate of female inactivity	Factor analysis over 52 variables

Yohe and Tol (2002)	Vulnerability to natural disasters	– Business – Economic – Institutional – Risk – Social	10	– Income per capita – Land area	Indicator
Chakraborty et al. (2005)	Social vulnerability for evacuation assistance (USA)	– Economic – Material – Social	10	– Number of housing units – Number of mobile homes – group quarters – % of persons with disability – households with no vehicles	Indicator
Cutter et al. (2003)	Social vulnerability to environmental hazards	– Business – Demographic – Economic – Material	11	– % of minority per race – % employed in extractive industries; services and transportation – Median age – Commercial density	Factor analysis over 42 variables
Brooks et al. (2005)	Vulnerability to natural disasters	– Economic – Institutional – Social	11	– Average calorie intake – Government effectiveness – Literacy – Maternal mortality – No access to clean water – Voice and accountability	Correlation analysis over 46 possible vulnerability variables
Lonergan et al. (2000)	Vulnerability to climate change	– Economic – Institutional – Natural – Social	12	– Access to safe water – Child mortality – Energy imports – Expenditure in defense – Fertility rate – Food import dependency – Water Resources per capita	Indicator
Manuel–Navarrete et al. (2007)	Vulnerability to hydrometeorological disasters in Central America and the Caribbean	– Agricultural – Demography – Economic – Land – Risk – Social organisation	13	– Ecosystem conversion – Erosion – Expansion of agriculture – Failure to communicate knowledge – Presence of slums – Migration rural/urban – Population growth	Methodological framework

(continued)

Table 12.3 (continued)

Paper, Year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Yusuf and Francisco (2010)	Vulnerability to climate change in Southeast Asia	– Agricultural – Economic – Risk – Material – Social	13	– Electricity coverage – Extent of irrigation – Multiple hazard risk map – Fixed phones line – Road density	Indicator
Graziano (2013)	Vulnerability of communities dimension in Italy	– Demographic – Institutional – Social	13	– Accidents at work – Crime damages per capita – Death rate from several diseases – Traffic accidents per capita	Factor analysis over 57 variables
Colburn et al. (2016)	Social vulnerability in fishing dependent communities to climate change	– Demographic – Land – Economics – Business	13	– Poverty – Crime index – % females separated – % self employed – % of people receiving social security – No. Of fishing permits – Dealers with landing – Pounds of landing	Indicator
Flanagan et al. (2011)	Social vulnerability to disaster in New Orleans	– Economic – Social	15	– Crowding – % multi-unit structure – % persons who speak English less than well – % of single parents with children under 18	Indicator
Akter and Mallick (2013)	Economic vulnerability to cyclones in Bangladesh	– Demographic – Material – Risk – Institutional – Economic	15	– Religion – Proximity to the cyclone shelter – Distance from the coast – Assistance after the cyclone – Credit – Propensity to save – Elite acquaintance	Indicator

Islam et al. (2014)	Vulnerability to disasters in Bangladesh	– Agricultural – Economic – Natural – Risk – Social	15	– % of agricultural labor – Distance from river or paved road – Distance from administrative office – % of sanitary latrines – loan/income per household – Unemployment	Multi-hazard Index
Inter American Development Bank (IDB) (2011)	Community resilience to natural disaster for Belize	– Agricultural – Economic – Natural – Risk – Social	16	– Capital stock – Imports and exports – Investment – Arable land and permanent crops – Inflation – Dependency on agriculture – Soil degradation	Indicator
Martins et al. (2012)	Vulnerability to seismic risk in Vila Franca, Azores, Portugal	– Demography – Economic – Material – Risk	16	– Buildings (%) – Building constructions/year – Building characteristics – Family structure – Gender	Multicriteria analysis
Brenkert and Malone (2005)	Vulnerability to climate change in India	– Agricultural – Economic – Institutional – Land – Material – Natural – Risk	17	– Cereal production/crop area – Fertilizer use/crop land area – % Land unmanaged – Population at flood risk – Renewable supply – SO_2 / state area – Water use	Indicator
Polsky et al. (2007)	Generic community water system vulnerability to drought	– Agricultural – Institutional – Material – Natural	18	– Conservation program of technology – Emergency plan – Frequency and intensity of drought – Rainfall correlation – Safe yield	Framework
Ibarràn et al. (2010)	Vulnerability to climate change in Mexico	– Agricultural – Economic – Material – Natural – Social	19	– Precipitation – Air pollution/state area	Indicator

(continued)

Table 12.3 (continued)

Paper, Year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Cardona (2005)	Vulnerability to disasters in the Americas	– Exposure and susceptibility – Lack of resilience – Socio-economic fragility	24	– Debt servicing – Environmental sustainability index – Governance index (Kaufmann) – Hospital beds per 1000 people – Insurance of infrastructure and housing – Television sets per 1000 people	Indicator
Cutter and Finch (2008)	Vulnerability to disasters in the USA	– Business – Demography – Economic – Social	28	– Earnings in all industries – New residential housing unit permits – Social security beneficiaries	PCA

Annex 2

Table 12.4 Papers analysed for the resilience review

Paper, year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Several authors[a]	Regional economic resilience	– Economic	1	– Employment – GVA – Real per capita GDP – Regional productivity	Econometric analysis
Boschma (2015)	Evolutionary economic resilience	– Business – Economic – Institutional	3	– Institutional adaptability – Knowledge Networks – Techno-industrial variety	Theoretical framework
Foster (2007)	Regional economic resilience	– Demographic – Economic	4	– % Population change – Poverty measure	Methodological framework
Estoque and Murayama (2014)	Socio-ecological resilience	– Institutional – Natural – Social	5	– Ecosystem service index – Good governance index – Human Development Index	Indicator
Cardona et al. (2012)	Community resilience to natural disaster	– Business – Institutional – Risk	8	– Aids and donations – External and internal credit – Insurance – Deficit – New taxes – Reserve funds for disasters	Indicator
Inter American Development Bank (IDB) (2011)	Community resilience to natural disaster for Belize	– Institutional – Natural – Social	8	– Gender Development Index – Social expenditure – Television set per capita – Hospital beds per capita – Environmental sustainability index	Indicator

(continued)

Table 12.4 (continued)

Paper, year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Walker et al. (2009)	Regional economic resilience	– Agricultural – Economic – Natural – Social	10	– Biodiversity measure – Farm income – High multiplier economic – Riverine ecosystem – Sectors balance among values – Soil acidity – Water infrastructure	Indicator
Hallegatte (2014)	Economic resilience to natural disasters	– Business – Economic – Institutional – Social	10	– Economic diversification – Income inequality – Interest rate – Reconstruction duration in years – Ripple effects – Social protection – Value of a statistical life	Indicator
Martin and Sunley (2015)	Economic resilience	– Business – Economic – Institutional	10	– Business confidence – Economic dynamism – Export – External relations – Openness	Theoretical framework
Foster (2007)	Regional economic resilience	– Business – Demographic – Economic – Social	12	– Civic infrastructure – Home ownership – Metropolitan stability – Voter participation – Regional affordability – Educational attainment – Without disability	Indicator
Graziano (2013)	Community resilience in Italy	– Social	12	– Foundations, gyms, arts or sports organizations, libraries, nurseries per capita – Lifelong learning – Newspapers sold per capita – Rate of medical staff	Factor analysis over 57 variables

(continued)

Table 12.4 (continued)

Paper, year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Briguglio et al. (2009)	Regional economic resilience	– Business – Economic – Institutional – Social	13	– Impartiality of courts – Intellectual property rights – Judicial independence – Military interference – Political system – Banking industries	Indicator
Chan et al. (2014)	Resilience to natural disasters in Taiwan	– Economic – Institutional – Land – Material – Natural – Social	13	– Accuracy of weather forecasts – Disaster prevention plans – Environmentally sensitive area – Individual capability – Public facilities – Rescue capability – Slope area conservation – Spatial land use – Vulnerable population	Analytic Network Process (ANP)
Östh et al. (2015, 2018)	Regional economic resilience in Sweden and the Netherlands	– Demographic – Economic – Land – Social	13	– Accessibility – local deviation from the national industrial mix – Rank in the business climate – Working population not receiving a sickness benefit	Indicator
Sherrieb et al. (2010)	Community resilience in Mississippi counties	– Business – Economic – Land – Social	19	– Corporate tax revenues – % Creative class occupations – Net business gain/ loss rate – Property crime rate – Religious adherents – % Two-parent families – Urban influence	Indicator

(continued)

Table 12.4 (continued)

Paper, year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Graziano (2013)	Regional economic resilience	– Business – Economic – Material – Social	19	– Application of designs – Application of models – Broadband services – Electrical network – Energy networks – Non-food consumption/total – Liquidity ratio – Pensions per capita – Patents business density – Return on equity	Factor analysis over 52 variables
Mayunga (2007)	Community resilience: Capital based approach	– Demographic – Economic – Institutional – Land – Material – Social	24	– Accessibility to transports – Air quality – Business/industry – Dependency ratio – Household characteristics – Housing quality – Informal sociability – Number of housing units – Population density – Public meetings	Indicator
Cutter et al. (2008)	Community resilience to natural disaster	– Economic – Institutional – Land – Material – Natural – Risk	29	– Wetland, forests and national and local parks – Counselling services – Local understanding of risk – Quality of life – Erosion rates – % Impervious surface – Municipal revenues – Emergency response plans – Zoning and building standards	Indicator

(continued)

Table 12.4 (continued)

Paper, year	Kind of assessment	Subdivision	Nr. of variables	Variables	Method
Cutter et al. (2010)	Community resilience to natural disaster	– Business – Demographic – Economic – Institutional – Material – Risk – Social	36	– Number of mobile houses – Number of physicians – Public school density – % Population in storm-ready communities – Population participating in Community Rating System for Flood risk – % Population with a telephone – % Population with a vehicle – Large to small business ratio – % Vacant rental units	Indicator

[a]Note: Capello et al. (2015); Cellini and Torrisi (2014); Crescenzi et al. (2016); Cuadrado-Roura and Maroto (2016); Di Caro (2015); Doran and Fingleton (2015); Eraydin (2016); Fingleton et al. (2012); Fratesi and Rodríguez-Pose (2016); Giannakis and Bruggeman (2015); Lagravinese (2015); Palaskas et al. (2015); Xiao et al. (2016)

References

Akter S, Mallick B (2013) The poverty–vulnerability–resilience nexus: evidence from Bangladesh. Ecol Econ 96:114–124

Berry PM, Rounsevell MDA, Harrison PA, Audsley E (2006) Assessing the vulnerability of agricultural land use and species to climate change and the role of policy in facilitating adaptation. Environ Sci Policy 9(2):189–204

Boschma R (2015) Towards an evolutionary perspective on regional resilience. Reg Stud 49 (5):733–751

Brenkert AL, Malone EL (2005) Modeling vulnerability and resilience to climate change: a case study of India and Indian states. Clim Change 72(1):57–102

Briguglio L (1995) Small island developing states and their economic vulnerabilities. World Dev 23 (9):1615–1632

Briguglio L, Cordina G, Farrugia N, Vella S (2009) Economic vulnerability and resilience: concepts and measurements. Oxford Dev Stud 37(3):229–247

Brooks N, Adger WN, Kelly PM (2005) The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Global Environ Change 15(2):151–163

Bruneau M, Chang S, Eguchi R, Lee G, O'Rourke T, Reinhorn A, Shinozuka M, Tierney K, Wallace WA, von Winterfeldti D (2003) A framework to quantitatively assess and enhance the seismic resilience of communities. Earthq Spectra 19:733–752

Capello R, Caragliu A, Fratesi U (2015) Spatial heterogeneity in the costs of the economic crisis in Europe: are cities sources of regional resilience? J Econ Geogr 15(5):951–972
Cardona OD (2005) Indicators of disaster risk and risk management: Program for Latin America and the Caribbean: Summary Report. Inter-American Development Bank
Cardona OD, van Aalst MK, Birkmann J, Fordham M, Mc Gregor G, Perez R, Pulwarty RS, Schipper ELF, Sinh BT (2012) Determinants of risk: exposure and vulnerability. In Field CB, Barros V, Stocker TF, Qin D, Dokken DJ, Ebi KL, Mastrandrea MD, Mach KJ, Plattner GK, Allen SK, Tignor M, Midgley PM (eds) Managing the risks of extreme events and disasters to advance climate change adaptation. A special report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, pp 65–108
Cellini R, Torrisi G (2014) Regional resilience in Italy: a very long-run analysis. Reg Stud 48 (11):1779–1796
Chakraborty J, Tobin GA, Montz BE (2005) Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. Nat Hazard Rev 6(1):23–33
Chan SL, Wey WM, Chang PH (2014) Establishing disaster resilience indicators for Tan-sui river basin in Taiwan. Soc Indic Res 115(1):387–418
Christopherson S, Michie J, Tyler P (2010) Regional resilience: theoretical and empirical perspectives. Camb J Regions Econ Soc 3:3–10
Colburn LL, Jepson M, Weng C, Seara T, Weiss J, Hare JA (2016) Indicators of climate change and social vulnerability in fishing dependent communities along the Eastern and Gulf Coasts of the United States. Mar Policy 74:323–333
Crescenzi R, Luca D, Milio S (2016) The geography of the economic crisis in Europe: national macroeconomic conditions, regional structural factors and short-term economic performance. Camb J Regions Econ Soc 9(1):13–32
Cuadrado-Roura JR, Maroto A (2016) Unbalanced regional resilience to the economic crisis in Spain: a tale of specialisation and productivity. Camb J Regions Econ Soc 9(1):153–178
Cutter SL (1996) Vulnerability to environmental hazards. Prog Hum Geogr 20(4):529–539
Cutter SL, Finch C (2008) Temporal and spatial changes in social vulnerability to natural hazards. Proc Natl Acad Sci USA 105(7):2301–2306
Cutter SL, Boruff BJ, Shirley WL (2003) Social vulnerability to environmental hazards. Soc Sci Q 84(2):242–261
Cutter SL, Barnes L, Berry M, Burton C, Evans E, Tate E, Webb J (2008) A place-based model for understanding community resilience to natural disasters. Global Environ Change 18:598–606
Cutter SL, Burton CG, Emrich CT (2010) Disaster resilience indicators for benchmarking baseline conditions. J Homel Secur Emerg Manag 7(1):Article 51
Di Caro P (2015) Recessions, recoveries and regional resilience: evidence on Italy. Camb J Regions Econ Soc 8(2):273–291
Ding Q, Chen X, Hilborn R, Chen Y (2017) Vulnerability to impacts of climate change on marine fisheries and food security. Mar Policy 83:55–61
Doran J, Fingleton B (2015) Resilience from the micro perspective. Camb J Regions Econ Soc 8 (2):205–223
Duval R, Elmeskov J, Vogel L (2007) Structural policies and economic resilience to shocks. OECD Economics Department Working Papers No. 567
ECLAC (2003) Handbook for estimating the socio-economic and environmental effects of disasters, United Nations Economic Commission for Latin America and the Caribbean
Eraydin A (2016) Attributes and characteristics of regional resilience: defining and measuring the resilience of Turkish regions. Reg Stud 50(4):600–614
Estoque RC, Murayama Y (2014) Social–ecological status index: a preliminary study of its structural composition and application. Ecol Indic 43:183–194

Faggian A, Gemmiti R, Jaquet T, Santini I (2017) Regional economic resilience: the experience of the Italian local labor systems. Ann Reg Sci 58:1–18
Field EH, Seligson HA, Gupta N, Gupta V, Jordan TH, Campbell KW (2005) Loss estimates for a Puente Hills blind-thrust earthquake in Los Angeles, California. Earthq Spectra 21(2):329–338
Fingleton B, Garretsen H, Martin R (2012) Recessionary shocks and regional employment: evidence on the resilience of UK regions. J Reg Sci 52(1):109–133
Flanagan BE, Gregory EW, Hallisey EJ, Heitgerd JL, Lewis B (2011) A social vulnerability index for disaster management. J Homel Secur Emerg Manag 8(1):Article 3
Flatø M, Muttarak R, Pelser A (2017) Women, weather, and woes: the triangular dynamics of female-headed households, economic vulnerability, and climate variability in South Africa. World Dev 90:41–62
Foster KA (2007) Case study approach to understanding regional resilience. Working paper 2008–07. Institute of Urban and Regional Development, University of California, Berkeley
Fratesi U, Rodríguez-Pose A (2016) The crisis and regional employment in Europe: what role for sheltered economies? Camb J Region Econ Soc 9(1):33–57
Gallopín GC (2006) Linkages between vulnerability, resilience, and adaptive capacity. Global Environ Change 16(3):293–303
Giannakis E, Bruggeman A (2015) Economic crisis and regional resilience: evidence from Greece. Papers Reg Sci. https://doi.org/10.1111/pirs.12206
Godschalk DR, Kaiser EJ, Berke PR (1998) Integrating hazard mitigation and local land use planning. In: Burby RJ (ed) Cooperating with nature: confronting natural hazards with land-use planning for sustainable communities. Joseph Henry Press, Washington, DC, pp 85–118
Graziano P (2013) Vulnerability and resilience of the economic, social and environmental dimensions of Italian provinces. Regional Studies Association, European conference
Haddad BM (2005) Ranking the adaptive capacity of nations to climate change when socio-political goals are explicit. Global Environ Change 15(2):165–176
Haimes Y (2009) On the definition of resilience in systems. Risk Anal 29(4):498–501
Hallegatte S (2014) Economic resilience: definition and measurement. World Bank Policy Research Working Paper No. 6852. Available at SSRN: https://ssrn.com/abstract=2432352
Holling CS (1973) Resilience and stability of ecological systems. Annu Rev Ecol Evol Syst 4:1–23
Hudson R (2010) Resilient regions in an uncertain world: wishful thinking or a practical reality? Camb J Region Econ Soc 3:11–25
Ibarraràn ME, Malone EL, Brenkert AL (2010) Climate change vulnerability and resilience: current status and trends for Mexico. Environ Dev Sustain 12(3):365–388
IDB (2011) Indicators for disaster risk and risk management – programme for Latin-America and The Caribbean. Belize. Technical notes no. IDB-TN-276
Islam MM, Sallu S, Hubacek K, Paavola J (2014) Vulnerability of fishery-based livelihoods to the impacts of climate variability and change: insights from coastal Bangladesh. Reg Environ Change 14(1):281–294
Jongman B, Kreibich H, Apel H, Barredo JI, Bates PD, Feyen L, Ward PJ (2012) Comparative flood damage model assessment: towards a European approach. Nat Hazard Earth Syst Sci 12 (12):3733–3752
Kajitani Y, Tatano H (2009) Estimation of lifeline resilience factors based on empirical surveys of Japanese industries. Earthq Spectra 25(4):755–776
Koks EE, de Moel H, Aerts JC, Bouwer LM (2014) Effect of spatial adaptation measures on flood risk: study of coastal floods in Belgium. Reg Environ Change 14(1):413–425
Koks EE, Jongman B, Husby TG, Botzen WJW (2015) Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. Environ Sci Policy 47:42–52
Kythreotis AP, Bristow GI (2017) The 'resilience trap': exploring the practical utility of resilience for climate change adaptation in UK city-regions. Reg Stud 51(10):1530–1541
Lagravinese R (2015) Economic crisis and rising gaps North–South: evidence from the Italian regions. Camb J Region Econ Soc 8(2):331–342

Lonergan S, Gustavson K, Carter B (2000) The index of human insecurity. AVISO (Ottawa, Ont) 6:1–7
MacKinnon D, Derickson KD (2013) From resilience to resourcefulness: a critique of resilience policy and activism. Prog Hum Geogr 37(2):253–270
Manuel-Navarrete D, Gomez JJ, Gallopín G (2007) Syndromes of sustainability of development for assessing the vulnerability of coupled human–environmental systems. The case of hydro meteorological disasters in Central America and the Caribbean. Global Environ Change 17 (2):207–217
Marin G, Modica M (2017) Socio-economic exposure to natural disasters. Environ Impact Assess Rev 64:57–66
Martin RL (2012) Regional economic resilience, hysteresis and recessionary shocks. J Econ Geogr 12:1–32
Martin R, Sunley P (2015) Towards a developmental turn in evolutionary economic geography? Reg Stud 49(5):712–732
Martins VN, Silva DS, Cabral P (2012) Social vulnerability assessment to seismic risk using multicriteria analysis: the case study of Vila Franca do Campo (São Miguel Island, Azores, Portugal). Nat Hazard 62(2):385–404
Mayunga JS (2007) Understanding and applying the concept of community disaster resilience: a capital-based approach. Summer academy for social vulnerability and resilience building, pp 1–16
Meerow S, Newell JP (2015) Resilience and complexity: a bibliometric review and prospects for industrial ecology. J Ind Ecol 19(2):236–251
Meroni F, Pessina V, Squarcina T, Locati M, Modica M, Zoboli R (2016) The economic assessment of seismic damage: an example for the 2012 event in Northern Italy. In: CERU (ed) International conference on urban risk. CERU – European Centre on Urban Risks, Lisbon (Portugal), pp 323–330. ISBN:978-989-95094-1-2
Modica M (2014) Does the EU have homogeneous urban structure area? The role of agglomeration and the impact of shocks on urban structure. In: ERSA conference papers (no. ersa14p229). European Regional Science Association
Modica M, Reggiani A (2014) An alternative interpretation of regional resilience: evidence from Italy. In: ERSA conference papers (No. ersa14p369). European Regional Science Association
Modica M, Reggiani A (2015) Spatial economic resilience: overview and perspectives. Network Spatial Econ 15(2):211–233
Modica M, Zoboli R (2016) Vulnerability, resilience, hazard, risk, damage, and loss: a socio-ecological framework for natural disaster analysis. Web Ecol 16(1):59–62
Modica M, Reggiani A, Nijkamp P (2017a) Methodological advances in Gibrat's and Zipf's laws: a comparative empirical study on the evolution of urban systems. In: Shibusawa H, Sakurai K, Mizunoya T, Uchida S (eds) Socioeconomic environmental policies and evaluations in regional science. Springer, Singapore, pp 37–59
Modica M, Zoboli R, Pagliarino E (2017b) Mapping the environmental pressure due to economic factors. The case of Italian coastal municipalities. Argomenti (8), 73–105
Modica M, Reggiani A, De Vivo N, Nijkamp P (2018) Ageing and labour market development: testing Gibrat's and Zipf's Law for Germany. In: Modelling aging and migration effects on spatial labor markets. Springer, Cham, pp 285–309
Mustafa D (1998) Structural causes of vulnerability to flood hazard in Pakistan. Econ Geogr 74 (3):289–305
Östh J, Reggiani A, Galiazzo G (2015) Spatial economic resilience and accessibility: a joint perspective. Comput Environ Urban Syst 49:148–159
Östh J, Reggiani A, Nijkamp P (2018) Resilience and accessibility of Swedish and Dutch municipalities. Transportation 45:1051–1073
Palaskas T, Psycharis Y, Rovolis A, Stoforos C (2015) The asymmetrical impact of the economic crisis on unemployment and welfare in Greek urban economies. J Econ Geogr 15(5):973–1007

Pelling M (2003) The vulnerability of cities: natural disasters and social resilience. Earthscan, Sterling, VA

Pimm SL (1984) The complexity and stability of ecosystems. Nature 307:321–326

Polsky C, Neff R, Yarnal B (2007) Building comparable global change vulnerability assessments: the vulnerability scoping diagram. Global Environ Change 17(3):472–485

Reggiani A, Hudec O, Siserova M (2016) Resilience capacity and vulnerability: the case of Slovakia. In: ERSA conference papers (No. ersa16p86). European Regional Science Association

Ribot JC (1995) The causal structure of vulnerability: its application to climate impact analysis. GeoJournal 35(2):119–122

Rose AZ (2007) Economic resilience to natural and man-made disasters: multidisciplinary origins and contextual dimensions. Environ Hazard 7:383–398

Rose AZ (2017) Benefit-cost analysis of economic resilience. In: Cutter S (ed) Oxford research encyclopedia of natural hazard science. Oxford, New York

Rose AZ, Krausmann E (2013) An economic framework for the development of a resilience index for business recovery. Int J Disast Risk Reduct 5:73–83

Rose AZ, Liao SY (2005) Modelling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. J Reg Sci 45:75–112

Rose A, Lim D (2002) Business interruption losses from natural hazards: conceptual and methodological issues in the case of the Northridge earthquake. Environ Hazard 4(1):1–14

Rose A, Oladosu G, Lia SY (2007) Business interruption impacts of a terrorist attack on the electric power system of Los Angeles: customer resilience to a total blackout. Risk Anal 27(3):513–531

Rose AZ, Sue Wing I, Wei D, Wein A (2016) Economic Impacts of a California Tsunami. Nat Hazard Rev 17(2):1–12

Sarewitz D, Pielke R, Keykhah M (2003) Vulnerability and risk: some thoughts from a political and policy perspective. Risk Anal 23(4):805–810

Sherrieb K, Norris FH, Galea S (2010) Measuring capacities for community resilience. Soc Indic Res 99(2):227–247

Somers S (2009) Measuring resilience potential: an adaptive strategy for organizational crisis planning. J Contingencies Crisis Manag 17(1):12–23

Sterlacchini S, Zazzeri M, Genovese E, Modica M, Zoboli R (2016) Flood damage in Italy: towards an assessment model of reconstruction costs. In: EGU General Assembly 2016, held 17–22 April 2016 in Vienna Austria, p 13135

UNDP (2015) Human development report 2015—work for human development. Published for the United Nations Development Programme (UNDP), New York

Van Der Veen A, Logtmeijer C (2005) Economic hotspots: visualizing vulnerability to flooding. Nat Hazard 36:65–80

Vincent K (2004) Creating an index of social vulnerability to climate change for Africa. Tyndall Center for Climate Change Research. Working Paper 56:1–41

Walker BH, Abel N, Anderies JM, Ryan P (2009) Resilience, adaptability, and transformability in the Goulburn-Broken Catchment, Australia. Ecol Soc 14(1):12

Wei YM, Fan Y, Lu C, Tsai HT (2004) The assessment of vulnerability to natural disasters in China by using the DEA method. Environ Impact Assess Rev 24(4):427–439

Wein A, Rose AZ (2011) Economic resilience lessons from the ShakeOut earthquake scenario. Earthq Spectra 27(2):559–573

Xiao J, Boschma R, Andersson M (2016) Industrial diversification in Europe. The differentiated role of relatedness. Papers in evolutionary economic geography no. 16.27. Utrecht University, Utrecht

Yohe G, Tol RS (2002) Indicators for social and economic coping capacity—moving toward a working definition of adaptive capacity. Global Environ Change 12(1):25–40

Young S, Balluz L, Malilay J (2004) Natural and technologic hazardous material releases during and after natural disasters: a review. Sci Total Environ 322(1):3–20

Yusuf AA, Francisco H (2010) Hotspots! Mapping climate change vulnerability in Southeast Asia. In: Economy and environment program for Southeast Asia. Available at http://www.idrc.ca/eepsea/

Zou LL, Wei YM (2009) Impact assessment using DEA of coastal hazards on social-economy in Southeast Asia. Nat Hazard 48(2):167–189

Marco Modica is Assistant Professor at the Gran Sasso Science Institute, L'Aquila, Italy. His primary research interests focus on the economic evaluation of external shocks such as natural disasters, with a special attention on the resilience of socio-economic systems. Currently, he is investigating the fields of Climate Change Economics and Policy and Spatial Resilience. His approach in these subjects involves using natural catastrophes as social experiments to explain the effects on the regional economic but also in order to identify the economic impact of such disasters. Dr. Modica earned his doctoral degree in Economics, Markets and Institutions from the IMT Institute for Advanced Studies Lucca (Italy) in 2013.

Aura Reggiani is Full Professor of Economic Policy at the University of Bologna, Department of Economics (since 2001), after being Associate Professor of Economic Policy (1992–2001). She also chairs the courses of 'Advanced Economic Policy and Methods', 'Methods of Economic Analysis', and 'Transport Economics' at the University of Bologna (Italy), School of Economics, Management and Statistics. She is a specialist in spatial and transport economics and modelling, with particular reference to the study of network evolution and complexity, from both the theoretical and empirical viewpoint, and of the associated policies. Since 1991, she has been a Fellow of the Netherlands Institute of Advanced Studies (NIAS) of the Royal Dutch Academy, in connection with her works on network dynamics and evolutionary theories. Aura Reggiani has a Ph.D. in Economics from the Department of Spatial Economics at the Free University of Amsterdam (the Netherlands).

Peter Nijkamp is emeritus Professor in regional and urban economics and in economic geography at the VU University, and connected to the Jheronimus Academy of Data Science (JADS) of the division Smart Cities ('s-Hertogenbosch, The Netherlands), Royal Institute of Technology (KTH), Stockholm (Sweden) and A. Mickiewicz University, Poznan (Poland). He is member of editorial/advisory boards of more than 30 journals. According to the RePec list he belongs to the top-30 of well-known economists world-wide. He is also a fellow of the Royal Netherlands Academy of Sciences, and past vice-president of this organization. He has served as president of the governing board of the Netherlands Research Council (NWO). In 1996, he was awarded the most prestigious scientific prize in the Netherlands, the Spinoza award.

Part III
Economic Modeling and Decision-Making

Chapter 13
Advantages of the Regional and Sectoral Disaggregation of a Spatial Computable General Equilibrium Model for the Economic Impact Analysis of Natural Disasters

Yoshio Kajitani and Hirokazu Tatano

Abstract Computable general equilibrium (CGE) models are promising for estimating the economic losses of natural disasters. This type of model has a sound theoretical foundation and can explain both forward and backward linkages in an economy; hence, it is suitable for predicting the economic impact of supply and demand shocks during a disaster. Spatial and sector classifications for the CGE model are key elements that affect the performance of the model. Although physical damage to an area by a hazard is local, the damage induces higher-order effects on flows that can spread to other areas, and constructing the CGE model on a fine spatial scale is necessary for describing these effects. Sectoral disaggregation would also improve the quality of the model if key industries that have low substitutability and cause supply chain impacts are separated from other sectors with higher substitutability. This study validates the spatial and sectoral disaggregation effects of the CGE model through a case study of the Great East Japan Earthquake and Tsunami in 2011. In addition, this study examines whether two patterns of the elasticity of substitution parameters for interregional trade contribute to improving the forecasting capability of the CGE model.

Y. Kajitani (✉)
Faculty of Engineering and Design, Kagawa University, Takamatsu, Japan
e-mail: kajitani@eng.kagawa-u.ac.jp

H. Tatano
Disaster Prevention Research Institute, Kyoto University, Uji, Japan
e-mail: tatano@imdr.dpri.kyoto-u.ac.jp

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_13

13.1 Introduction

A major advantage of using computable general equilibrium (CGE) models for economic analysis is that they can describe economic structure in great detail and can be applied flexibly to complex real-world economies by changing the functional forms and parameters of the model. This flexibility can also be an advantage in modeling an economy in a disaster. For example, as described in Rose and Liao (2005), disaster mitigation behaviors, such as water conservation and water substitution, are reflected in a production function with constant elasticity of substitution (CES). Thus, the quality of the CGE model for capturing an economy after a disaster depends on these parameters and model setting arrangements fitted in a disaster scenario.

However, the applicability of CGE models to disaster impact analysis has been questioned. As discussed by Greenberg et al. (2007), a major criticism of using the CGE model for disaster impact analysis is that "the assumption that consumers and producers optimize is debatable." The model may derive over-optimized results for disaster impact analysis. They also stated that "a chief criticism leveled at CGE models is that they rely on external sources for some of the elasticity values required during their calibration," citing Partridge and Rickman (1998). For example, the parameter for the elasticity of substitution, which is used in CES functions for describing trading patterns among goods in different regions, is a typical area that needs refinement for both disaster and non-disaster cases. To solve this problem, Kajitani and Tatano (2018) presented a sensitivity analysis on the elasticity of substitution for each interregional trade good and demonstrated that the best combination of elasticity parameters in a spatial CGE (SCGE) model has a good ability to forecast production losses in different sectors and regions in the case of the Great East Japan Earthquake and Tsunami in 2011.

Sectoral/regional disaggregation is another area for improving the quality of impact assessments. In past major disasters, some sectors, such as the transportation manufacturing sector, have been vulnerable due to supply chain damage. This type of damage can easily occur because of the shortage of automobile parts, which have a significantly low elasticity of input substitutability. A model where the transportation equipment manufacturing sector contains both the finished products and parts may not capture this type of supply chain impact. Regional disaggregation also plays an important role if the same sector produces different goods in different regions (i.e., the Armington import elasticity assumption) at more detailed regional scales.

Based on this background, this work provides a case study where an SCGE model is applied to disaster impact analysis with different sector/regional aggregation patterns. The basic model structure and validation strategy follow Kajitani and Tatano (2018). Similar to the previous work, we further explore the applicability of the SCGE model by examining two different elasticity of substitution parameters, but more intensive study is conducted to derive implications from sector/regional disaggregation for the model.

13.2 Model Outline

13.2.1 Short-Run Settings of CGE Models for Disaster Impact Analysis

The application of CGE models to disaster impact analysis has drawn attention over the past 25 years. Rose and Guha (2004) noted that the advantages of CGE models have been highlighted since the early 1990s but that applications of the model have been "limited to simple stylized examples." They also classified the configurations of CGE models for disaster impact analysis in terms of time scales. For example, in a very short-run case where the period is projected to last less than 7 days, "a CGE model is appropriate here but with input and import elasticities[1] set very low (probably less than 0.1)." Our later case study covers the martial law period (less than 30 days) in their classification, where the central government may control an economy, or the short-run period (less than 6 months), where input substitutions or other resiliency measures occur. In the short-run period, they assume that the input elasticities are also low, generally less than 1, but import elasticities can be large if transportation networks are not extensively damaged. These discussions are critical for constructing appropriate models on different time scales.

To validate the plausible elasticity of substitution for interregional trades, Kajitani and Tatano (2018) conducted a sensitivity analysis on the parameter values and compared industrial production estimates with the observed production after the Great East Japan Earthquake. In their analysis of nine regional CGE models, those with small elasticities less than or equal to 0.32 are found to obtain the best estimates. In particular, no substitutability (elasticity is 0) is evidenced for the transportation machinery sector.

The disaster-specific settings of a CGE model are reported in Tatano and Tsuchiya (2008). They applied a CGE model to an earthquake disaster by using putty-clay assumptions.[2] In the analysis, production factors, normally capital and labor, are assumed to be substitutable and mobile before an event and are used to formulate the optimal production capacity. Following the disaster, a low substitutability of factors is assumed in the short run.[3] Putty-clay models are typically used to consider economic rigidity. Atkeson and Kahoe (1999) observed that the ways that

[1]Input elasticities concern the substitutions among factor inputs or intermediate inputs, whereas import elasticities involve the substitutions among imports from different regions.

[2]Putty-clay models assume different substitutability of production factors before and after the capital is installed, with substitutability usually being zero for clay. On the other hand, putty-putty models assume substitutability both before and after and often the same level of substitutability.

[3]To be more rigorous, this assumption and the degree of substitutability have to be verified by observations, but we assume that the substitutability between capital and labor becomes very low under difficult conditions.

capital formation is affected by electricity price are more consistent with the estimates of the putty-clay model than the standard putty-putty model.

Our focus is on short-term flow losses (several weeks or months), for which CGE models with several constraints may be valid. For example, although price might be fixed, idle capital may increase rather than having all available capital allocated and used across sectors and regions. The difference in an economy during normal and disaster periods would remain as small as possible because continuous recovery activities would restore the original economic conditions in many sectors. Because many businesses expect the economy to return to the original conditions, adjustment to the tentative gap between supply and demand is expected to be slow during the short-run period after a disaster. Accordingly, Oosterhaven and Bouwmeester (2016) proposed an impact assessment model based on an interregional input–output model with the theory of minimum information gain.

This type of arrangement in CGE models can be interpreted as a short-run CGE model. As Bourguignon et al. (1983) claimed, "most of the existing models, for instance, are built along neo-classical assumptions which seem quite appropriate in the long-run—i.e., capital-labor substitution, full employment, market-clearing prices, etc.—but might be somewhat inadequate in the short or medium run," and they examined the CGE model combining both short-run and long-run characteristics based on the basic structure proposed by Taylor and Lysy (1979).[4] In their short-run model, putty-clay production functions, unemployment related to nominal wage, and price rigidities were introduced. These types of short-run assumptions may be appropriate for disaster impact analysis because a series of shocks, including recovery activities, prevent the effective adjustment of resources during a disaster.

As described in the mathematical formulas in Sect. 13.3, typical short-run settings are used to describe the economic impacts occurring several months after a disaster. These settings include immobile capital and labor among regions and sectors, no income change in the household sector,[5] and the ability to decrease labor inputs instead of full employment.[6] Our case study targets a monthly analysis, which is challenging in the application of a CGE model. Such a short-run case necessitates more investigation of adaptation behaviors, such as utilizing inventories in the short-period after the disaster. These arrangements of the model are beyond the scope of this paper, but incorporating several past studies, such as adopting a sequential industrial model (Okuyama et al. 2004) that incorporates capacity limitations and inventory in a time-phased production system, has the potential to strengthen the

[4]Taylor and Lysy (1979) investigated the effects on income redistribution with a one-sector model characterized by fixed capital, exogenous investments, and nominal changes in the prime cost (Keynesian), and they demonstrated that the model produces a relatively insensitive functional income distribution.

[5]In our model, personal income directly affects household consumption levels. Fixing the income in a model works to slow the change in consumption levels after the disaster. This assumption may also need to be modified based on further empirical study.

[6]The downward rigidity of labor cost is also used by Rose and Guha (2004) to model the decrease in labor input.

short-run analysis. More discussion of the deficits and promising arrangements of our current model to fit the disaster condition in the short run is given in Kajitani and Tatano (2018).

13.2.2 Approaches to Comparative Study Among Different Models

Here, we briefly describe the approach to investigate the effects of regional/sectoral disaggregation of the SCGE model as well as the effects of different values for the interregional substitution parameters.

(a) First, we construct three different SCGE models in Japan: a 9-regional and 29-sectoral version (hereinafter referred to as the 9-region/29-sector model), a 9-regional and 30-sectoral version (9-region/30-sector model), and a 47-regional and 29-sectoral version (47-region/29-sector model). We assume that the automobile sector is key for estimating supply chain impacts, and hence, the sector is disaggregated into parts and passenger car sectors in a 30-sector model to see the effects of sectoral disaggregation. A 47-region/29-sector model is compared with a 9-region/29-sector model to see the effects of regional disaggregation. Details regarding the model and regional/sectoral settings are given in Sects. 13.3 and 13.4.1, respectively.
(b) The shocks to production capacities in each industry in each of the first 3 months after the Great East Japan Earthquake are available in Kajitani and Tatano (2014). These data sets are utilized to set production shocks for the impact study. The method of setting shocks is described in Sect. 13.4.2.
(c) Indices of industrial production (IIPs), which are standardized monthly observed production, are employed to validate the estimated production obtained from each model. The sector and regional classifications are basically consistent with the classification of the manufacturing sector in a 29-sector model. The details are given in Sect. 13.4.2.
(d) The elasticity of substitution for interregional trades are also varied for deriving the implications for plausible disaster impact assessments. Our case adopted two different patterns, which are explained in Sect. 13.4.3.
(e) The constructed models (a) with different substitution parameter values for interregional trade (d) are simulated with the shocks (b). The results are compared with the observed values (c). The quality of the forecasting capability of each model is evaluated by examining root mean square errors between the estimated and observed production as well as the visual comparisons given in Sect. 13.5.

13.3 Description of the SCGE Model

Several models considering the various assumptions during a disaster are briefly explained here. An introduction to the basic structures and applications of CGE models is available in many textbooks (e.g., Shoven and Whalley 1992; Hertel 1997; Dixon and Jorgenson 2013), so we will not recap the details of the basic model and calibration process. The relevant data sets, such as input–output tables and elasticity of substitutions, have also been estimated and updated by many organizations and individual researchers (e.g., Badri and Walmsley 2008).

This study uses a simple structure for the CGE model that is described in Ueda (2010). This model eliminates the government sector as a separate item and instead combines government consumption with household consumption. The model might be viewed as the most basic structure, allowing the study to focus on analyzing the distribution of available resources and goods among domestic industrial and household sectors and avoiding the black-box characteristics of more complex CGE models. The parameters and variables that must be clearly distinguished in the equations between the normal and disaster cases are suffixed by 0 (normal case) and 1 (disaster case). The equations without a 0 or 1 suffix are assumed to be identical for the normal and disaster cases.

1. Industrial Sector (Firms)

Firms are assumed to have the production structures shown in Fig. 13.1 during both disaster and normal periods.[7] Domestic final product Xd_j^s in the second layer in Fig. 13.1 is determined by inputting composite goods from each sector and value added based on a Leontief production function given by

$$Xd_j^s = \min\left(\frac{V_j^s}{a_{vj}^s}, \frac{x_{1j}^s}{a_{1j}^s}, \frac{x_{2j}^s}{a_{2j}^s}, \cdots, \frac{x_{nj}^s}{a_{nj}^s}\right), \tag{13.1}$$

where s is the region suffix ($s \in S$, $S = \{1, \ldots, R\}$), i and j are industrial sector suffixes ($i, j \in N$, $N = \{1, \ldots, n\}$), V_j^s is the amount of value added, x_{ij}^s is the amount of composite goods for intermediate inputs, and a_{vj}^s, a_{ij}^s are the input–output coefficients. From Eq. (13.1), the uses of the composite goods and value added are obtained by

$$x_{ij}^s = a_{ij}^s Xd_j^s, \tag{13.2}$$

$$V_j^s = a_{vj}^s Xd_j^s. \tag{13.3}$$

[7]Because the use of imports is not separated into intermediate and final demand in the original input–output table, one type of Armington composite for imported and domestic goods is used for both intermediate and final demand, as shown in the bottom layers. In total, the technology tree is consistent with the Japanese interregional input–output table used in this research.

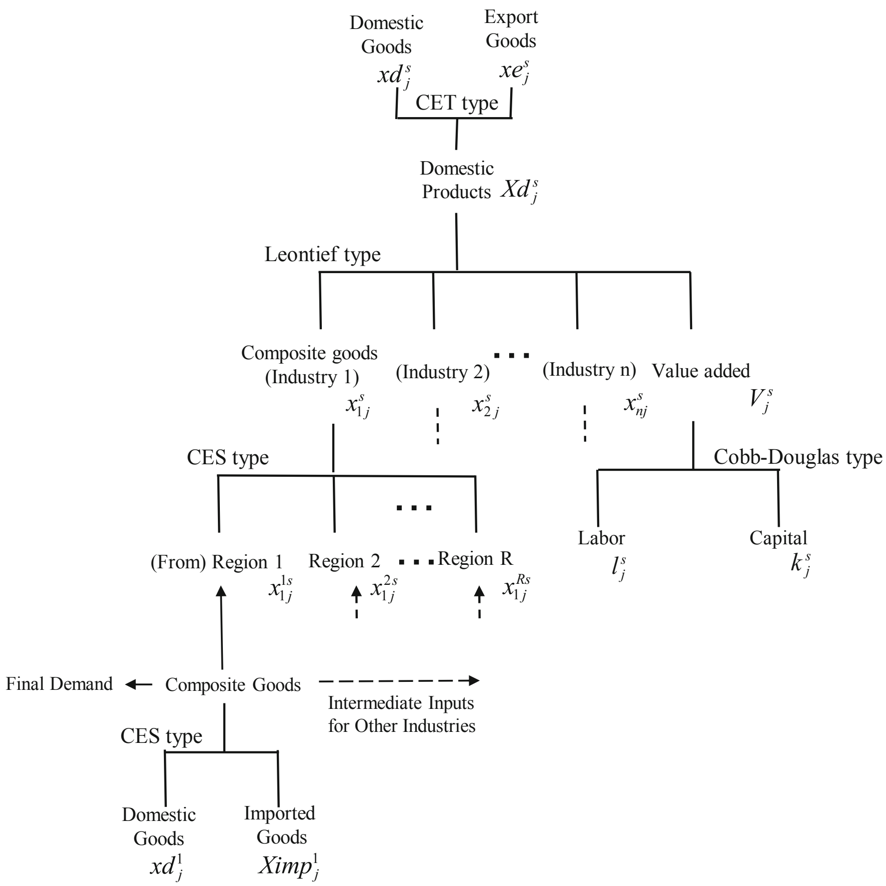


Fig. 13.1 Technology tree for the proposed model

The capital and labor requirements (the third layer on the right-hand side in Fig. 13.1) are determined by solving the cost minimization problem

$$\begin{aligned} C_{v_j^s}\left(w_j^s, r_j^s\right)V_j^s &= \min_{l_j^s, k_j^s} w_j^s l_j^s + r_j^s k_j^s \\ s.t.\ \ f_{V_j^s}\left(l_j^s, k_j^s\right) &= V_j^s, \end{aligned} \tag{13.4}$$

where w_j^s is wages, r_j^s is capital rent, l_j^s is labor input, k_j^s is capital input, and $C_{v_j^s}$ is the cost function for a single value added. For the value-added function $f_{v_j^s}$, we assume the Cobb–Douglas function (13.5)

$$f_{V_j^s}\left(l_j^s, k_j^s\right) = \eta_j^s \left(l_j^s\right)^{\alpha_j^s} \left(k_j^s\right)^{1-\alpha_j^s}, \tag{13.5}$$

where η_j^s is a total factor productivity and α_j^s is output elasticity of labor ($1 - \alpha_j^s$: output elasticity of capital). Then, the following factor demands of labor and capital are obtained based on the cost minimization problem (13.4).

$$l_j^s = \frac{\alpha_j^s}{w_j^s} \frac{1}{\eta_j^s} \left(\frac{w_j^s}{\alpha_j^s}\right)^{\alpha_j^s} \left(\frac{r_j^r}{1-\alpha_j^s}\right)^{1-\alpha_j^s} \cdot V_j^s \tag{13.6}$$

$$k_j^s = \frac{1-\alpha_j^s}{r_j^s} \frac{1}{\eta_j^s} \left(\frac{w^s}{\alpha_j^s}\right)^{\alpha_j^s} \left(\frac{r_j^s}{1-\alpha_j^s}\right)^{1-\alpha_j^s} \cdot V_j^s \tag{13.7}$$

Next, composite goods on the left-hand side of the third layer in Fig. 13.1 are assumed to follow the CES production function with the input of goods (final products) from all regions. The Armington assumption is used for the composite procedure, so each type of inbound imported goods is treated as different. The use of the goods from each region is determined by the cost minimization problem given in Eq. (13.8) as

$$\begin{aligned} C_{x_{ij}^s} x_{ij}^s &= \min_{x_{ij}^{rs}} \sum_{r \in S} P_i^r x_{ij}^{rs} \\ s.t.\ x_{ij}^s &= \phi_{ij}^s \left(\sum_{r \in S} \beta_{ij}^{rs} x_{ij}^{rs} \frac{\psi_i - 1}{\psi_i}\right)^{\frac{\psi_i}{\psi_i - 1}}, \end{aligned} \tag{13.8}$$

where ϕ_{ij}^s is a scale parameter, β_{ij}^{rs} is a share parameter, and ψ_i is an elasticity of substitution parameter. By solving Eq. (13.8), the price of composite good $C_{x_{ij}^s}$ is acquired.

$$C_{x_{ij}^s} = \frac{1}{\phi_{ij}^s} \left[\sum_{r \in S} \beta_{ij}^{rs} \psi_i P_i^r 1 - \psi_i\right]^{\frac{1}{1-\psi_i}} \tag{13.9}$$

Applying Shephard's lemma (first derivative of Eq. (13.9)), the amount of inputs from each region, x_{ij}^{rs}, for the interregional intermediate composite goods, x_{ij}^s, are determined as

$$x_{ij}^{rs} = \left[\phi_{ij}^s\right]^{\psi_i - 1} \left[\frac{\beta_{ij}^{rs} C_{x_{ij}^s}}{P_i^r}\right]^{\psi_i} \cdot x_{ij}^s. \tag{13.10}$$

Then, the cost of domestic production, $C_{xd_j^s}$, is determined by Eq. (13.11):

$$C_{Xd_j^s} Xd_j^s = C_{v_j^s} V_j^s \left(l_j^s, k_j^s \right) + \sum_{i \in I} C_{x_{ij}^s} x_{ij}^s \tag{13.11}$$

Domestic products are combined with imported goods, as shown in the first layer of Fig. 13.1. Similar to Eq. (13.8), the amounts of domestic and import goods are determined by the cost minimization problem (13.12)

$$\begin{aligned} P_j^s X_j^s &= \min_{xd_j^s,\, ximp_j^s} \left(Pd_j^s xd_j^s + Pm_j^s ximp_j^s \right) \\ s.t.\ X_j^s &= \phi_{imp_j^s} \left(\lambda_j^s xd_j^{s\ \frac{\psi m_j - 1}{\psi m_j}} + \left(1 - \lambda_j^s\right) ximp_j^{s\ \frac{\psi m_j - 1}{\psi m_j}} \right)^{\frac{\psi m_j}{\psi m_j - 1}}, \end{aligned} \tag{13.12}$$

where P_j^s is the price of composite goods, Pd_j^s and Pm_j^s are the prices of domestic and imported goods, respectively, X_j^s is the total supply of composite goods, $\phi_{imp_j^s}$ is a scale parameter, λ_j^s is a share parameter, and ψm_j is the elasticity of substitution. Solving problem (13.12) gives

$$P_j^s = \frac{1}{\phi_{imp_j^s}} \left[\left(\lambda_j^s \right)^{\psi m_j} \left[Pd_j^s \right]^{1 - \psi m_j} + \left(1 - \lambda_j^s \right)^{\psi m_j} \left[Pm_j^s \right]^{1 - \psi m_j} \right]^{\frac{1}{1 - \psi m_j}}. \tag{13.13}$$

Applying Shephard's lemma to Eq. (13.13), xd_j^s and $ximp_j^s$ are specified as

$$xd_j^s = \left[\phi_{imp_j^s} \right]^{\psi m_j - 1} \left[\frac{\lambda_j^s P_j^s}{Pd_j^s} \right]^{\psi m_j} \cdot X_j^s, \tag{13.14}$$

$$ximp_j^s = \left[\phi_{imp_j^s} \right]^{\psi m_j - 1} \left[\frac{\left(1 - \lambda_j^s \right) P_j^s}{Pm_j^s} \right]^{\psi m_j} \cdot X_j^s. \tag{13.15}$$

During a disaster, production capacity is reduced by a decrease in labor and capital factors, infrastructure disruption, or other adverse conditions. The disaster-induced restriction of the capital and labor market is reflected in the market conditions described later. The impact of infrastructure disruption on production capacity is explained by the change in total factor productivity, η_j^s. The method for setting η_j^s is given in Sect. 13.4.2.

The domestic sales and exports are determined by the following profit maximization problem based on the constant elasticity of technology function,

$$\begin{aligned} &\max_{xd_j^s,\, xe_j^s} \pi_j^s Xd_j^s = Pd_j^s xd_j^s + Pe_j^s xe_j^s \\ &s.t.\ Xd_j^s = \phi_{e_j^s} \left(\omega_j^s xd_j^{s\,\frac{\psi e_j+1}{\psi e_j}} + \left(1-\omega_j^s\right) xe_j^{s\,\frac{\psi e_j+1}{\psi e_j}} \right)^{\frac{\psi e_j}{\psi e_j+1}}, \end{aligned} \tag{13.16}$$

where π_j^s is the average price per unit of production, Pe_j^s is the price of exports, xe_j^s is the supply of exports, $\phi_{e_j^s}$ is a scale parameter, and ψe_j is the elasticity of transformation. Solving problem (13.16) gives

$$\pi_j^s = \frac{1}{\phi_{e_j^s}} \left[\left(\omega_j^s\right)^{-\psi e_j} \left[Pd_j^s\right]^{1+\psi e_j} + \left(1-\omega_j^s\right)^{-\psi e_j} \left[Pe_j^s\right]^{1+\psi e_j} \right]^{\frac{1}{1+\psi e_j}}, \tag{13.17}$$

$$xd_j^s = \left[\phi_{e_j^s}\right]^{-\psi e_j - 1} \left[\frac{\omega_j^s \pi_j^s}{Pd_j^s}\right]^{-\psi e_j} \cdot Xd_j^s, \tag{13.18}$$

$$xe_j^s = \left[\phi_{e_j^s}\right]^{-\psi e_j - 1} \left[\frac{\left(1-w_j^s\right)\pi_j^s}{Pe_j^s}\right]^{-\psi e_j} \cdot Xd_j^s. \tag{13.19}$$

2. Household Sector

Households determine the consumption of goods by the utility maximization problem

$$\begin{aligned} &V^s = \max U^s\left(F_1^s, \cdots, F_N^s\right) \\ &s.t. \sum_{j\in N} P_{F_j^s} F_j^s = I^s, \end{aligned} \tag{13.20}$$

where

$$U^s = \left(\sum_{j\in N} \gamma_j^s F_j^{s\,\frac{\sigma_h - 1}{\sigma_h}} \right)^{\frac{\sigma_h}{\sigma_h - 1}}, \tag{13.21}$$

and V^s is an indirect utility function, U^s is a direct utility function, F_j^s is demand for goods, $P_{F_j^s}$ is the consumer price of goods, γ_j^s is a share parameter of goods, and σ_h is an elasticity of substitution parameter.

Solving problem (13.20), F_j^s is obtained as

$$F_j^s = \left(\frac{\gamma_j^s}{P_{F_j^s}}\right)^{\sigma_h} \frac{I^s}{\sum_{j \in N} \left(\gamma_j^s\right)^{\sigma_h} \left(P_{F_j^s}\right)^{1-\sigma_h}}. \tag{13.22}$$

Similarly, the cost minimization behavior of households related to their consumption of regional goods is provided by Eq. (13.23).

$$\begin{aligned} P_{F_j^s} F_j^s &= \min_{d_j^{rs}} \sum_{r \in S} P_j^r d_j^{rs} \\ s.t.\ \ F_j^s &= \tau_j^s \left(\sum_{r \in S} \gamma_j^{rs} d_j^{rs} \frac{\sigma_{f_j} - 1}{\sigma_{f_j}}\right)^{\frac{\sigma_{f_j}}{\sigma_{f_j} - 1}} \end{aligned} \tag{13.23}$$

Here, τ_j^s is a scale parameter, γ_j^{rs} is a share parameter, σ_{f_j} is an elasticity of substitution parameter, and d_j^{rs} is the interregional imports of goods j. From Eq. (13.23), the price of goods is determined as

$$P_{F_j^s} = \frac{1}{\tau_j^s} \left[\sum_{r \in S} (\gamma^{rs})^{\sigma_{f_j}} \left(P_j^r\right)^{1-\sigma_{f_j}}\right]^{\frac{1}{1-\sigma_{f_j}}}. \tag{13.24}$$

From Shephard's lemma, the demand for composite goods delivered from each region is determined by

$$d_j^{rs} = \left[\frac{1}{\tau_j^s}\right]^{1-\sigma_{f_j}} \left[\frac{\gamma_j^{rs} PF_j^s}{P_j^r}\right]^{\sigma_{f_j}} \cdot F_j^s. \tag{13.25}$$

Income in the normal period is determined by labor supply $l_j^{s(0)}$, capital stock $k_j^s(0)$, wage $w_j^{s(0)}$, capital rent $r_j^{s(0)}$, and regional transfers of income $NX^{s(0)}$[8] using the equation

$$I^{s(0)} = \sum_{j \in N} \left(w_j^{s(0)} l_j^{s(0)} + r_j^{s(0)} k_j^{s(0)}\right) - NX^{s(0)}. \tag{13.26a}$$

During a disaster, nominal income is assumed to be same as that in the normal period.

[8]Income may be redistributed among regions through policies such as tax and social security spending.

$$I^{s(1)} = I^{s(0)} \tag{13.26b}$$

Equation (13.26b) assumes that no change occurs between the normal and disaster periods. That is, the differences in the ability to buy goods among regions do not change between the normal and disaster periods.[9]

3. Market Equilibrium Conditions

Market equilibrium conditions are given for conditions (a) and (b). In particular, the factor market equilibrium condition partly explains the downward factor price rigidity and unemployment, including the temporary reduction of labor, during disasters.

(a) Goods market clearing condition

The goods market clearing condition is

$$X_i^r = \sum_{s \in S} \sum_{j \in N} x_{ij}^{rs} + \sum_{s \in S} d_i^{rs}. \tag{13.27}$$

(b) Factor market equilibrium condition

For each daily period, the factor market equilibrium condition, which allows the movement of capital among sectors and the movement of both capital and labor among regions, is given as

$$\begin{aligned} \sum_{s \in S} l_j^{s(0)} &= \sum_{s \in S} L_j^{s(0)} \\ \sum_{j \in N} \sum_{s \in S} k_j^{s(0)} &= \sum_{j \in N} \sum_{s \in S} K_j^{s(0)}, \end{aligned} \tag{13.28a}$$

where $L_j^{s(0)}$ and $K_j^{s(0)}$ are the initial endowments, $r_j^{s(0)} = r^{(0)}$, and $w_j^{s(0)} = w_j^{(0)}$.[10]

Factor market conditions during a disaster can be set by the assumption of the downward price rigidity of labor. In this case, the following conditions may be considered valid.

---

[9]In reality, consumption patterns are likely to change during disaster and recovery periods (e.g. spending money on necessities rather than other commodities, such as avoiding entertainment). The effects of these shocks on the demand side have to be explored in a future study.

[10]Here, we assume that different types of labor exist in different sectors and are immobile between sectors.

$$\left(w_j^{s(1)} - w_j^{s(0)}\right)\left(l_j^{s(1)} - L_j^{s(1)}\right) = 0, \text{where } \ w_j^{s(1)} \geq w_j^{s(0)}, l_j^{s(1)} \leq L_j^{s(1)} \qquad (13.28b)$$
$$k_j^{s(1)} - K_j^{s(1)} = 0.$$

Here, $L_j^{s(1)}, K_j^{s(1)}$ are the post-disaster labor and capital endowments, respectively. The prices of capital $r_j^{s(1)}$ and labor $w_j^{s(1)}$ take distinct values among regions and sectors.

13.4 Data Sets for the Case Study of the 2011 Great East Japan Earthquake and Tsunami

13.4.1 Regional and Sectoral Settings of the Japanese Input–Output Table

The regional and sectoral settings of a CGE model are determined by the classifications of the available data sets, especially the disaggregation level of the input–output table. The interregional input–output table published by the Ministry of Economy, Trade and Industry in 2005 (METI 2010) is the most popular survey-based data for Japan (partially non-survey-based) and is used in our case study. In the table, Japan is divided into nine regions (Fig. 13.2), and 53 sectors are classified.

Forty-seven regional versions are also available, but they are constructed by a non-survey approach. The input–output table is estimated by the RAS method based on the nine interregional input–output tables, 47 intraregional input–output tables, and other data sets such as the interregional commodity flow census. The data are estimated by the Mitsubishi Sougou Research Institute, and details regarding the procedure are explained by Miyagi et al. (2003). Regarding the precision of the version we adopted, the difference between the total of inputs (columns) and outputs (rows) is less than 0.0005%.

From the nine regional input–output tables, the 30 industrial sectors shown in Table 13.1 are selected in this study with a special focus on automobile parts (9-region/30-sector model). In general, production in the total transport machinery sector is susceptible to downstream damage flowing from damage to small-parts producers. Fifty-three sectors are aggregated into 30 sectors (mainly non-manufacturing sectors are aggregated) to reduce computation time. For deriving the effect of sector disaggregation, this study also employs the 29-sector model in which the automobile parts and passenger cars sectors are aggregated (9-region/29-sector model).

For the study based on the 47-region input–output table, 29 industrial sectors are selected so that the sector classification becomes consistent with the 9-region/29-sector model (47-region/29-sector model). Basically, the 47-region input–output table does not originally include an automobile parts sector, which is combined

Fig. 13.2 Classification of Japanese regions

with passenger cars. The case study later reveals the potential advantages in sectoral/regional disaggregation cases.

13.4.2 *Production Capacity Loss Rate for Setting External Shocks to Production Systems*

In the ordinary application of CGE models to disaster impact analysis, shocks to production systems are set by decreasing capital stocks. These data sets are usually provided by local or central governments because they are essential for estimating recovery costs. However, particularly in short-run conditions, production capacity is

Table 13.1 Classification of industrial sectors

Sector name	
Agriculture, forestry, and fishery	Transportation machinery (automobile parts/passenger cars)[a]
Mining	Transportation machinery (other finished products)
Food	**Transportation machinery (automobile parts)**[b]
Apparel and textile	Precision machinery
Wood and wood products	Other manufacturing
Paper/pulp	Construction
Chemicals	Utilities
Refineries and coal	Communication
Glass/stone/clay	Transportation
Steel	Wholesale and retail
Non-ferrous metal	Financial, insurance, and real estate
Metal	Medical services
General machinery	Business services
Electrical machinery	Personal services
Electronics	Others

[a]Automobile parts are aggregated in the 29-sector models but not in the 30-sector model
[b]Included in only nine regional versions

determined by the functionality of the production systems rather than by the damaged stocks. The functionality of a production system can be easily lost without costly damage, for example, by the dislocation of production machinery.

Our study uses the production capacity loss rates (PCLRs) estimated by Kajitani and Tatano (2014). The PCLRs are derived from the vulnerability and resilience characteristics of various industrial sectors considering the extent of ground motion and tsunami hazard during the Great East Japan Earthquake and from the infrastructure disruption and evacuation that occurred because of the Fukushima Daiichi nuclear disaster.

The primary causes for increases in PCLRs are assumed to be damage to production facilities, labor supply, and infrastructure. Although reductions in labor affect production capacity, damage to production facilities and lifeline damage are the main factors in the case of past earthquake disasters in Japan. PCLRs are suitable for describing the maximum production loss but are only weakly related to actual recovery costs because costless recovery activities (e.g., cleaning up and relocation of machinery) are dominant during earlier periods after a disaster. However, if investments in recovery become large over time (e.g., reconstruction of buildings), it is necessary to incorporate the cost of recovery to estimate flow losses properly. Our case study does not yet include recovery investment, but it should be considered in longer-term analysis.

Figure 13.3 illustrates the examples of the PCLRs estimated by Kajitani and Tatano (2014) for five severely damaged prefectures at the Great East Japan Earthquake. In the figure, “factor damage” and “lifeline impact” indicate the sources that

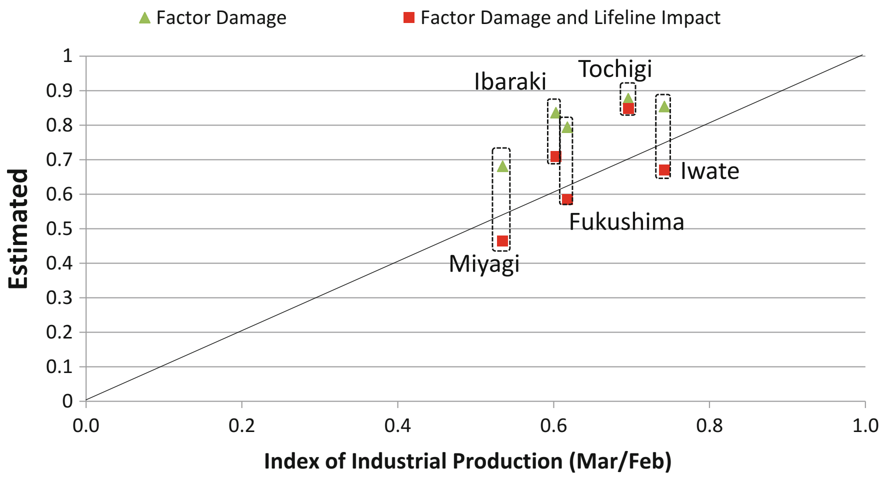


Fig. 13.3 Comparison of estimated monthly PCLRs and IIPs (observed production) in March 2011 (facility damage and lifeline impact are component models considered for estimating the corresponding PCLRs. The observed IIPs are standardized by the IIPs in February.)

affect PCLRs.[11] The different combinations of these sources were investigated to determine the size of the effects of different sources. The figure corresponds to the case of March 2011, and the estimated PCLRs considering all damage sources are better fit to the observed IIPs in the severely affected prefecture.

The IIPs are available every month in each prefecture (47 regions). For the comparison with the estimates in a later case study, we employ the nine-region version that aggregates the 47-region version. The IIPs in 16 sectors are selected. The classifications are almost consistent with the mining and manufacturing sectors in terms of the I-O table given in Table 13.1. However, in IIPs, electric machinery and electronics are aggregated into the electric machinery sector, and all the transportation machinery sectors are also aggregated into one automobile machinery sector.

The conversion of the PCLRs to the shocks of the value-added function in a CGE model is explained as follows. First, recall Eq. (13.5) for the disaster case:

$$f_{V_j^s}\left(L_j^{s(1)}, K_j^{s(1)}\right) = \eta_j^{s(1)}\left(L_j^{s(1)\alpha_j^s} K_j^{s(1)1-\alpha_j^s}\right). \tag{13.29}$$

Then, the PCLR (corresponding to the case, "factor damage and lifeline impact" are considered in Fig. 13.3) and production functions have the relationship

[11] "Factor damage" is the case where damages to production facilities and labors are considered, and "lifeline impact" is the case where the impacts of lifeline (electricity, water, and gas) disruption duration are considered. Different types of engineering-based models, such as a fragility curve, are employed to calculate the impacts of each source on production capacities.

$$1 - PCLR_j^s = \eta_j^{s(1)} \left(L_j^{s(1)\alpha_j^s} K_j^{s(1)1-\alpha_j^s} \right) / \eta_j^{s(0)} \left(L_j^{s(0)\alpha_j^s} K_j^{s(0)1-\alpha_j^s} \right). \tag{13.30}$$

Here, the pre-disaster production is considered at a maximum level because production factors are fully utilized.

Next, we assume that the infrastructure disruption affects only parameter $\eta_j^{s(1)}$.[12] Setting $\overline{PCLR}_j^s$ as the estimate assuming that key infrastructure is not disrupted (corresponding to the case, only "factor damages" are considered in Fig. 13.3), the relationships in Eq. (13.30) can be rewritten as

$$1 - \overline{PCLR}_j^s = \left(L_j^{s(1)\alpha_j^s} K_j^{s(1)1-\alpha_j^s} \right) / \left(L_j^{s(0)\alpha_j^s} K_j^{s(0)1-\alpha_j^s} \right), \tag{13.31}$$

because $\eta_j^{s(1)}$ is identical to $\eta_j^{s(0)}$.

Considering that the input structure for capital and labor follows a putty-clay assumption in the area affected by disaster, the production restriction is determined by either factor, and the following relationship holds:

$$\frac{K_j^{s(1)}}{K_j^{s(0)}} = \frac{L_j^{s(1)}}{L_j^{s(0)}} = 1 - \overline{PCLR}_j^s. \tag{13.32}$$

Note that $K_j^{s(1)}$ and $L_j^{s(1)}$ are interpreted as hypothetical capital and labor endowments because the corresponding PCLRs consider the functional damage to production facilities, which is different from stock losses (in monetary terms) and employee losses.

From Eqs. (13.30) and (13.31), $\eta_j^{s(1)}$ can be obtained by

$$\eta_j^{s(1)} = \frac{\left(1 - PCLR_j^s \right) \eta_j^{s(0)}}{1 - \overline{PCLR}_j^s}. \tag{13.33}$$

By using Eqs. (13.32) and (13.33), the PCLR is converted to the shock to the value-added function in a CGE model. In summary, we have modeled lifeline damages in productivity shock, which is a standard approach in much of the literature these days, and have modeled factor damage by reducing the capital stock and labors accordingly in each sector. We have modeled both the economic impacts of the shock (impacts of lifeline and factor damages right after the event) and the recovery. Therefore, net impacts are estimated from our analysis later to be consistent with the observed productions.

---

[12] One of the alternative approaches could be that PCLR is reflected in only the hypothetical capital losses. However, we reflect the impacts of infrastructure disruptions on the efficiency parameter because the interpretation is easier if the capital losses are induced by facility damage and recovery and the total productivity factor is reduced due to lifeline damage.

The PCLRs for the Great East Japan Earthquake are estimated for Iwate, Miyagi, and Fukushima prefectures (Tohoku region) and for Ibaraki and Tochigi prefectures (Kanto region) in a previous study (Kajitani and Tatano 2014) (Fig. 13.3). Because the production capacities in the other prefectures in the Tohoku region (Akita, Aomori, Yamagata) are not considered, the IIPs are used for the shocks of manufacturing sectors, and no shock is considered for non-manufacturing sectors in these prefectures for the 9-region models. To obtain the overall production capacities in the Tohoku and Kanto regions, we use the average production capacities weighted by the number of employees in each prefecture. However, only the production capacity losses for the five severely affected prefectures are used for the 47-region model because the interregional impact in the Tohoku region can be explained by the 47-region model but not by the 9-region models, as shown later in the case study.

13.4.3 Elasticity of Substitution Parameters for the Assessment of Supply Chain Effects

Typically, the short-term impacts of any economic shocks are treated by setting low values of the elasticity of substitution parameters for a CGE model. If a substitution parameter of a damaged sector is small (i.e., it is difficult to replace the goods and services produced by the company with those of other industries in the same sector), then using inputs from the damaged sector, all the sectors are likely to reduce their production because they have difficulty in substituting inputs from different regions.

In the following analysis, the basic parameters for the elasticity of substitution for interregional imports, which were estimated by Koike et al. (2012), are used for the baseline data set, which is customized for Japanese interregional trade. Koike et al. (2012) evaluated the parameter values based on input–output tables and the national census of commodity flows conducted every 5 years from 1980 to 2005. The estimates are relatively low (less than 1 for most sectors), even for the long-run case in Japan. Considering that the substitutability is unlikely to be higher in manufacturing sectors than in non-manufacturing sectors, the elasticity of substitution for the non-manufacturing sector is set to 0.25 as an arbitrary but reasonable value. Tables 13.2 and 13.3 summarize the baseline elasticities of substitution parameters for the manufacturing and non-manufacturing sectors, respectively, and the parameters for interregional trade for each manufacturing sector.

For comparison with the baseline case, the case where the elasticity of substitution for interregional trade is halved is examined. In addition, the cases where the elasticity is set to 0 in the automobile parts sector are also simulated,[13] considering

[13]The substitution parameter is set to 0 only for the automobile parts sector for the nine-region/30-sector model and in the combined automobile parts and passenger cars sector for 9-region/29-sector and 47-region/29-sector models.

Table 13.2 Parameter values for the elasticity of substitution in Japan

Classification	Sector	Values
Interregional composite goods	Manufacturing	0.74–0.96 (See Table 13.3 for more details)
	Non-manufacturing	0.25
Demand for final composite goods	All sectors	0.8
Imported and domestic composite goods	Manufacturing	0.5
	Non-manufacturing	0.25

Table 13.3 Parameter values for the elasticity of substitution on interregional trade in manufacturing sectors

Sector name	ψ, σ_f	Sector name	ψ, σ_f
Agriculture, forestry, and fishery	0.83	Non-ferrous metal	0.74
Mining	0.8	Metal	0.84
Food	0.85	General machinery	0.86
Apparel and textile	0.87	Electrical machinery	0.89
Wood and wood products	0.87	Electronics	0.89
Paper/pulp	0.85	Transportation machinery (passenger cars)	0.96
Chemicals	0.78	Transportation machinery (other finished products)	0.96
Refineries and coal	0.88	Transportation machinery (automobile parts)	0.96
Glass/stone/clay	0.90	Precision machinery	0.93
Steel	0.81	Other manufacturing	0.87

that the supply chain effects are particularly important in this sector. It is a feature of the calibration of the CGE model that computation time increases as the elasticity parameter decreases. In our study of the 47-region model, no result was obtained for some cases where a baseline parameter value of less than half was used. The simulation is intended not to estimate the best values of the substitution parameter during a disaster but rather to derive the potential applicability of CGE models for disaster impact analysis by changing the elasticity parameter values. More calculations are necessary for calibrating the substitution parameter values.[14]

The elasticity parameter between different composite goods for final demand is set at 0.8 based on Ichioka (1991). For the substitution or transformation parameters between domestic and imported goods or export goods, we use smaller values (manufacturing: 0.50; non-manufacturing: 0.25). These values should be

[14]For example, grid search (setting several parameter values that are allocated by the same small interval in the possible range of each parameter and trying all combinations) would help to find better parameter values, but the computation time is likely to be very high.

investigated based on the observations of household demand and international trade during a disaster; however, this is beyond the scope of this paper.

13.5 Application to the 2011 Great East Japan Earthquake and Tsunami

13.5.1 Comparisons of Different CGE Models by RMSEs

To compare the performance of the models using different regional segmentations and substitution parameter values, RMSEs, which can be calculated from the estimated and observed IIPs, are used.[15]

For example, RMSEs for regions $s \in S$ and sectors $j \in N$ and periods $t \in T$[16] are defined by

$$RMSE = \sqrt{\frac{1}{\mathrm{M}} \sum_{s \in R,\, j \in J,\, t \in T} \left(IIPest_j^{st} - IIPobs_j^{st} \right)^2}, \tag{13.34}$$

where M is the number of samples compared and $IIPest_j^{st}$ and $IIPobs_j^{st}$ are respectively the observed and estimated IIPs, which are the standardized production output (Production in February is set as 1).

Sensitivity analysis of the elasticity of the substitution parameters for composite goods among domestic regions is performed with parameter values that are equal to or half of the baseline value for all sectors. In addition, 0 (Leontief case) is applied to the substitution parameters in the automobile parts (equivalently, in the transportation machinery sector for the 29-sector models) for the half substitution parameters in the other sectors.

Table 13.4 lists the results for different settings of the model for March, April, and May 2011 (3-month total). In the substitution parameter columns, 0, 0.5, and 1 indicate the ratio of the values of substitution parameters to the baseline value. RMSEs are shown with a special focus on Tohoku (severely affected area) and Kanto (large trade volume with the Tohoku region). Similarly, the results for each month are provided in Table 13.5. In all cases, the basic parameters, except the exogenous substitution parameters, are calibrated, and all endogenous variables, such as production, have very small residuals compared with those in the benchmark data sets. The first and third results (No. 1 and No. 3) in Table 13.4, which are the cases of 9-region/29-sector and 9-region/30-sector models with a baseline CES parameter, respectively, have the same and the largest RMSEs of all the estimates.

[15]For comparison, automobile parts, passenger cars, and other finished transportation machinery products are aggregated by the production quantity weights.

[16]Set T includes the following elements: March, April, and May of 2011.

Table 13.4 RMSEs of the estimated IIPs in March, April, and May (3-month total)[a]

		Intermediate (ψ)		Final demand (σ_f)		RMSEs				IIP[c]
No.	No. of Regions[b]	Automobile	Other	Automobile	Other	All regions	Tohoku	Kanto	Other	All
1	9(29)	1	1	1	1	0.133	0.167	0.147	0.124	0.974
2	9(29)	0	0.5	0	0.5	0.118	0.167	0.116	0.107	0.940
3	9(30)	1	1	1	1	0.133	0.166	0.147	0.124	0.974
4	9(30)	0	0.5	0	0.5	0.114	0.163	0.105	0.105	0.932
5	47(29)	1	1	1	1	0.125	0.124	0.134	0.123	0.967
6	47(29)	0	0.5	0	0.5	0.112	0.132	0.1022	0.110	0.918

[a]The number of samples compared is 360 (eight regions $\times$ 16 industrial sectors – four non-observed sectors = 120 samples/month). The Okinawa region is excluded because the size of its economy is smaller than that of the other regions

[b]The sector number is given in brackets

[c]Estimated IIPs. The averaged observed IIP for 3 months for Japan in total is 0.867

Table 13.5 RMSEs of the estimated IIPs in March, April, and May[a]

No.	Month	No. of regions[b]	Intermediate (ψ)		Final demand (ψ)		RMSEs				IIP[c]
			Automobile	Other	Automobile	Other	All regions	Tohoku	Kanto	Other	
7	March	9(29)	1	1	1	1	0.112	0.099	0.183	0.097	0.966
8	March	9(29)	0	0.5	0	0.5	0.085	0.099	0.143	0.066	0.936
9	March	9(30)	1	1	1	1	0.112	0.099	0.183	0.097	0.966
10	March	9(30)	0	0.5	0	0.5	0.081	0.098	0.132	0.065	0.927
11	March	47(29)	1	1	1	1	0.111	0.115	0.166	0.097	0.958
12	March	47(29)	0	0.5	0	0.5	0.080	0.101	0.117	0.067	0.900
13	April	9(29)	1	1	1	1	0.159	0.201	0.148	0.152	0.973
14	April	9(29)	0	0.5	0	0.5	0.144	0.201	0.115	0.137	0.936
15	April	9(30)	1	1	1	1	0.159	0.201	0.148	0.152	0.973
16	April	9(30)	0	0.5	0	0.5	0.141	0.200	0.103	0.135	0.927
17	April	47(29)	1	1	1	1	0.147	0.137	0.135	0.151	0.964
18	April	47(29)	0	0.5	0	0.5	0.140	0.159	0.107	0.142	0.897
19	May	9(29)	1	1	1	1	0.124	0.182	0.096	0.115	0.985
20	May	9(29)	0	0.5	0	0.5	0.117	0.182	0.081	0.107	0.970
21	May	9(30)	1	1	1	1	0.123	0.182	0.095	0.115	0.985
22	May	9(30)	0	0.5	0	0.5	0.113	0.180	0.071	0.104	0.962
23	May	47(29)	1	1	1	1	0.112	0.120	0.090	0.114	0.981
24	May	47(29)	0	0.5	0	0.5	0.106	0.129	0.078	0.106	0.951

[a]The number of samples compared is 120 for each case (monthly comparison)
[b]The sector number is given in brackets
[c]Estimated IIPs. The observed IIPs in March, April, and May for Japan in total are 0.835, 0.853, and 0.911, respectively. The IIP in February is set as 1

This level of sector disaggregation does not affect the estimates in the case where the baseline CES parameter is used. However, the estimates from the 47-region/29-sector model improve with the baseline CES parameter settings (No. 5), especially in the Tohoku region, in terms of smaller RMSEs. Slight improvements can also be observed in Kanto and the other regions. Monthly estimates in Table 13.5 are also better (Nos. 11, 17, 23) than the corresponding estimates from the 9-region models (Nos. 7, 9, 13, 15, 19, 21).

Comparing Nos. 2, 4, and 6 with Nos. 1, 3, and 5, respectively, demonstrates that the estimates improve as the elasticity of substitution decreases in both the 9- and 47-region models. Thus, the baseline parameter values may not be suitable for this level of short-run disaster impact assessment. The monthly study also confirms this result. Overall, the 47-region model with 0 and half elasticity of substitution for automobile and other sectors, respectively (No. 6), produced the estimate with the lowest RMSE.[17] The difference from the results of other competitive models is significant at the 1% level when the Wilcoxon signed-rank test (Wilcoxon 1945) is used, with the null hypothesis of identical probability distributions of two errors produced by different models. Thus, regional disaggregation can be a promising way to improve the model performance, but the estimated IIP for Japan in total (an average of 3 months) is still larger than the observed IIP (the observed IIP is 0.867, and the estimated IIP is 0.918).

Sectoral disaggregation also contributes to enhancing forecasts when smaller elasticity parameter values are adopted. In our case, the 9-region/30 sector model produces significantly smaller RMSEs than those obtained for the 9-region/29 sector model.

13.5.2 Analysis of Spatial and Sectoral Impacts

Figure 13.4 compares the IIPs estimated by the 9-region models for all the manufacturing sectors and the corresponding IIPs in each region and month (i.e., weighted averages across sectors based on production outputs). The substitution parameter is half (elasticity of substitution (EOS): 0.5 in the figure), and the overall trend in the estimated IIPs is consistent with the observed IIPs in the severely damaged areas (Tohoku and Kanto) and in the other areas. The 9-region/30-sector model estimates slightly less production than the 9-region/29-sector model does. For a normal substitution parameter (EOS: 1), the estimates do not follow the observed values as well as in the previous cases.[18] However, even in the estimates obtained

[17]For the nine-region model, Kajitani and Tatano (2018) found a better estimate for the case of even smaller elasticities of substitution in interregional trade (0 for automobile parts and 1/3 as the normal case for other sectors). Nonetheless, the RMSE in the best 47-region model in this study (RMSE = 0.1118) is slightly smaller than that in the best 9-region model (RMSE = 0.1126).

[18]We omitted the case of the 9-region/29-sector model because it does not exhibit a change from the 9-region/30 sector model.

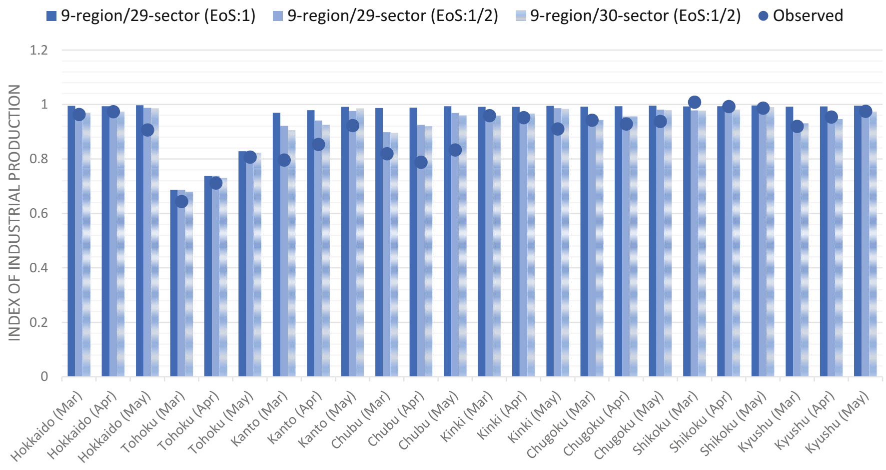


Fig. 13.4 Estimated IIPs with different elasticity parameter settings and observed IIPs in March (9-region model)

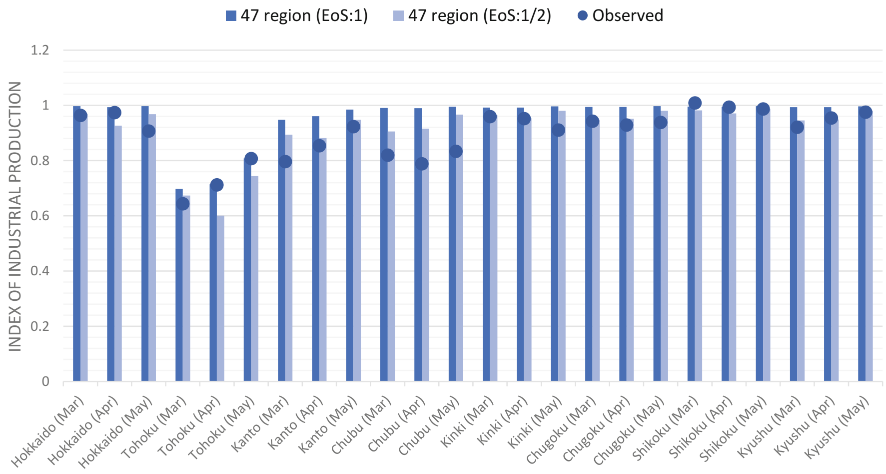


Fig. 13.5 Estimated IIPs with different elasticity parameter settings and observed IIPs in March (47-region model)

from the better model (EOS: 0.5), especially in the Chubu region, the model consistently overestimates the production in each month. The supply chain impacts may not be reflected adequately in the model in the primary industrial sectors, such as the transportation machinery sector, which has a large production share in the Chubu region. This is one of the reasons why the discrepancy between the observed and the estimated IIPs is generated.

The estimates of the 47-region/29-sector model are also plotted in Fig. 13.5. The estimated IIPs are consistently larger than the observed IIPs in many regions and

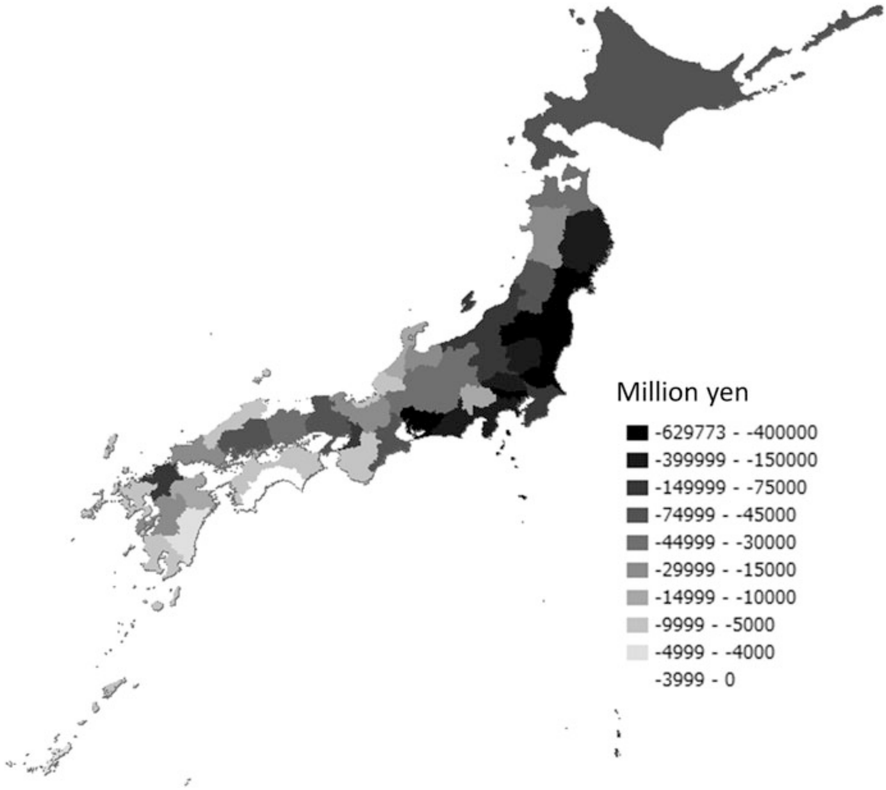


Fig. 13.6 Production losses in each prefecture (March)

sectors, except Tohoku, in the case of the baseline substitution parameter. In contrast, in the case of the half substitution parameter, a larger decrease in the estimated IIPs is seen in the Tohoku region (apart from the observed IIPs), but the estimated IIPs in other regions fit better with the observed values. In total, this case produces the best estimates among all the cases. Detecting the best parameter values is beyond the scope of this study, but this result implies the need to consider that the substitution parameter can depend on the spatial scale/distance.[19]

The spatial impacts explained by the production losses in 47 regions are geographically plotted in Figs. 13.6, 13.7, and 13.8 for March, April, and May, respectively (the results of the best model). The production losses are explained by a monetary term, the price of which is set as the pre-disaster level. Large impacts are seen in the severely affected prefectures in the eastern part of Tohoku and

[19]More investigations are needed, but models at a finer spatial scale may require higher substitution parameter values depending on distances from the disaster hit area if production outsourcing occurs at a closer distance.

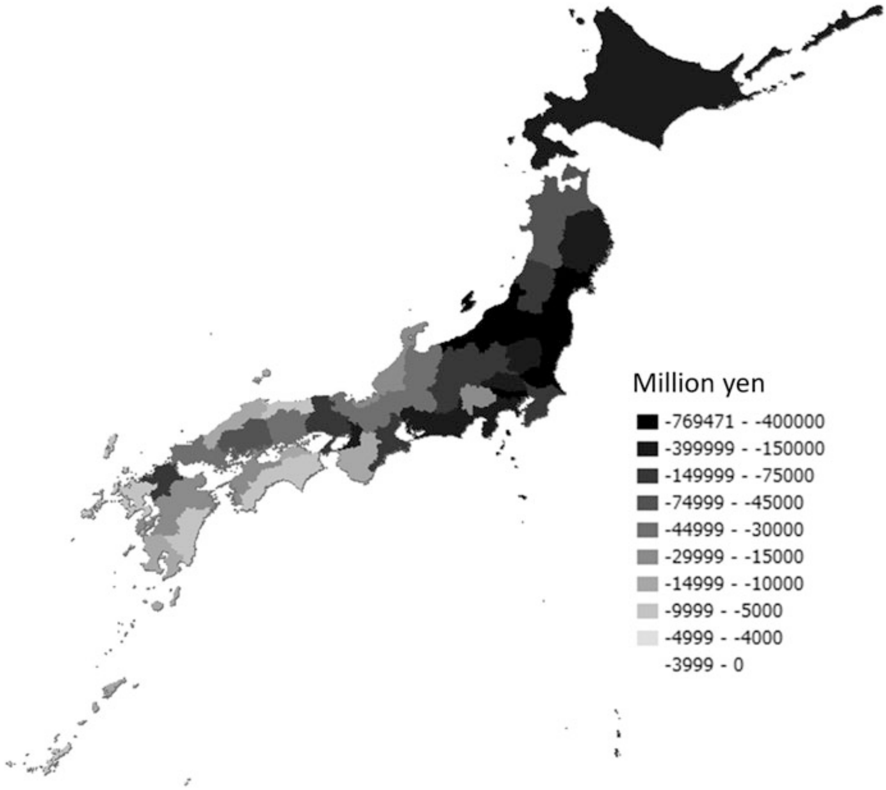


Fig. 13.7 Production losses in each prefecture (April)

surrounding regions as well as in the major cities in other regions (e.g., Aichi in Chubu, Osaka in Kansai, and Fukuoka in Kyushu).

13.5.3 Analysis of Sectoral Impact

For the analysis of sectoral impact, the production losses in March calibrated by the 9-region and 47-region models are examined as a representative result. The results in April and May indicate similar conclusions.

In Figs. 13.9 and 13.10, the estimated and observed IIPs for the 9-region/30-sector and 47-region/29-sector models are compared, respectively. We use the model with smaller substitution parameter values (0 for the automobile manufacturing sector and half-size for the remaining sectors), which produce the IIPs with the smallest RMSEs. Each plot corresponds to a regional and sectoral IIP. Most of the smaller IIPs come from the data from severely affected regions. In both cases, some observed values exceed 1, but the estimated IIP does not because of the model

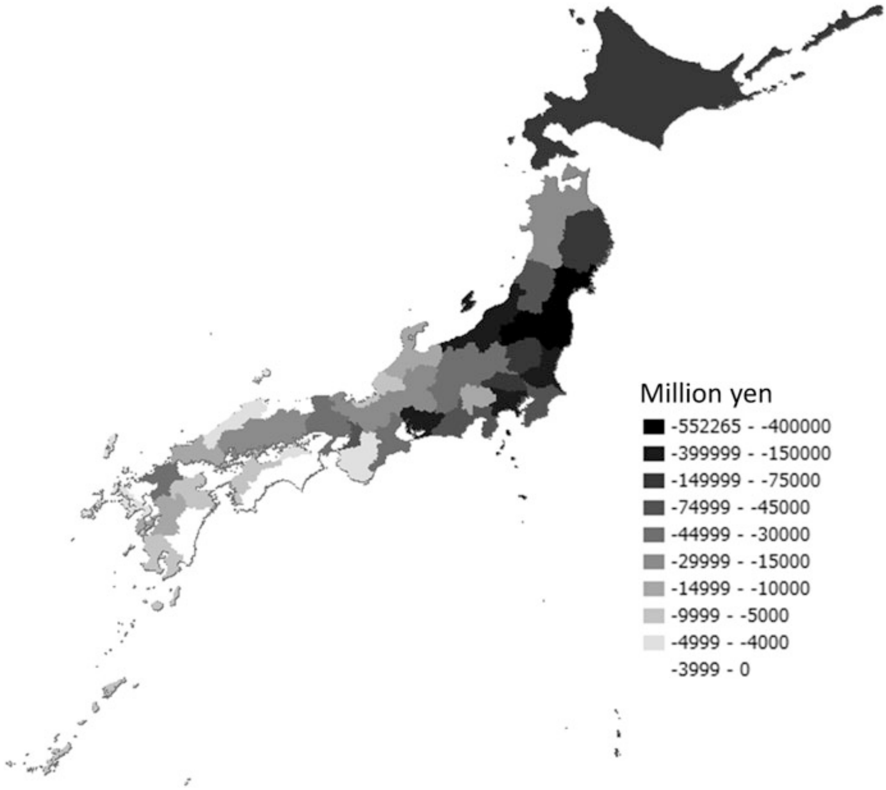


Fig. 13.8 Production losses in each prefecture (May)

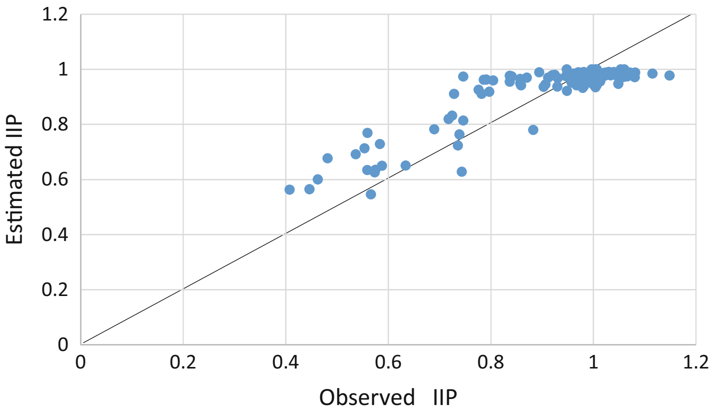


Fig. 13.9 Comparison between estimated and observed IIPs in March 2011 (9-region/30-sector model)

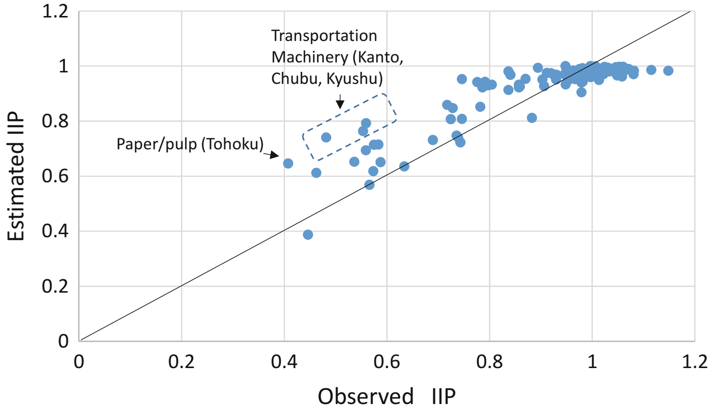


Fig. 13.10 Comparison between estimated and observed IIPs in March 2011 (47-region/29-sector model)

assumption that maximum production (full capacity) occurs before a disaster; however, there can be idle capacity even before a disaster.

The IIPs estimated by both models trace the observed values relatively well. However, the results indicate that the supply chain impacts are not as fully reflected by the 47-region model in the transportation machinery sector, as highlighted in the dashed box in Fig. 13.10. The figure is omitted, but a similar diagram can be obtained for the 9-region/29 sector model with regard to the plots of the automobile manufacturing sector. The total production losses in each sector summed by all regions are shown in Fig. 13.11. Production losses in most sectors are consistent among the sectoral estimates by the 9-region and 47-region models. The largest difference is seen in the transportation machinery sector. In summary, identifying and separating the key sectors that have small substitution parameters can be an effective approach for estimating the impacts of a disaster.

However, the reality is more difficult. In the Great East Japan Earthquake on March 11, 2011, the production decrease in automobile sector was large in the Kanto region due to the damage to a semi-conductor company. This damage also causes wide supply-chain impacts on automobile sectors all over Japan. This effect is not reflected in our study, and can be one of the reasons why our model overestimates the IIPs in this sector. More sector by sector analysis based on reality is required for understanding the gap between the observed and estimated values.

13.6 Conclusions

We examined the performance of an SCGE model applied to the Great East Japan Earthquake of 2011. The typical short-run settings of the CGE model were used, such as no mobility in production factors and no change in nominal income, and the

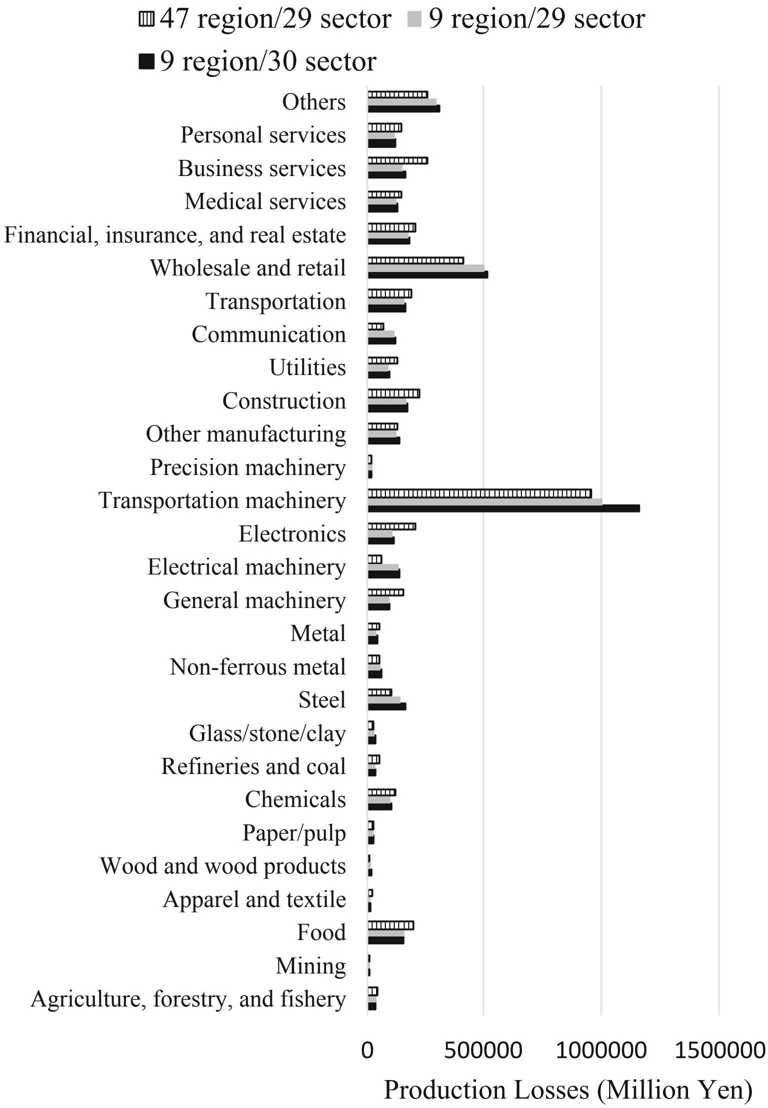


Fig. 13.11 Production losses in each sector (March 2011)

elasticity of substitution parameters used were small. We focused on the disaggregation of regional and sectoral classifications. Comparing the forecasting capabilities of three different models (9-region/29-sector, 9-region/30-sector, and 47-region/29-sector models), we obtained the following results.

The 9-region/30-sector model had the advantages that the input–output table was constructed from survey data and that the reliability of the data set was high. In addition, the sectoral disaggregation level was higher for identifying key sectors that should be disaggregated. In our case, the disaggregation of the transportation sector into parts and finished products improved the estimation of production loss in this sector. However, given the large spatial scale of the region, the goods within a sector were completely substitutable among the same regions and supply-chain impacts less likely to occur.

The 47-region model had an advantage in explaining fine-scale impacts, and smaller RMSEs showed that it outperformed both 9-region models. The model showed the impacts of production shocks in the severely damaged prefecture on the surrounding prefectures, which must be assumed as initial shocks by the observed data in 9-region models.

In all three cases, the best performance was seen when the substitution parameters for interregional trade were smaller than the baseline parameter values (0 for the automobile manufacturing sector and half-size for the remaining sectors). However, the appropriate values of substitution parameters for the 47-region models must be investigated further to explain the supply chain impacts in more detail because the various combinations of parameter values exist and have not been tested yet.

In summary, further studies are needed, but it is necessary to determine the key sectors to which a small substitution parameter should be applied and to divide the physically damaged region from surrounding regions on a small spatial scale. Constructing these baseline statistics would help to improve the performance of SCGE models for disaster impact analysis.

Other issues that have not been discussed in this research are important for improving the models. For example, changes in consumption patterns, such as the increased ratios of expenditure on durable and necessary goods by consumers after a disaster, are not considered in this research. In our study, the estimated IIPs are larger than the observed IIPs in many cases, which indicates that additional shocks may be needed to obtain better estimates. We need to investigate supply-side shocks more fully, but the consideration of demand-side shock is another possibility for improving the estimates. For any cases, the model assumptions should be updated by using data and information for various disasters to identify better model settings for disaster impact analysis.

Acknowledgements We would like to thank the editors and two anonymous reviewers for their constructive comments. We also acknowledge Taylor and Francis and the International Input-Output Association because this chapter is derived in part from an article published in Economic Systems Research (28 Sep 2017, copyright: International Input-Output Association, available online: http://www.tandfonline.com/doi/full/10.1080/09535314.2017.1369010).

References

Atkeson A, Kahoe PJ (1999) Models of energy use: putty-putty versus putty-clay. Am Econ Rev 89:1028–1043

Badri NG, Walmsley TL (2008) Global trade, assistance, and production: the GTAP 7 Data Base. Center for Global Trade Analysis, Purdue University

Bourguignon F, Michel G, Miqueu D (1983) Short-run rigidities and long-run adjustments in a computable general equilibrium model of income distribution and development. J Dev Econ 13:21–43

Dixon PB, Jorgenson D (eds) (2013) Handbook of computable general equilibrium modeling, Vols. 1A and 1B, Handbooks in economics. North-Holland, Amsterdam

Greenberg MR, Lahr M, Mantell N (2007) Understanding the economic costs and benefits of catastrophes and their aftermath: a review and suggestions for the U.S. Federal Government. Risk Anal 27:83–96

Hertel TW (ed) (1997) Global trade analysis: modeling and applications. Cambridge University Press, New York

Ichioka O (1991) Applied general equilibrium analysis. Yuhikaku, Tokyo. (In Japanese)

Kajitani Y, Tatano H (2014) Estimation of production capacity loss rate after the Great East Japan earthquake and Tsunami in 2011. Econ Syst Res 26(1):13–38

Kajitani Y, Tatano H (2018) Applicability of a spatial computable general equilibrium model to assess the short-term economic impact of natural disasters. Econ Syst Res 30(3):289–312

Koike A, Ito K, Nakao T (2012) Estimation of Armington elasticities in Japan. J Jpn Soc Civil Eng 68:55–61. In Japanese

Ministry of Economy, Trade and Industry (METI) (2010) 2005 Interregional input-output table. http://www.meti.go.jp/statistics/tyo/tiikiio/result/result_02.html (In Japanese). Accessed 22 Sept 2014

Miyagi T, Ishikawa Y, Yuri S, Tsuchiya K (2003) The construction of interregional input-output table at prefecture level using intraregional input-output tables. Infrastruct Plann Rev 20 (1):87–95. In Japanese

Okuyama Y, Hewings GJD, Sonis M (2004) Measuring economic impacts of disasters: interregional input-output analysis using sequential interindustry model. In: Okuyama Y, Chang SE (eds) Modeling spatial and economic impacts of disasters. Springer, New York, pp 77–101

Oosterhaven J, Bouwmeester MC (2016) A new approach to modeling the impact of disruptive events. J Reg Sci 56(4):583–595

Partridge MD, Rickman DS (1998) Regional computable general equilibrium modeling: a survey and critical appraisal. Int Reg Sci Rev 21(3):205–248

Rose A, Guha G (2004) Computable general equilibrium modeling of electric utility lifeline losses. In: Okuyama Y, Chang SE (eds) Modeling spatial and economic impacts of disasters. Springer, New York, pp 119–141

Rose A, Liao S (2005) Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. J Reg Sci 45:75–112

Shoven JB, Whalley J (1992) Applying general equilibrium. Cambridge University Press, Cambridge, UK

Tatano H, Tsuchiya S (2008) A framework for economic loss estimation due to seismic transportation network disruption: a spatial computable general equilibrium approach. Nat Hazard 44:253–265

Taylor L, Lysy FJ (1979) Vanishing income redistributions: Keynesian clues about model surprises in the short run. J Dev Econ 6:11–29

Ueda T (ed) (2010) Regional and urban economics analysis with excel. Corona, Tokyo. (In Japanese)

Wilcoxon F (1945) Individual comparisons by ranking methods. Biometrics Bull 1(6):80–83

Yoshio Kajitani is Professor of Faculty of Design and Engineering in the Kagawa University, Japan. He graduated from the Faculty of Engineering, Kyoto University in 1997, and completed Master Program at Department of Statistical and Actuarial Science, Faculty of Science, The University of Western Ontario (currently, Western University) in 1999. He obtained Doctor of Engineering from the Kyoto University in 2004. His major is disaster risk management, especially focusing on socio-economic impacts of natural disasters. His research interests are mainly in the development of new risk simulation models and tools, where he adopts Statistics, Economics and Transportation/ Utility Engineering, for disaster prevention, reduction and recovery.

Hirokazu Tatano is a professor at the Disaster Prevention Research Institute, Kyoto University, Japan. From September 2010, he is serving a role of Vise President of International Society of Integrated Disaster Risk Management (IDRiM Society). He is also currently serving as a secretary general of the Global Alliance of Disaster Research Institutes, which established at the occasion of the second global summit of research institutes for disaster risk reduction, March 19–20th 2015. He received his M.Sc. and Ph.D. in civil engineering from the Kyoto University. Much of Dr. Tatano's research is on the economics of natural hazards, and he has done pioneering research on economic consequence analysis. Another major focus of his research has been on resilience to natural disasters at the levels of the individual business, market, and regional economy.

Chapter 14
The Economic Impacts of Climate Change on Grain Production and Policy Implications: A CGE Model Analysis

Wei Xie, Qi Cui, and Tariq Ali

Abstract The adverse effects of extreme disasters on crop production, often assessed using crop models or field experiments, may be overestimated as these methods focus on natural impacts while ignoring the behavioral changes of farmers and international traders. This study takes barley as an example and uses GTAP model (a global economic equilibrium model) to showcase the role of the behavioral changes and to assess the economic impact of climate change on crop production after the occurrence of most extreme disasters. The results show that under RCP 8.5, the impact of extreme disasters on barley yields in China and Australia are –12% and –25.8%, respectively. After considering farmers and international traders' behavioral change, the effects of climate change on barley production in China and Australia are reduced to –0.38% and –3.5%, respectively. Variations in production level mainly depend on the extent of farmers' ability to expand barley sown area and the severity of government intervention in agricultural exports. In order to reduce the impact of disasters on food supply, it is necessary to give full play to the role of market mechanisms and to reduce government interventions in trade.

W. Xie (✉)
China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China
e-mail: xiewei.ccap@pku.edu.cn

Q. Cui
School of Economics and Resource Management, Beijing Normal University, Beijing, China
e-mail: cuiqi@bnu.edu.cn

T. Ali
School of Economics and Management, North China University of Technology, Beijing, China

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_14

14.1 Introduction

Climate change is widely considered as a significant challenge for the future global food system. To design climate adaptation policies in the agriculture area, it is necessary to assess the consequences of climate change on agricultural production. This requires the knowledge of both physical and economic effects of climate change on agricultural production under different representative concentration paths (RCPs).

There are various estimated impacts of climate change on agriculture in literature, but most of them only used field experiments or crop models to assess the physical impacts of climate change. The existing studies indicate that crop yield would be negatively affected by climate change, although the impacts of climate change are quite different among different regions (Lobell et al. 2011; Wheeler and Von Braun 2013; Rosenzweig et al. 2014). Recently, some studies began to focus on the economic impacts of climate change on food security, such as Nelson et al. (2014). However, previous studies seldom considered the different contribution of free and restricted markets in alleviating the impacts of climate change (Reilly and Hohmann 1993; Ciscar et al. 2011; Brown et al. 2017). For example, disasters generally increase crops price to some extent. Then in the event of a new disaster, farmers try to increase inputs as high as they can to prevent production losses according to their experience with the price increase during the previous disaster. On the contrary, if the markets have some interventions or the trade is restricted, farmers may not experience true price signals in the wake of a disaster, and when the new disaster occurs, they may not increase inputs to that extent.

On the other hand, previous studies have often focused on the impacts of the slowly changing climate on agricultural production, such as the average changes in temperature and precipitation in future. However, climate change increases the frequency and severity of extreme weather events, such as extreme heat and drought (Meehl et al. 2000; Cheng et al. 2012), which more seriously threaten global food production. Unfortunately, the impacts of extreme weather events on cropping systems are seldom quantified, as their rare occurrence makes it hard to be adequately calibrated and tested (Field et al. 2014).

Based on the discussion above, the overall goal of this study is to assess the economic impacts of extreme weather events on global grain production and analyze the contribution of different market rules. Considering that this study focuses on the unique role of market and trade, a specific crop—barley (also with limited case studies)—is taken as an example. The reason for not modeling a general impact on all crops is that if we evaluate the impact on all grains, the results with the interaction of different grains will make the analysis more complicated. It will be hard to distinguish whether the contributions (positive or negative) are coming from market and trade channels, or from the land substitution among different grains (e.g., if comparative advantage changes due to climate change, other grains experiencing light impacts may leave some additional land for barley production and might significantly ameliorate the reduction in barley production). Moreover, though barley is taken as the focus crop, the mechanism in this study aplies to the economic impacts of extreme disaster on the production of other grains and the policy implications are also suitable for other grains.

14.2 Methodology and Scenarios

To address the issues mentioned above, the economic impacts of extreme weather events on global barley production are assessed based on global economic model (global trade analysis project model, GTAP). The selection of disaster events under RCP scenarios (for simplicity, this study only considers the best scenario of RCP2.6 and the worst scenario of RCP8.5) during 2011–2100 and the corresponding climate data (e.g., temperature and precipitation during growing season of barley) are provided by Earth System Models (ESMs); Then using the climate data under disaster scenarios, the crop model (DSSAT) provides the physical change of barley yield; Finally, the GTAP model uses the yield change as shock to simulate the economic impacts and the role of market and trade on barley production around the globe.

14.2.1 The Method to Select Disaster Events and Simulate Physical Yield Change

In this study, we define disasters as concurrent global drought and heat extremes (more severe than 100-year events), the primary mechanisms by which climate damages crop production (Lobell et al. 2013; Lesk et al. 2016). Below we outline the detailed steps of selecting disaster events over this century:

- First, we calculate the global barley drought and heat disaster threshold values corresponding to 1 in 100 year probability in historical data (1981–2010): (1) we estimate standard precipitation index (SPI ≤ -1.0) and extreme degree days 30 °C + (EDD) for each grid in all barley planting regions during barley growth period (spring and winter barley) from 1981 to 2010; (2) we adopt a weighted average method to calculate annual global drought and extreme heat index; (3) we fit the annual global barley drought and heat indices with Pearson-III distributions, and use the fitted curves to derive the global barley drought index and heat index corresponding to 1-in-100-year probability. Hence, we get the global barley drought and heat disaster threshold values.
- Then, we use barley drought and heat disaster threshold values to select concurrent global drought and heatwaves in the future under climate change as projected by five different global climate models (to reflect the uncertainty of ESM models, the ESM models in this study include GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M). We select disaster years when both global extreme drought and extreme heat concurrently strike in the same growing season of the same year. All modeled disaster years are selected to simulate global barley yield using the process-based crop model.

Based on the disaster years selected above, we simulate global barley yield change due to disasters on gridded level by the CSM-CERES-Barley module, which is part of the Decision Support System for Agrotechnology Transfer (DSSAT) version 4.6 (Hoogenboom et al. 2015). The gridded formatted inputs used to drive the DSSAT model include daily weather data, soil parameters, crop calendar data, and management information. The process of using the DSSAT model is as follows:

- We start by modeling barley yields across the world during the historical period (1981–2010). Barley yield is simulated at $0.5° \times 0.5°$ grid scale, with two main production systems (spring barley and winter barley) and two water management scenarios (fully irrigated and rainfed). Historical national barley production is aggregated from simulated gridded yield, and weighted by grid cell barley areas around 2000 from the gridded global dataset by combining two data products of Monfreda et al. (2008) and Spatial Production Allocation Model (You et al. 2009).
- Second, we tune and calibrate model parameters related to crop genotype characteristics so that the simulated yields from 1981 to 2010 were comparable to the statistical data.
- Third, barley yields across the world are simulated during disaster years under five ESMs and two RCPs.
- Fourth, global and national yields are aggregated from gridded values.
- Finally, national/regional and global yield change is calculated, which is the deviation from the national/regional or global yield average of 1981–2010.

The detailed description of how to apply ESMs and DSSAT model to simulated future barley physical yield change can be found from the working paper by Xie et al. (2018).

14.2.2 The Global Economic Model

The GTAP is a well-known multi-regional computable general equilibrium model, which is widely used in assessing the impacts of climate change and policy changes (Hertel et al. 2010; Bosello et al. 2012; Golub et al. 2013). The model is based on the assumptions that producers minimize their production costs, and consumers maximize their utilities subject to a set of certain common constraints. Supplies and demands of all commodities clear by adjusting prices in perfectly competitive markets. Representative consumers of each country or region are modeled as having a non-homothetic Constant Difference of Elasticity (CDE) demand function. On the production side, firms combine intermediate inputs and primary factors (e.g., land, labor, and capital) to produce commodities with constant-return-to-scale technology. Intermediate inputs are composites of domestic and foreign components, with the foreign component differentiated by region of origin (the Armington assumption).

Data in this paper comes from GTAP database version 9 (with the base year of 2011) provided by GTAP center of Purdue University. The standard GTAP database contains 140 countries or regions and 57 sectors. In the standard GTAP database, barley is included in the sector of “other grains.” We split barley from “other grains” according to the data on barley production and use (FAO 2017) and commodity trade data (DESA/UNSD 2017). Finally, we aggregate the GTAP database into 18 sectors while ensuring that all the competing and complimenting sectors for barley are present in the most disaggregated form (see Appendix Table 14.3). At the same time, we aggregate the GTAP database into 33 regions but keep the details for all the main barley producing, consuming, and trading regions (see Appendix Table 14.4).

The yield shocks for barley were incorporated into the GTAP model via changes in land use efficiency for the land used by barley in each region [parameter "afe" in Eqs. (14.1) and (14.2)]. Land use efficiency affects both price and demand for land in the following two equations. Except the land use efficiency parameters, we keep land substitution parameters among different crops and the substitution of land and other inputs (labor, capital and others) at their original values of GTAP database to represent the optimal situation.

Equation of price of primary factor composite in each sector/region (the following equations are in percentage form, same here after):

$$pva_{j,r} = \sum_{k=1}^{n} \left(SVA_{k,j,r} * \left(pfe_{k,j,r} - afe_{k,j,r}\right)\right) \qquad (14.1)$$

where

j = production commodity (industry) ; r = region; k = endowment commodity
pva = firms' price of value added in industry j of region r
pfe = firms' price for endowment commodity k in ind. j, region r
SVA = share of k in total value added in j in r
afe = sector/region specific average rate of primary factor k augmenting technology change

Endowment commodities' input to each regions/industries:

$$qfe_{k,j,r} = -afe_{k,j,r} + qva_{j,r} - ESUBVA_j * \left(pfe_{k,j,r} - afe_{k,j,r} - pva_{j,r}\right) \qquad (14.2)$$

where

qfe = demand for endowment k for use in industry j in region r
qva = value added in industry j of region r
ESUBVA = elasticity of substitution between capital/labor/land, in production of value added in j.

14.2.3 Scenarios for GTAP Simulations

To assess the economic impacts of extreme weather events on global grain production and identify the contribution of market adjustment, two types of simulation scenarios are constructed. First, we assume extreme weather events only affect a single country and take China and Australia as two separate examples. While

China is the biggest importer of barley in the world, Australia is the biggest exporter of barley. This set of simulations would investigate how the regional barley production changes when considering the domestic market adjustments. In this simulation, the economic impacts of extreme weather events on barley production are simulated using the GTAP model under both RCP scenarios, with the shocks to barley yield change in China and Australia, separately. Secondly, we assess the impacts of extreme weather events on global barley production through shocking barley yield of all countries simultaneously to consider the effects of trade on barley production. Comparing the results of these two scenarios with the physical yield shocks from process-based crop model simulation could reveal the role of the domestic market and global trade in buffering the impacts of extreme weather events.

14.3 Simulation Results and Analysis

14.3.1 Physical Yield Loss of Barley

Among the 450 modeled years of each RCP (2011–2100 projections in each of the five ESM models), we identify 17 and 139 disaster events with 100-year extremes of drought and heat under RCP2.6 and RCP8.5, respectively. It is noted that the disaster event refers to a global extreme event rather than certain region (s) experiencing the disaster (the reality is that some regions experience severe losses, some regions experience light losses while some regions experience positive impacts). In other words, we select the disaster event using the global average disaster severity index, rather than for some specific countries. We then model barley yields changes in 34 world regions (most of which are individual countries) when the world experience 100-year extreme disasters using the process-based crop model (DSSAT). The average barley yield changes due to disasters under five ESM models during 2011–2100 for each region are shown in Table 14.1.

Most countries would experience barley yield loss under both RCP scenarios, with higher yield losses under RCP 8.5 higher than those under RCP 2.6. Under RCP 8.5, Denmark and Estonia have barley yield decline by over 45% due to extreme weather events. Most of the other countries/regions have barley yield loss between 10 and 30% due to the disasters. However, under RCP 8.5 scenario, five regions also experience an increase in barley yield, with Romania seeing a yield increase of around 15%. Under RCP 2.6, Denmark faces the most severe yield losses by around 35%. Most of the other countries/regions have barley yield loss of less than 20%. In contrast, ten regions have barley yield increase, and among them, Romania has the biggest yield increase by about 28%. Interestingly, as the biggest barley importer, the yield loss in China is lower than the global average level. The barley yield in China increases by 2.7% under RCP 2.6 and declines by 12.05 % under RCP 8.5, respectively. Australia, the biggest exporter of barley, would have yield loss more severe than the global average under RCP 8.5 (25.77% for RCP 8.5; 2.25% for RCP 2.6).

Table 14.1 The average impacts of extreme weather events on barley yield for each region during 2011–2100 under RCP 2.6 and RCP 8.5 (%)

Aggregated regions	RCP 2.6	RCP 8.5
Australia	–2.25	–25.77
Rest of Oceania	–4.65	–20.07
China	2.70	–12.05
Japan	5.40	3.89
Rest of Asia	–3.03	–19.67
India	–5.87	–17.66
Canada	–6.67	–10.24
USA	–2.10	14.27
Rest of North America	–2.86	–24.21
Argentina	–9.17	–21.59
Brazil	–7.41	–28.35
Rest of South America	–7.93	–23.29
Rest of America	–12.44	–21.25
Austria	–9.37	–14.22
Belgium	–3.32	–0.70
Czech Republic	–16.16	–26.02
Denmark	–34.82	–49.36
Estonia	–17.99	–47.26
France	–8.28	–13.95
Germany	–16.26	–27.54
Ireland	–14.09	–31.76
Italy	–3.23	–13.02
Netherlands	–7.82	–16.11
Poland	–10.93	–21.83
Portugal	6.02	–12.56
Spain	12.87	–10.89
Great Britain	–6.45	–20.37
Rest of EFTA	–10.47	–29.66
Romania	27.59	14.88
Russia	3.78	1.26
Ukraine	0.32	6.61
Rest of Europe	6.28	–10.35
South Africa	12.69	–12.42
Rest of Africa	6.95	–19.65

Source: Crop simulation model

Note: To save space, we only present average changes under 5 ESMs during 2011–2100. In fact, for each event, there will be different spatial pattern of barley yield change

14.3.2 Barley Production Loss only Considering the Domestic Market Response

For the first set of GTAP scenarios, we simulate the impacts of extreme weather events on barley production using barley yield change for individual country, while keeping barley yield in other countries unchanged (similar to small country assumption that the disaster effects from other countries will not be transmitted to the focus country, which is also the assumption in simulations using a single regional CGE model). We take single-country simulations of China and Australia as two separate examples to analyze the role of the domestic market in buffering climate change impacts. Under each run of the simulations, we only feed one disaster event shock (barley yield change) for China or Australia into the GTAP model. This give us 17 and 139 simulation results for each country under RCP2.6 and RCP8.5, respectively. To save space, we only present average changes under five ESMs during 2011–2100 in the following analysis.

Under the China-only scenario, the economic impacts of extreme weather events on barley production in China are lower than the physical impacts estimated from the global crop model under RCP8.5. The barley output would decline by 3.34% under RCP 8.5 (Table 14.2), which is significantly less than the direct impacts of extreme weather events on barley yield (12.05% loss) (Table 14.1). As the extreme weather events intensify, the farmers would improve their field management, such as intensifying labor use, irrigation, and pesticide application in order to maintain the barley production to a certain level. Thus incremental input of these endowments and intermediates buffer the barley output decline at least partly (the bars of 'yield change' and 'single country simulation' in Fig. 14.1). It is also seen that when only China suffers from extreme weather events, the domestic price of barley will increase moderately by 3.78% under RCP 8.5.

At the same time, China needs to increase its barley import (increase by 1.69%) and reduce barley export (decrease by 8.31%) to meet its domestic demand. Considering changes in domestic production and net import, the barley supply in China would decrease slightly under RCP 8.5 (i.e., –0.54%) (Table 14.2).

A similar story could be found in Australia's case (Fig. 14.1), where Australia would have a larger output decrease of barley (6.21%) under RCP 8.5 (Table 14.2), due to decline in its barley yield of 25.77% (Table 14.1). As the biggest exporter of barley, the production damage of barley in Australia would reduce its barley export significantly (i.e., –6.93%). Considering the domestic production and net import of barley, the extreme weather events have slightly negative impacts on barley supply in Australia (i.e., –0.23% under RCP 8.5). We observe similar patterns under RCP 2.6 for Australia; China experiences positive yield change of barley under RCP2.6,

Table 14.2 The impacts of extreme weather events on barley production, trade and supply from single country simulations of China and Australia and global simulation (%)

	China		Australia	
	RCP 2.6	RCP 8.5	RCP 2.6	RCP 8.5
Output	0.66	–3.34	–0.42	–6.21
Import	–0.33	1.69	0.39	6.06
Export	1.7	–8.31	–0.47	–6.93
Supply	0.11	–0.54	0.00	–0.23
Domestic price	–0.72	3.78	0.31	4.80

Source: GTAP simulation

Note: To save space, we only present average changes under 5 ESMs during 2011–2100. In fact, for each event, there will be different impacts on barley production, trade, supply and price

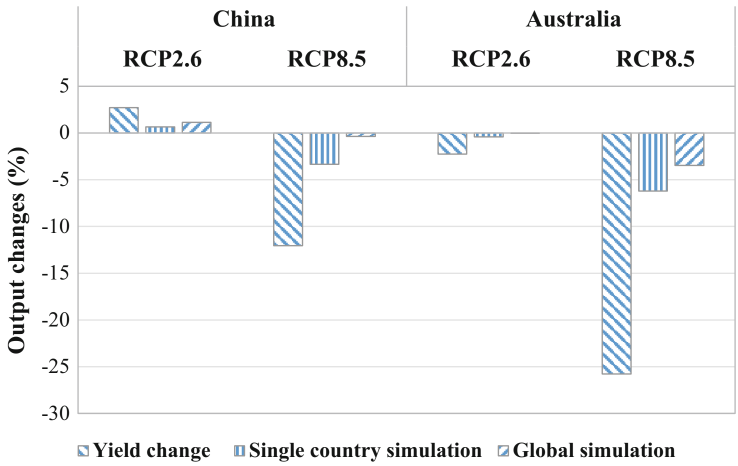


Fig. 14.1 Barley output changes from single country simulations and global simulation due to yield changes for China and Australia (note: to save space, we only present average changes under five ESMs during 2011–2100. In fact, for each event, there will be different impacts)

therefore, China will reduce the land area for barley and we can see China's barley output will decrease (Table 14.2 and Fig. 14.1). The results of these two simulations show that the domestic market could effectively reduce the damage to barley production and maintain domestic supply.

14.3.3 Barley Production Loss Considering Both the Domestic Market and International Trade Responses

For the second set of GTAP scenarios, we simulate the impacts of extreme weather events on barley production using barley yield change from all regions to consider the interactions among regions through trade. We only feed one disaster event shock (barley yield change) for all regions into GTAP model every time (as noted previously, the disaster event refers to a global extreme event rather than certain region experiencing the disaster—the fact is that some regions experience severe losses, some regions experience light losses while some regions experience positive impacts). So we get 17 and 139 simulation results for all countries under RCP2.6 and RCP8.5, respectively. To save space, we only present average changes under five ESMs during 2011–2100 for each country in the following analysis.

Figure 14.1 shows that the barley output would fall by 3.48% and 0.38% under RCP 8.5 for Australia and China, respectively when considering the effects of international trade response, which are lower than the impacts of extreme weather events when only considering the domestic market response. Comparing the results among the physical yield change, the first and the second sets of GTAP simulations (Fig. 14.2), it is found that we cannot overlook the vital role of global trade in

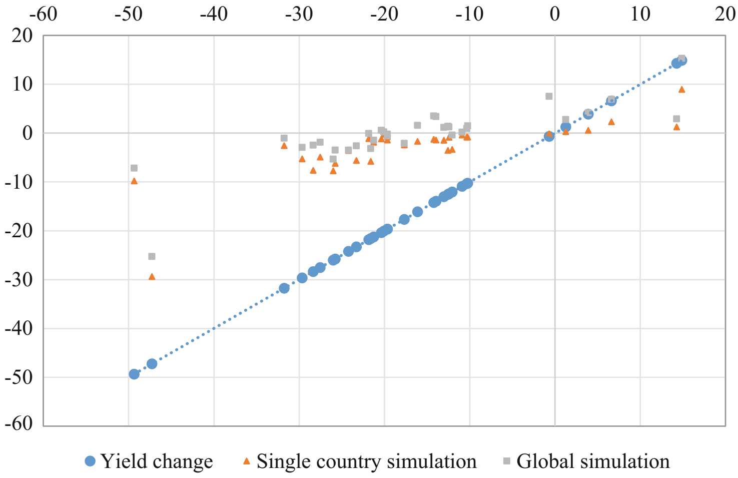


Fig. 14.2 Comparison of the physical yield change and the barley output change in first and second set of GTAP simulation under RCP 8.5 (note: to save space, we only present average changes under five ESMs during 2011–2100. In fact, for each event, there will be different impacts)

buffering the impacts of extreme weather events. Figure 14.2 shows the barley output changes for all regions when only considering the domestic market response and when considering both the domestic market and international trade response against their physical barley yield changes. For the countries suffering from extreme weather events, their barley output changes from the global simulation are scattered above those from single country simulations, which are higher than the yield changes. These results suggest that countries negatively affected by extreme weather events could benefit not only from the domestic market but also from global trade. In contrast, for the countries with slight yield losses or positive yield changes, their output changes from the global simulation are scattered above the output changes from single country simulations. This signifies that the global trade provides opportunities to these countries to enhance their barley production. We observe similar trends for Australia, China and the other countries under RCP 2.6 but with lower magnitudes.

The reason is that when considering international trade, farmers expect to increase more inputs to expand production and increase the export to other countries to gain more incomes. Although during the disaster, the international trade rules are predefined, from a long run view, if the trade is restricted, the disaster is far less likely to increase the price to a general level, and farmers will not increase inputs to an optimal level to avoid losses in the new disaster. Our results also show that using a single regional CGE model usually over-estimates the grain production loss due to climate change.

Figure 14.2 also shows that the domestic market response contributes more production increase than international trade response for most countries/regions. For domestic market response, the production increase mainly depends on the countries' ability to increase inputs to production and their preference for the affected crop, i.e., barley. It is noted that for different countries the production loss can be different, even if they experience the same barley yield change. For international trade response, disaster, as an external shock, changes the comparative advantage of planting barley for different countries. If we have integrated international markets, for the countries with slight yield loss or positive yield change, they usually try to increase input to expand export and gain profit according to their experience. For the severely hit countries, if they want to increase input to satisfy export demand, the loss outweighs the gains. Importantly, international trade mainly contributes to countries with slight yield loss or positive yield change and has little contribution to the counties that are more seriously hit by the disasters.

14.4 Conclusions and Policy Implications

The impacts of climate change on grains (measured in terms of changes in production) are often assessed using crop models or field experiments. However, these methods may overestimate or underestimate the impacts of disasters on crop production because they only focus on physical impacts while ignoring the behavioral changes of farmers and international traders. This study takes barley as an example and uses GTAP model (a global economic model) to reflect those behavioral changes and to assess the economic impacts of extreme drought and heat on crops and analyze the role of the domestic market and international trade. First, we select disaster events using ESM model and derive the barley yield changes for 34 key countries/regions using process-based crop model due to the most extreme drought and heat disasters under RCP 2.6 and RCP 8.5. Second, we use GTAP model to simulate how countries can change their crop production after perceiving barley yield losses (due to disasters); how international traders adjust their trade volumes in the face of changing comparative advantage and finally changing the farmers' behavior and ultimately agricultural production.

Our study shows that the impacts of extreme weather disasters on barley production are much lower than the corresponding physical yield changes when considering the domestic market response, and can reduce further when considering international trade effects. Moreover, countries with positive yield shocks would have larger benefits from global barley trade than those countries with negative yield shocks.

When a disaster occurs, farmers usually increase inputs (labor, irrigation, and pesticide and others) to adapt to climate change by themselves. However, if the domestic market and international trade are free of distortions and barriers, the price will increase to some extent in time of disaster. Then in the new disaster, farmers will increase inputs as high as they can to prevent production losses according to their experience with the price increase during the previous disaster; On the contrary, if the markets have some interventions or the trade is restricted, farmers cannot experience general price change with previous disasters, and when new a disaster occurs, they may not increase inputs to that extent. It is concluded that free market is also an effective adaptation measure for climate change and disasters. In order to buffer the impact of disasters on food supply, it is necessary to give full play to the role of market mechanisms and to reduce government intervention in the domestic market and global trade. Although this study takes barley as an example, the policy implications apply to other crops as well.

Acknowledgments The authors thank Professor Erda Lin, Wei Xiong, and Jie Pan's team from China Academy of Agriculture Sciences for their contribution to providing simulation data on physical yield changes using ESM and DASSAT. The authors also thank Professor Adam Rose, Yasuhide Okuyama, and two anonymous reviewers for their constructive comments to improve this write-up.

Appendix

Table 14.3 Sectoral aggregation scheme

Aggregated sectors	GTAP original sectors
Barley	Split from the original "other grains" sector
Beer	Split from the original "beverage and tobacco" sector
Trade	Trade
Recreational services	Recreational services
Other beverage and tobacco	Beverage and tobacco after splitting out beer
Wheat	Wheat
Other grains	Cereal grains nec after splitting out barely
Rice	Paddy rice; Processed rice
Edible oils	Oil seeds; Vegetable oils and fats
Cotton	Plant-based fibers
Other agriculture	Sugar cane, sugar beet; Vegetables, fruit, nuts; Crops nec; Forestry
Livestock	Bovine cattle, sheep and goats, horses; Animal products nec; Raw milk; Wool, silk-worm cocoons; Fishing; Bovine meat products; Meat products nec; Dairy products
Processed food	Sugar; Food products nec
Energy	Coal; Oil; Gas; Petroleum, coal products ; Electricity; Gas manufacture, distribution
Extraction	Minerals nec; Mineral products nec; Ferrous metals; Metals nec; Metal products
Light manufacturing	Textiles; Wearing apparel; Leather products; Wood products; Paper products, publishing; Chemical, rubber, plastic products; Motor vehicles and parts; Manufactures nec
Heavy manufacturing	Transport equipment nec; Electronic equipment; Machinery and equipment nec
Transportation and communication	Transport nec; Water transport; Air transport; Communication
Other Services	Water; Construction; Financial services nec; Insurance; Business services nec; Public Administration, Defense, Education, Health; Dwellings

Table 14.4 Regions aggregation scheme

Aggregated regions	GTAP original regions
Australia	Australia
Rest of Oceania	New Zealand, Rest of Oceania
China	China
Japan	Japan
Rest of Asia	Hong Kong, South Korea, Mongolia, Taiwan, Republic of China, Rest of East Asia, Brunei Darussalam , Cambodia , Indonesia , Laos , Malaysia Philippines , Singapore, Thailand, Vietnam, Rest of Southeast Asia, Bangladesh, Nepal, Pakistan, Sri Lanka, Rest of South Asia, Kazakhstan, Kyrgyzstan, Rest of Former Soviet Union, Armenia, Azerbaijan, Georgia, Bahrain, Iran, Israel, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, United Arab Emirates, Rest of Western Asia
India	India
Canada	Canada
USA	United States of America
Rest of North America	Mexico, Rest of North America
Argentina	Argentina
Brazil	Brazil
Rest of South America	Bolivia, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela, Rest of South America
Rest of America	Costa Rica, Guatemala, Honduras, Nicaragua, Panama, El Salvador, Rest of Central America, Dominican Republic, Jamaica, Puerto Rico, Trinidad and Tobago, Caribbean
Austria	Austria
Belgium	Belgium
Czech Republic	Czech Republic
Denmark	Denmark
Estonia	Estonia
France	France
Germany	Germany
Ireland	Ireland
Italy	Italy
Netherlands	Netherlands
Poland	Poland
Portugal	Portugal
Spain	Spain
Great Britain	Great Britain
Rest of EFTA	Cyprus, Finland, Greece, Hungary, Latvia, Lithuania, Luxembourg, Malta, Slovakia, Slovenia, Sweden, Switzerland, Norway, Rest of EFTA
Romania	Romania
Russian	Russian Federation
Ukraine	Ukraine
Rest of Europe	Albania, Bulgaria, Belarus, Croatia, Rest of Eastern Europe, Rest of Europe

(continued)

Table 14.4 (continued)

Aggregated regions	GTAP original regions
South Africa	South Africa
Rest of Africa	Egypt, Morocco, Tunisia, Rest of North Africa, Benin, Burkina Faso, Cameroon, Cote d Ivoire, Ghana, Guinea, Nigeria, Senegal, Togo, Rest of Western Africa, Central Africa, South Central Africa, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Tanzania, Uganda, Zambia, Zimbabwe, Rest of Eastern Africa, Botswana, Namibia, Rest of South African Customs Union, Rest of the World

References

Bosello F, Nicholls R, Richards J, Roson R, Tol RJ (2012) Economic impacts of climate change in Europe: sea-level rise. Clim Change 112:63–81

Brown ME, Carr ER, Grace KL, Wiebe K, Funk CC, Attavanich W, Buja L (2017) Do markets and trade help or hurt the global food system adapt to climate change? Food Policy 68:154–159

Cheng CS, Auld H, Li Q, Li G (2012) Possible impacts of climate change on extreme weather events at local scale in south–central Canada. Clim Change 112(3–4):963–979

Ciscar JC, Iglesias A, Feyen L, Szabó L, Regemorter DV, Amelung B et al (2011) Physical and economic consequences of climate change in Europe. Proc Natl Acad Sci USA 108 (7):2678–2683

DESA/UNSD (2017) United Nations Comtrade database. https://comtrade.un.org/data

FAO (2017) Data available on the website. http://www.fao.org/faostat/en/

Field CB, Barros VR, Mach K, Mastrandrea M (2014) Climate change 2014: impacts, adaptation, and vulnerability. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change

Golub A et al (2013) Global climate policy impacts on livestock, land use, livelihoods, and food security. Proc Natl Acad Sci USA. https://doi.org/10.1073/pnas.1108772109

Hertel TW, Burke MB, Lobell DB (2010) The poverty implications of climate-induced crop yield changes by 2030. Glob Environ Chang 20:577–585

Hoogenboom G et al (2015) Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6 (http://dssat.net). DSSAT Foundation, Prosser, WA

Lesk C, Rowhani P, Ramankutty N (2016) Influence of extreme weather disasters on global crop production. Nature 529(7584):84–87

Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. Science 333(6042):616–620

Lobell DB et al (2013) The critical role of extreme heat for maize production in the United States. Nat Clim Change 3:497–501

Meehl GA, Zwiers F, Evans J, Knutson T, Mearns L, Whetton P (2000) Trends in extreme weather and climate events: issues related to modeling extremes in projections of future climate change. Bull Am Meteorol Soc 81(3):427–436

Monfreda C, Ramankutty N, Foley JA (2008) Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochem Cycles 22:GB1022

Nelson GC et al (2014) Climate change effects on agriculture: economic responses to biophysical shocks. Proc Natl Acad Sci USA 111:3274–3279

Reilly J, Hohmann N (1993) Climate change and agriculture: the role of international trade. Am Econ Rev 83(2):306–312

Rosenzweig C, Elliott J, Deryng D, Ruane AC, Müller C, Arneth A, Neumann K (2014) Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc Natl Acad Sci USA 111(9):3268–3273

Wheeler T, Von Braun J (2013) Climate change impacts on global food security. Science 341 (6145):508–513

Xie W et al (2018) Decreases in global beer supply due to extreme drought and heat. Nat Plants 4:964–973

You L et al (2009) Spatial production allocation model (SPAM) 2000, version 3 Release 2 (IFPRI, Washington, DC). http://MapSpam.info

Wei Xie is an assistant professor at the Peking University, China. His research focus on economics of climate change; agricultural sustainable development and food security. He has visited University of Southern California, Purdue University and Development Research Center of China for working on CGE models in recent years. Currently he is PI of 3 projects funded by NSFC and MOST in China. Dr. Xie has published in journals including Nature, Nature Plants, Risk Analysis, Global Food Security, China Economic Review and China Agricultural Economic Review. Based on his research, he also submitted several policy briefs to the government to aid policy decisions.

Qi Cui is an assistant professor at the Beijing Normal University, China. His research interest includes economics of climate change, food consumption, food policy, energy economics, and CGE models. Previously, he worked as Post-Doctoral Fellow at the Peking University. Dr. Cui earned his doctoral degree in Agricultural Economics from Chinese Academy of Sciences in 2016. Recent research has been published in Nature Plants, China Economic Review, China Agricultural Economic Review, Journal of Cleaner Production, etc.

Tariq Ali is an associate professor at the North China University of Technology and Senior Research Fellow at the Peking University, China. His primary research interests are agricultural economics; international trade; resource economics; economics of climate change; and economic impact of disasters. Previously, he has worked as assistant professor at the Government College University Faisalabad, Pakistan and Post-Doctoral Fellow at the Chinese Academy of Sciences, Beijing, China. Dr. Ali earned his doctoral degree in Agricultural Economics from Chinese Academy of Sciences in 2012.

Chapter 15
Spatio-Temporal Drought Risk Analysis Using GIS-Based Input Output Modeling

Sheree Pagsuyoin, Joost Santos, Gustavo Salcedo, and Christian Yip

Abstract Recent studies in the area of disaster risk management emphasize the increasing likelihood and adverse consequences of droughts. Droughts can have widespread severe impacts; for example, in 2016, the northeastern region of the United States experienced record levels of rainfall shortage, forcing regional government agencies to issue warnings and emergency advisories to the public. During drought events, the economic losses due to water shortage and government-mandated restriction measures create costly cascading effects due to the interconnected and interdependent nature of the economic sectors. Such sectors have different degrees of dependence on water, and often there is a lack of coordination in implementing sector-specific resilience measures, which makes the drought recovery management a complex and daunting task. Indeed, water is a critical resource and it is essential in producing a myriad number of goods and services in the economy. In the current chapter, the authors develop a new modeling framework for drought risk management by integrating spatial analysis and dynamic input-output modeling to better understand the direct and indirect effects of drought scenarios on interdependent sectors of a regional economy. A decision support tool that utilizes the geographic information systems (GIS) platform was also developed to perform the following functions: (1) model the time-varying impacts of drought scenarios on a regional economy, (2) simulate the responses of individual sectors throughout various stages of the drought recovery timeline, and (3) estimate the regional economic losses and potential benefits of implementing different categories of drought management policies. The utility of the integrated IO-GIS

S. Pagsuyoin · G. Salcedo
Department of Civil and Environmental Engineering, University of Massachusetts-Lowell, Lowell, MA, USA
e-mail: Sheree_Pagsuyoin@uml.edu; gustavo_salcedo@student.uml.edu

J. Santos (✉) · C. Yip
Department of Engineering Management and Systems Engineering, George Washington University, Washington, DC, USA
e-mail: joost@gwu.edu; cmyip@gwu.edu

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_15

framework and decision support tool is demonstrated in a case study of the historic and widespread drought that occurred in the State of Massachusetts in 2016.

15.1 Introduction

Climate change, previously considered a problem of the future, is now an issue of great concern in the present. Its impacts extend across all major sectors that support and maintain modern life. The recent Paris Agreement has re-emphasized the need for international cooperation, increased awareness, and robust strategies for building climate resilience (UNFCCC 2015). One of the most critical environmental issues associated with climate change is water scarcity (Rockstrom et al. 2009). While the implications of the linkage between climatic effects and the water balance is not fully understood, it is important to anticipate future risks that could lead to severe economic disruptions and long-term socio-economic impacts.

The increasing gap between water demand and available supply has been a perennial problem in water balance forecasting. In recent years, a rising number of publications predict that current patterns of water consumption, coupled with population growth, rapid urban development, and climate change, will result in water shortages in the short and long-term (Schlosser et al. 2014; Jones et al. 2002). A study by Addams et al. (2009) estimates that the global water deficit will be at 40% by 2030. In the United States, the US Government Accountability Office (GAO) reports that 40 out of 50 states can expect below average water conditions over the next 10 years (GAO 2014). Roy et al. (2012) also predict that nearly a third of all US counties will experience higher risks of water deficits by mid-century. These shortages further tighten the already stiff competition for water among water-dependent production sectors such as the agriculture, energy, and manufacturing industries (Rowland 2005).

Water scarcity is not a new issue, yet it continues to pose unacceptable risks that can undermine growth and development (Pagsuyoin and Santos 2015). Water is one of the most abundant resources on earth, covering 70% of the earth surface; however, only 1% is accessible for domestic and industrial use (Shiklomanov 1993). As a result, upwards of 1 billion people worldwide lack access to adequate water, and nearly 2.7 billion experience water scarcity for at least 1 month each year (WWF 2017). Water supply continues to diminish as current sources become progressively stressed from over withdrawal. This problem is exacerbated by rapid population growth, along with the associated increased demands for food and energy production (UNWWAP 2016). It is even more pronounced during periods of drought when production sectors face greater competition for limited water. These issues—population growth, development, water—are intertwined; thus, there is a need to address the risks associated with water shortage from a holistic point of view. This is especially critical during drought periods when economic sectors exhibit varying levels of vulnerability and resilience to the effects of diminished water supply. During periods of elevated water scarcity, policymakers face the challenge of equitably allocating water across all production sectors (Ward and Pulido-Velazquez 2012).

Drought management strategies aim to provide universal access to water while balancing the issues of supply and demand. However, it is challenging to accomplish this since delivering water at an affordable rate cannot be achieved without adding a complex financial dimension (UN 2016). Of particular interest in this chapter is the evaluation of vulnerability and resilience over time and space during the drought timeline and in the ensuing recovery phase. This information is critical in determining the efficacy of drought risk management strategies stemming from the potential resolution of the complex issues associated with water scarcity.

In the current study, we develop a spatio-temporal decision support system (DSS) for examining regional vulnerabilities and resilience to varying drought severity and duration. The mathematical formulation of the DSS is based on the input-output (IO) modeling framework, and is implemented on a GIS platform to enhance flexibility in delineating affected areas as drought progresses and enable the visualization of changes in regional vulnerabilities during the drought timeline and the subsequent recovery phase. The remainder of this chapter is organized into four sections. In Sect. 15.2, we perform a brief review of literature that focus on drought risk assessment and management. In Sect. 15.3 we discuss the water input-output (IO) model and its integration with a GIS-interface. In Sect. 15.4 we present an application of the GIS-based water IO model to a drought case study in the state of Massachusetts. Finally in Sect. 15.5, we summarize the findings and research contributions of this chapter, and identify areas for future work.

15.2 Overview of Drought Risk Analysis

Risk analysis can be qualitatively structured into two separate categories: (1) risk assessment and (2) risk management. In particular, this section provides an overview of risks associated with droughts, which serves as motivation for the proposed integrated modeling framework for evaluating spatio-temporal resilience to severe drought events.

15.2.1 Drought Risk Assessment

The process of assessing drought risks is based on the risk assessment framework formulated by Kaplan and Garrick (1981), and is centered on evaluating threats connected to droughts, the likelihood of its occurrence, and impacts if they were to happen.

Humans significantly stress freshwater systems in two ways. The first stressor stems from straining water resources; while resources are replenished overtime, this process does not happen at a constant rate or during precise intervals. As the global water demand rapidly increases, many water resources are now at their capacity limits (OECD 2012). The second stressor is through contamination; agriculture, industry, and all the wastes associated with modern life contribute to water pollution. Both stressors intensify the potential occurrence of future water shortages. The US Intelligence Community Assessment (2012) states that "water problems—when combined with poverty, social tensions, environmental degradation, ineffectual leadership, and weak political institutions—contribute to social disruptions that can result in state failure. Competition for limited water can lead to the proliferation of socio-environmental conflicts (Martín and Justo 2015), posing risks to the peace and prosperity of populations worldwide.

In order to estimate the economic impacts of disasters such as droughts, the methods for impact evaluation must be comprehensive and should include direct and indirect costs, as well as intangible reactions (Okuyama 2007). Several approaches have been proposed and implemented to analyze the impacts of drought across various interdependent sectors. Horridge et al. (2005) and Rose and Liao (2005) applied computable general equilibrium (CGE) modeling to simulate the regional and sector-based economic impacts of water service disruptions. Seung et al. (2000) also employed similar techniques to examine the economic outcomes of water trade-off between agriculture and recreation in Nevada. Howitt et al. (2005) developed a Positive Mathematical Programming (PMP) model to estimate the economic impacts of water-related polices and shocks to agriculture in California. Hubacek and Sun (2005) developed an input-output (IO) model to simulate how future economic and societal shifts may affect water usage in China. Pagsuyoin and Santos (2015) employed dynamic IO model extensions to contrast outcomes of different drought scenarios in metropolitan Northern Virginia. Cazcarro et al. (2013) employed multi-regional IO modeling to evaluate water footprints and water trade-off among production sectors in Spain. These diverse methodologies are capable of assessing broad economic concepts of drought scenarios and how the consequences impact resource use and production. The application of the IO model for drought analysis will be the focus of this work. The mathematical formulations and applications of the proposed model are discussed further in subsequent sections of this chapter.

15.2.2 Drought Risk Management

The analysis of drought risk management focuses on key areas that parallel those found in the risk assessment section. To describe the dimensions for managing different levels of exposure to a given risk, Haimes (1991) proposed identifying what can be done, trade-offs, and impacts of decisions on future options. By transitioning from risk assessment to risk management of drought, various strategies begin to take shape in order to alleviate the consequences and enable resilience-based practices. As water scarcity grows, risk management strategies need to be well designed to reduce the potential severity of otherwise significant consequences. Through quantifying the risks and anticipating the potential impacts, the combination of risk analysis, will provide information to develop requirements and set priorities for best drought management strategies.

In multiple literature sources on drought management policies, a major emphasis is placed on the relationship between water scarcity and the economy (UNWWAP 2016; OECD 2012). Due to this intersection, various drought management strategies aim to promote policy change that will continue to support economic development while working to satisfy the increasing water demand. Postel (2000) highlights that water scarcity is a global issue that requires a global effort through policies that promote water efficiency and overall productivity. This risk management approach attempts to satisfy the increasing demands for water while protecting the natural water ecosystems. Blignaut and Heerden (2009) explore the Accelerated and Shared Growth Initiative for South Africa (AsgiSA) that aims to increase economic growth. It was found that half of the proposed projects would have a water-intensive nature. When water supply is already limited, countries like South Africa are especially challenged when implementing economic development plans without considering and incorporating water-related policies. While it is important to explore future developments to promote macro-economic growth, water policies must be implemented in parallel. Equitable water allocation should also be considered, especially when competition for limited water exists between water-intensive agriculture and more highly valued manufacturing industries (Martin-Carrasco et al. 2013).

Furthermore, Santos et al. (2014) presented three primary categories of risk management options that can help in mitigating the consequences of droughts. Such risk management options, namely, reducing the initial level of water supply disruption, managing water consumption, and prioritizing water-use dependencies, are summarized in Table 15.1.

Since water is a key resource in many economic activities, droughts can cause tremendous economic losses that propagate through interdependent sectors in a region. Each economic sector exhibits varying resilience and vulnerability to drought depending on its reliance on water availability. Understanding these sector vulnerabilities is essential in drought risks assessment, especially in formulating mitigation strategies that provide that most benefit to the region as a whole.

Table 15.1 Categories of drought risk management options

Risk management category	Potential measure of performance	Risk management implications
Reducing the initial level of water supply disruption	This can be measured as the level of water availability disruption on a scale between 0 and 100%	The level of water availability disruption could be reduced using alternative or back-up water supply sources
Managing water consumption	This can be measured as the effect of water consumption adjustments for different economic sectors at a particular time period	Production losses can be decreased through implementation of water usage restriction and conservation strategies
Prioritizing water use dependencies	This can be measured as the water usage of a particular sector as a proportion of its output	Water-use dependencies across different sectors can be prioritized based on their criticality to the region

15.3 Water Input-Output Model

Natural disasters such as droughts, as well as other disruptive events, can lead to costly economic losses. The inherent interdependencies across various sectors of the economy further exacerbate the direct consequences caused by a disaster, creating widespread and cascading effects. In a seminal study of disaster impacts on businesses, Webb et al. (2000) asserted that the incurred direct and indirect losses are quite significant and are often in the same order of magnitude as the costs associated with damaged properties and physical infrastructure systems. In quantifying the direct and indirect losses caused by disasters, it is necessary to assess the strength of interdependencies across multiple sectors of a regional economy to better understand how losses dynamically propagate throughout the recovery horizon.

The input-output model and computable general equilibrium are two of the most common methods used in assessing the economic losses triggered by disasters across interdependent sectors. In recent applications, such models have also been utilized in evaluating the impact of resilience strategies in reducing a disaster's consequence in terms of the magnitude of losses as well as recovery period. Resilience is defined as the ability of a system to absorb or cushion itself against the consequences of disruptive events. Rose (2009) provides detailed reviews of economic resilience definitions, categories, and strategies. Compared to the IO model, the CGE has a more complex model structure which can accommodate the analysis of elasticity and distribution parameters associated with different factors of production. Hence, CGE can be used to explicitly model various resilience strategies such as factor substitutions (Rose and Liao 2005). Although CGE captures the nonlinear economic relationships across various economic sectors, it is data-intensive and requires longer model setup and computation time relative to the IO model. Furthermore, there is a tendency for CGE to underestimate economic losses because it assumes that substitutions could quickly occur (Albala-Bertrand 2013), which is not often the case especially for disasters with relatively short recovery horizons. In this work, economic losses will be assessed using an "inoperability" measure to extend the capability of the traditional IO model, which we believe to be appropriate in conducting spatial analysis of drought scenarios. The vast availability of IO data and its relative simplicity is ideal for the analysis to be performed in the case study for the state of Massachusetts. The US Bureau of Economic Analysis (BEA) is the agency primarily responsible for releasing the official IO accounts for the US at both national and regional levels. In subsequent sections of this article, we have customized the IO model to enable the assessment of drought scenarios in the study region, and subsequently to estimate the ripple effects across various economic sectors.

Wassily Leontief developed the economic IO model, which is a systematic and tractable accounting framework capable of tracking the flow of commodities and services across various consuming and producing sectors of the economy (Leontief 1936). Subsequently, the economic scope of the IO model has significantly grown and has extended to other fields, such as energy and environmental sustainability (Miller and Blair 2009). The IO model is supported by many databases that are collected and published by statistical and census agencies in many nations. Furthermore, the economic multipliers that typically accompany the IO tables allow the estimation of the direct and indirect changes in the production output of various sectors given a unit change in the demand for a particular sector. Hence, the IO model is arguably a useful and practical tool that can guide the formulation of economic policies in both regional and national settings. From a policymaking standpoint, government officials can prioritize the management and continuity of operations of critical sectors, especially in the aftermath of disruptive events. From a business management standpoint, the IO model can help identify critical resource inputs and the extent to which resource limitations can impair the production of final goods or services. Dietzenbacher and Lahr (2004) published a book that features traditional and emerging theories and applications of the IO model, such as energy conservation, environmental impact analysis, and many others.

The applications of the IO model in the domain of disaster risk management has markedly grown in recent years. A case in point, the concept of "inoperability" has been used to link economic analysis with engineering applications, notably in assessing the reliability of infrastructure systems in the aftermath of disruptive events. The IO model has been revisited by Haimes and Jiang (2001) to account for the inoperability metric, or the reduced capacity of a sector to produce the necessary level of output required by other sectors. *Inoperability* is a continuous variable ranging between 0 (ideal operability) and 1 (total inoperability). It is a dimensionless quantity that can be interpreted as the complement of reliability, i.e., a perfectly reliable system has a reliability value of 1 (or an inoperability of 0). There have been numerous papers that utilize the inoperability metric in the context of disaster risk management, including in man-made disasters (Santos and Haimes 2004), electric power outage scenarios (Anderson et al. 2007), disease outbreaks (Orsi and Santos 2010), hurricanes (Resurreccion and Santos 2013), and droughts (Pagsuyoin and Santos 2015), among others. Nonetheless, the inoperability-based IO model has been criticized in terms of its novelty (Dietzenbacher and Miller 2015) and limited applicability (Oosterhaven 2017). Despite such criticisms, the authors argue that the inoperability variable is a unique feature of the model, which effectively links economics with the concept of reliability widely used in engineering and infrastructure network applications. The intuitiveness of the basic IIM formulation is the very reason why many applications and methodological extensions have followed. The early IIM papers were not only about economic analysis, per se. They were about describing interdependent infrastructure, hence emphasizing importance of the inoperability variable in the context of engineering applications.

The mathematical formulation of the dynamic inoperability IO model is presented in Eq. (15.1). Although this dynamic equation is structurally similar to the formulation by Lian and Haimes (2006), the drought-specialized model presented in this work allows adjustments in the inoperability levels to account for time-varying drought severity over the recovery timeline. In the case study, we specifically used daily increments, although the model can accommodate other time increments. Due to data availability, the interdependency matrix ($\mathbf{A}^*$) is based on annual IO values, but the units of production are normalized in daily values. The authors recognize that there have been recent attempts to temporally disaggregate the Leontief technical matrix (see, for example, Avelino 2017). Nonetheless, the use of annual data is deemed sufficient in this work since it represents the average levels of interdependencies across the economic sectors in a given year (i.e., predicting when a drought would strike is highly uncertain and beyond the scope of the current analysis). The approach is explained further in Sect. 15.4.3.

$$\mathbf{q}_{\boldsymbol{DIIM}}(t+1) = \mathbf{q}(t) + \mathbf{K}[\mathbf{A}^{*}\mathbf{q}(t) + \mathbf{c}^{*}(t) - \mathbf{q}(t)] \tag{15.1}$$

The variables in the formulation in Eq. (15.1) are interpreted as follows:

- **Sector Inoperability.** *Inoperability* is analogous to the concept of unreliability; it is the ratio of the change in production output, divided by the ideal production output. It is denoted by $\mathbf{q}(t)$, which is a vector comprising the inoperability values of various sectors at time t; hence $\mathbf{q}_{\boldsymbol{DIIM}}(t+1)$ is the new inoperability vector at the subsequent time increment, $(t + 1)$. Denoting the ideal production of the ith sector by x_i and the degraded production by $\tilde{x}_i$, the inoperability of each sector is defined as the ratio of unrealized production (i.e., ideal production minus degraded production) relative to the ideal production level of that industry sector. Mathematically, each element in the inoperability vector is expressed as $\left(x_i - \tilde{x}_i\right)/x_i$. The time-varying inoperability variable uses the same ratio, but indexed explicitly with t. To further explain the inoperability measure, consider a hypothetical sector with an ideal production of \$100. Let us suppose that that a disaster causes the output of this sector to reduce from \$100 to \$80. The production loss amounts to \$20, or an equivalent 20% reduction relative to the pre-disaster production output. Hence, the sector has an inoperability value of 0.20. This value is the direct inoperability, which will create a ripple effect of indirect inoperability to itself and also to other interdependent sectors.
- **Interdependency Matrix.** The $\mathbf{A}^{*}$ matrix describes the interdependencies across multiple sectors of the economy. It can be calculated based on the Leontief IO tables that are published by national statistical and census agencies. The interdependency matrix is a square matrix, with a size corresponding to the number of economic sectors. The row elements can provide insights on how inoperability can propagate from one sector to other sectors due to their interdependencies. Multiplying the interdependency matrix ($\mathbf{A}^{*}$) with the sector inoperability $\mathbf{q}(t)$ gives rise to the indirect inoperability due to the utilization of intermediate inputs required for the production of the goods and services for final use. Coupled with regional economic multipliers, the national IO tables can be used as the basis for constructing IO tables that are suitable for the regional scope of interest. In this work, the regionalization process utilizes location quotients based on ratios of national and state GDP data for each economic sector. This process of regionalization is performed to generate region-specific interdependency matrices such as the data sets for the Massachusetts drought case study in subsequent sections.

- **Demand Perturbation.** The demand perturbation component of the model, denoted by $\mathbf{c}^*(t)$, is a vector containing information on the disrupted levels of the production output of each sector due to a disaster. Similar to the inoperability vector, the demand perturbation is a dimensionless number ranging between 0 and 1. When a disaster occurs, supply levels can decrease, which subsequently limits the capacity to meet ideal demands. Hence, demand perturbation can be construed as a "forced" demand reduction. Suppose that level of supply of goods (or services) decreases in the aftermath of a disaster but the demand stays at the same level; to compensate for the supply shortfall, customers will be forced to reduce their demand. The equivalency assumption between supply reduction and "forced" demand reduction has been introduced in the static formulation of inoperability (Santos and Haimes 2004). In contrast, the dynamic formulation in Eq. (15.1) accommodates simultaneous demand and supply reductions, while also considering the impact of resilience on sector recovery.
- **Resilience Matrix.** A key innovation in the dynamic IIM is its ability to relate economic resilience with sector inoperability. In Eq. (15.1), the notation $\mathbf{K}$ represents a square matrix and a particular element describe the rates with which each sector recovers to its ideal production levels, corresponding to the pre-disaster state. Resilience describes a system's capability to absorb or cushion itself from an external shock, and ultimately recover its lost functionality (Holling 1973; Perrings 2001). The context of resilience differs across disciplines; the current chapter focuses on economic resilience. Rose and Liao (2005) have suggested different ways to categorize economic resilience such as static, dynamic, inherent, and adaptive among others. They also provided examples of resilience strategies that could potentially reduce economic losses or reduce the duration of recovery (e.g., inventory management, relocation, resource conservation, substitution, and production recapture, among others). In this chapter, $\mathbf{K}$ is formulated as a diagonal matrix that contains the inherent sector-specific resilience coefficients. Equation (15.1) also implies that when $\mathbf{K}$ is multiplied with the interdependency matrix $\mathbf{A}^*$, the resulting product represents the coupled or interdependent sector resilience. The concept of coupled resilience is particularly relevant when analyzing the dependence of a sector on other sectors in order to satisfy its ideal production. Even if a sector is initially unaffected by a disaster, it can be indirectly disrupted when other sectors are unable to provide its required production inputs. The estimation of the elements of the sector resilience matrix is based on the predicted recovery period, and the strength of sector coupling based on the interdependency matrix $\mathbf{A}^*$ values (see Lian and Haimes 2006).
- **Economic Loss.** Economic loss can be estimated on the basis of the inoperability values generated from Eq. (15.1). Multiplying the inoperability of a sector with its production output will give an estimate of the economic loss. The magnitude of economic losses can be used for prioritization purposes. A sector that incurs a higher economic loss relative to another sector is considered more critical. Both economic loss and inoperability measures provide different but complementary perspectives of prioritizing critical sectors. Inoperability provides a notion of the

extent to which a sector is functioning relative to its "as planned" reliability level; economic loss is a measure of the associated monetary loss.

The water input-output model developed for the drought analysis can be described as an integration of the dynamic inoperability IO model and spatial analysis. Geographic information systems (GIS) enable the visualization of the drought effects on various interacting sectors of a regional economy. The mathematical formulation of water use linkages in the model captures the dynamic interactions of economic sectors, specifically, their water-use and associated sector decompositions. Embedding both the input databases and simulation outputs (i.e., as risk metrics *inoperability* and *economic loss*) in GIS data layers facilitates flexibility in defining the spatial boundaries for each simulation period. For example, for simulations of period 1 (drought peak) and period 2 (intervention), the water IO model can be implemented for the entire region in period 1, and only for a sub-region in period 2. The integration of IO model outputs with GIS can be performed by using suitable programming platforms; for example, in the case study for the state of Massachusetts (Sect. 15.4), the water IO modeling is performed in MATLAB® (R2017a), which enables manipulation of GIS data through its mapping toolbox.

15.4 Massachusetts Case Study

15.4.1 Study Area

Massachusetts is located in northeastern US and has a 2016 population of 6.8 million (US Census Bureau 2016). Despite its relative small land area, it is the third most densely populated state, and has the sixth highest per capita gross domestic product (GDP) among all US states (US Census Bureau 2016; BEA 2015). It is subdivided into 14 counties: the relatively rural counties of Berkshire, Franklin, Hampden, and Hampshire in the western side, and the more urban counties of Barnstable, Bristol, Dukes, Essex, Middlesex, Nantucket, Norfolk, Plymouth, Suffolk, and Worcester in the eastern side (Fig. 15.1).

In 2008, the Massachusetts Legislature signed the Global Warming Solutions Act directing the state's Energy and Environmental Affairs office to convene an advisory board and analyze adaptation strategies for climate change. The advisory board's report, released in 2011, predicts that the changing climate will trigger more frequent extreme weather events in Massachusetts, including more intense and short-term drought periods (Table 15.2; MAEEA 2011). Altered timing of stream flows is also expected to further exacerbate existing stresses on available water supply. Some of these predictions are already being experienced, for example, due to insufficient groundwater flow during longer dry periods, several towns in Massachusetts (and in New Hampshire) have explored developing more expensive technologies like desalination. More recently in 2015 during the long moderate drought across the state, the town of Billerica imposed a 5-month ban on all outdoor water use during the day.

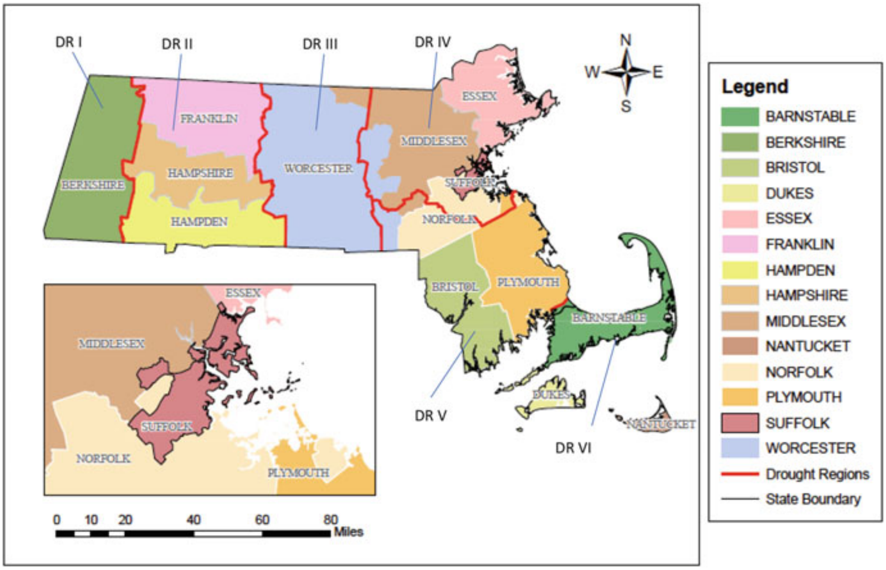


Fig. 15.1 Counties and drought regions in Massachusetts. The state is divided into six drought regions (DR): Western (DR I), Connecticut (DR II), Central (DR III), Northeast (DR IV), Southeast (DR V), and Cape Cod and Islands (DR VI). Inset photo shows Suffolk county, which encompasses the city of Boston

Historic severe drought was also experienced in most of the state, beginning Summer 2016 and lasting through the early part of 2017 (NDMC 2017); it compromised water distribution and prompted water trading among counties (Lowell Water Utilities 2016). This drought extended to the rest of northeast US, and is possibly the most widespread and severe drought to ever hit the region since the record multi-year drought recorded in the 1960s (Paulson et al. 1991).

The Drought Management Task Force (DMTF) in Massachusetts monitors drought conditions in six regions: Northeast, Southeast, Central, Connecticut River, Western, and Cape Cod and Islands. As can be inferred in Fig. 15.1, this categorization of drought regions (DR) is more reflective of political boundaries rather than of watershed boundaries. Massachusetts has 28 primary watersheds, some of which are shared with neighboring states. Some towns are also serviced by several watersheds. The DMTF advices towns regarding the current drought severity level; towns implement corresponding mitigation strategies at their discretion. Drought severity is ranked on five levels (Normal, Advisory, Watch, Warning and Emergency) based on seven drought indices (Table 15.2; MAEEA 2013). It is determined based on where the majority of drought indices occur, and on additional data regarding expected incoming weather patterns (MAOWR 2016).

Table 15.2 Drought categories for Massachusetts

Drought indicator	Drought severity level				
	Normal	Advisory	Watch	Warning	Emergency[d]
Standardized Precipitation Index	3-month > –1.5 or 6-month > –1.0 or 12-month > –1.0	3-month: –1.5 to –2.0 or 6-month: –1.0 to –1.5 or 12-month: –1.0 to –1.5	3-month < –2.0 or 6-month: –1.5 to –3.0 or 12-month = –1.5 to –2.0	6-month: < –3.0 or 12-month: = –2.0 to –2.5	12-month < –2.5
Crop Moisture Index[a]	0.0 to –1.0 Slightly dry	–1.0 to –1.9 Abnormally dry	–2.0 to –2.9 Excessively dry	< –2.9 Severely dry	< –2.9 Severely dry
Keetch-Byram Drought Index[a]	<200	200–400	400–600	600–800	600–800
Precipitation	1 month below normal[a]	2 month cumulative below 65% of normal	3 month cumulative < 65% or 6 month cumulative < 70% or 12 month cumulative < 70%	3 month cumulative < 65% and 6 month cumulative <65%, or 6 month cumulative <65% and 12 month cumulative <65%, or 3 month cumulative <65% and 12 month cumulative <65%	Same criteria as Warning and previous month was Warning or Emergency
Streamflow (7-day average compared to historic levels)	1 month below normal[b]	At least 2 out of 3 consecutive months below normal[b]	At least 4 out of 5 consecutive months below normal[b]	At least 6 out of 7 consecutive months below normal[b]	>7 months consecutive months below normal[b]
Groundwater Level (compared to historic data)	2 consecutive months below normal[b]	3 consecutive months below normal[b]	4–5 consecutive months below normal[b]	6–7 consecutive months below normal[b]	>8 consecutive months below normal[b]
Reservoir Level[c]	Reservoir levels at near normal for the year	Small index Reservoirs below normal	Medium index Reservoirs below normal	Large index Reservoirs below normal	Continuation of previous month's conditions

[a]Subject to change depending on repeated or extended occurrence at a specific drought level
[b]Defined as being within the lowest 25th percentile of the period of record
[c]Need to consult with water suppliers if below normal conditions are due to operational issues
[d]Drought scenarios that will be simulated for the Massachusetts case study

15.4.2 Data Collection and Synthesis

The present case study utilized an assembly of databases obtained from several sources. GIS maps embedded with geographic data attributes (political boundaries, drought regions, populations) were obtained from the website of the state of Massachusetts (mass.gov) and from the Massachusetts Drought Management Plan (2013). The economic data sets that were utilized included: (1) the national IO matrix comprising 71 economic sectors and adapted for Massachusetts (2) gross domestic product, (3) local area personal income, and (4) water input requirements of each sector derived from the *Use* matrix available through the United States Bureau of Economic Analysis website. The 71 economic sectors (Table 15.3) are adopted from the aggregated sector classification of the North American Industry Classification System (NAICS).

15.4.3 Drought Scenario

The water IO model extension was applied to evaluate the regional impacts of a 6-month (180 days) drought in Massachusetts. This duration reflects the most recent and widespread drought in 2016–2017 when drought severity levels in majority of the state were classified by the DMTF up to the emergency category. In this study, it was assumed that the drought progressions resulted in up to a 20% water reduction from normal operation, within range of water level reductions in Virginia and California for a similar drought category (Virginia DEQ 2017; CA Exec. Order No. B-29-15). As noted previously, the DMTF does not have the authority to impose water use restrictions on individual towns; towns implement their individual water management strategies during periods of drought.

The 180-day drought timeline was further divided into three periods similar to what was observed in the recent Massachusetts drought:

- Period 1, lasting 30 days when water reduction starts at 0% in day 0 and gradually increases to a peak level of 20% in day 30;
- Period 2, lasting 30 days of sustained 20% water reduction levels; and
- Period 3, lasting 120 days, when water availability improves towards normal conditions (i.e., water reduction at day 180 is ≈0%)

We note that in the present work, we used annual aggregated IO and economic data to simulate the regional impacts of the 6-month drought. We acknowledge that the productivity of sectors can vary significantly within the year (e.g., farms have higher outputs during harvest months), and using annual averaged data may not capture periods of high and low productivity for the economic region. The intent of our simplified approach is to demonstrate the utility of the water IO model extension without overly complicating the manipulation of spatio-temporal data inputs. Nevertheless, it is possible to operate the proposed IO model extension on an intra-

Table 15.3 Classification of economic sectors used in the study

Sector	Description	Sector	Description
S1	Farms	S37	Pipeline transportation
S2	Forestry, fishing, and related activities	S38	Other transportation and support activities
S3	Oil and gas extraction	S39	Warehousing and storage
S4	Mining, except oil and gas	S40	Publishing industries except internet
S5	Support activities for mining	S41	Motion picture and sound recording industries
S6	Utilities	S42	Broadcasting and telecommunications
S7	Construction	S43	Internet publishing and broadcasting
S8	Wood products	S44	Federal Reserve banks and credit intermediation
S9	Nonmetallic mineral products manufacturing	S45	Securities, commodity contracts, and investments
S10	Primary metals	S46	Insurance carriers and related activities
S11	Fabricated metal products	S47	Funds, trusts, and other financial vehicles
S12	Machinery	S48	Housing
S13	Computer and electronic products	S49	Real estate (except housing)
S14	Electrical equipment, appliances, and components	S50	Rental and leasing services
S15	Motor vehicles, bodies and trailers, and parts	S51	Lessors of intangible assets
S16	Other transportation equipment	S52	Computer systems design and related services
S17	Furniture and related products	S53	Miscellaneous professional and scientific services
S18	Miscellaneous manufacturing	S54	Management of companies and enterprises
S19	Food and beverage and tobacco products	S55	Administrative and support services
S20	Textile mills and textile product mills	S56	Waste management and remediation services
S21	Apparel and leather and allied products	S57	Educational services
S22	Paper products	S58	Ambulatory health care services
S23	Printing and related support activities	S59	Hospitals
S24	Petroleum and coal products	S60	Nursing and residential care facilities
S25	Chemical products	S61	Social assistance
S26	Plastics and rubber products	S62	Performing arts, spectator sports, and museums
S27	Wholesale trade	S63	Amusements, gambling, and recreation industries
S28	Motor vehicle and parts dealers	S64	Accommodation

(continued)

Table 15.3 (continued)

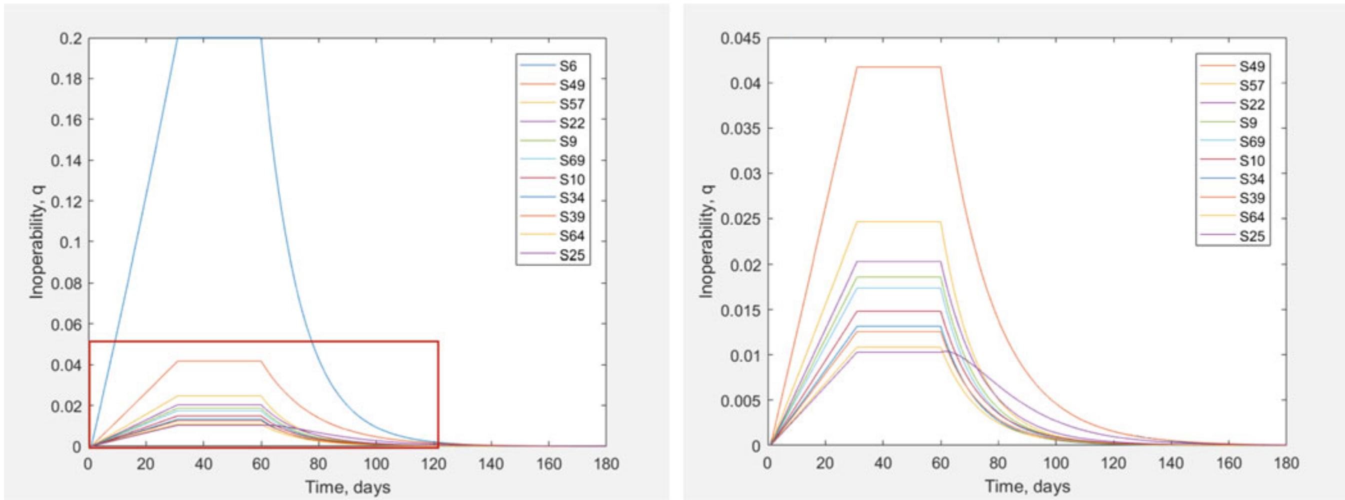
Sector	Description	Sector	Description
S29	Food and beverage stores	S65	Food services and drinking places
S30	General merchandise stores	S66	Other services, except government
S31	Other retail	S67	Federal government (defense)
S32	Air transportation	S68	Federal general government (no-defense)
S33	Rail transportation	S69	Military
S34	Water transportation	S70	State government
S35	Truck transportation	S71	Local government
S36	Transit and ground passenger transportation		

Source: Bureau of Economic Analysis (www.bea.gov)

annual basis. The formulation of the model is flexible and is designed to accept and process temporal data [e.g., quarterly data, see formulation in Eq. (15.1)], while its integration with a GIS platform allows for flexibility in delineating regional boundaries (e.g., when a drought intervention measure is implemented only to select sub-regions during the drought timeline).

15.4.4 Simulation Results

Figure 15.2 shows the top sector rankings for the inoperability metric for the 180-day drought scenario. The left panel shows the top 11 sectors, with the Utilities (water) sector having the highest inoperability and the slowest recovery rate during the last 120 days of the drought timeline. The Utilities sector also exhibits a disproportionately higher inoperability than the next ten sectors (maximum q of 0.2 for utilities versus a maximum q range of 0.01–0.042 for the next ten sectors). A close-up view of the inoperability values of the ten sectors is shown on the right panel, where the Real estate sector ($q = 0.045$, S49) shows a markedly higher inoperability than the other nine sectors (i.e., about twice the next ranked education services sector, S57). It is interesting to note that the manufacturing industry, a major contributor to the Massachusetts economy (US Census Bureau 2016), is well represented in the top rankings. The Farming sector, which is often shown as a critical economic sector in other regional drought risk studies (Ward and Michelsen 2002), is not represented because this sector has a much lower contribution to the production outputs of the state. It is also important to note that with the exception of the Chemicals manufacturing sector (S25), the other nine sectors have a much faster recovery rate than the Utilities sector, reaching near normal operations at about 120 days from the onset of drought. In contrast, the utilities sector takes about 160 days to reach the same level of recovery. The Chemicals sector also exhibit a slow recovery similar to the Utilities sector, indicating a higher dependence on the availability of water for its operation. Further, its inoperability increases further as drought eases before it starts to recover approximately 5 days later from the onset of the recovery



S49	Real estate (excluding housing)
S57	Educational services
S22	Paper manufacturing
S9	Nonmetallic mineral product manufacturing
S69	Military
S10	Primary metal manufacturing
S34	Water transportation
S39	Warehousing and storage
S64	Accommodation
S25	Chemical manufacturing

Fig. 15.2 Inoperability rankings for the State of Massachusetts. Left panel: top 11 sectors, including utilities sector (first). Right panel: closer view of boxed section in left panel

period. This phenomenon highlights the interdependency of the sectors and the ripple effects of disruption on the linkages within these interdependencies. While the drought condition eases, the production levels of all others sectors that provide inputs to the Chemicals sector are not recovering fast enough to enable the chemicals sector to experience the same recovery momentum as the other sectors. The increase in operability can also be viewed as a delayed response to the disruptions to its input sectors. Lastly, we note of the inoperability ranking for the Military sector (S69, ranked 6th, $q = 0.018$), which is comparable to the inoperability of the manufacturing industries. Based on these results, a 20% water reduction for 30 days within a 6-month drought period would translate to a ~2% loss on the military's ability to provide its ideal level of production output (or service). According to the Strategic Environmental Research and Development Program (2018), the Department of Defense operates a significant number of water and wastewater treatment facilities across the US, catering to more than three million people living and working in various military facilities and installations. When compared with the six-sigma measure (a commonly used concept in the area of statistical quality control), the magnitudes of the resulting inoperability values are quite significant. To wit, the threshold failure rate in six-sigma analysis is three parts per million, or equivalently, an inoperability of 0.0000034. To further elucidate this comparison, suppose a sector experiences a 6% loss in production. This is equivalent to an inoperability of 0.06, which would dissatisfy the six six-sigma quality threshold by several orders of magnitude.

To further examine the spatio-temporal patterns of the inoperability values among the top sectors, a plot of the q values for all drought regions over time are shown in Fig. 15.3 for three sectors: Real estate (S49, ranked 2nd), Non-metallic minerals manufacturing (S9, rank 5th), and Chemicals manufacturing (S25, ranked 11th). For

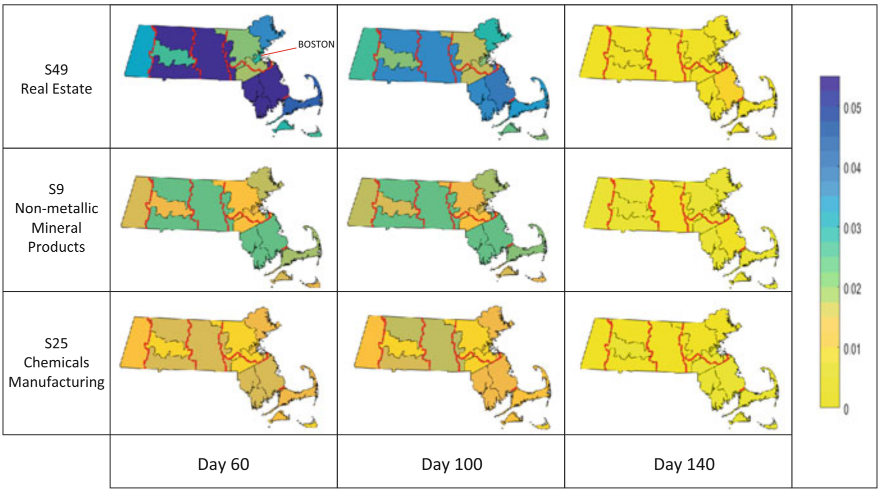
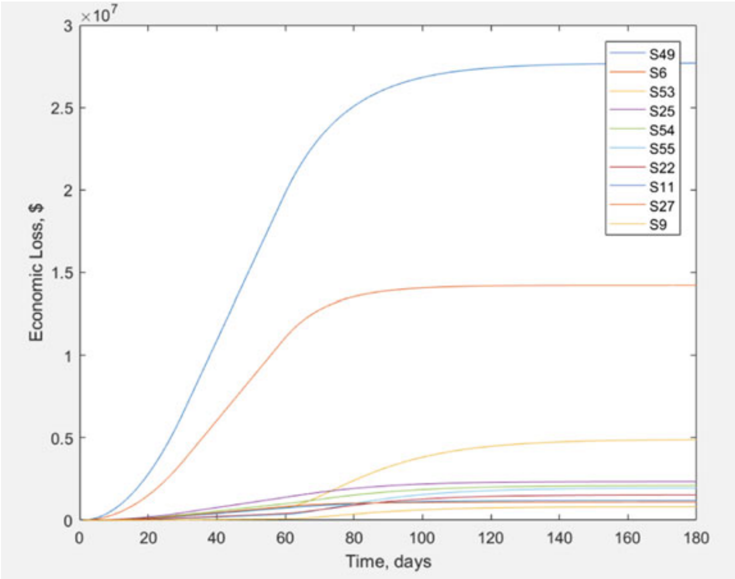


Fig. 15.3 Inoperability values by county for sectors S49, S9, and S2



S49 Real estate (excluding housing)
S6 Utilities
S53 Miscellaneous professional, scientific, and technical services
S25 Chemical manufacturing
S54 Management of companies and enterprises
S55 Administrative and support services
S22 Paper manufacturing
S11 Fabricated metal product manufacturing
S27 Wholesale trade
S9 Nonmetallic mineral product manufacturing

Fig. 15.4 Economic loss rankings for the State of Massachusetts

all sectors, the highest inoperabilities (also higher than state averages) are observed in DR II (Connecticut), DR III (Central), and DR V (Southeast); the most distinct discrepancies in inoperability values for all drought regions are observed for the real estate sector. Within the most affected regions, Hampshire (in DR II), parts of Norfolk (in DR III), and a small section of Middlesex (in DR V) are comparatively better off than the rest of severely affected regions. Further, the recovery of Bristol (in DR V) is slightly faster not just for the real estate sector but also for the minerals and chemicals manufacturing sectors. It is worth noting that in terms of inoperability for the real estate sector, the city of Boston and its immediate surrounding suburban areas (Suffolk county) are not as affected by the water disruption in contrast to the more rural areas in western Massachusetts or in the southeastern urban to peri-urban regions.

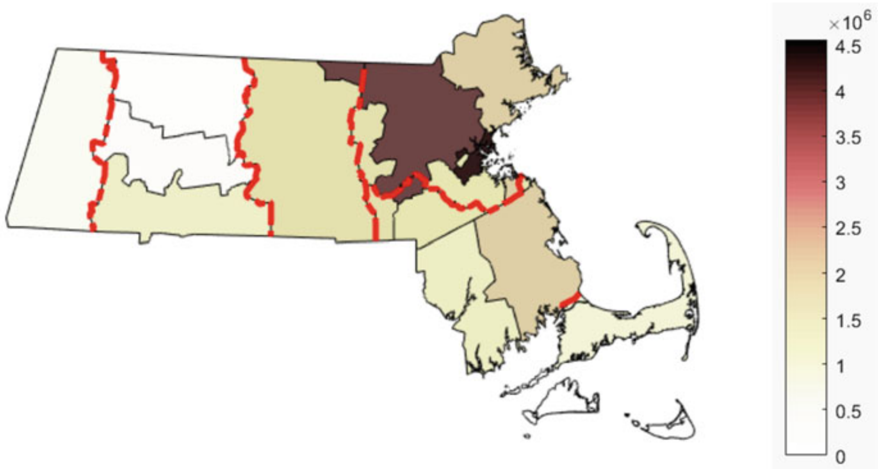


Fig. 15.5 Economic loss (in US$) by county for real estate sector

Figure 15.4 depicts the top ten rankings for the economic loss metrics. The total loss for the whole of Massachusetts is \$69 million (0.014% of state GDP in 2016), and 67.5% of this is incurred by the top three sectors: Real estate (S49, 40%), Utilities (S49, 20.5%), and Miscellaneous services (S53, 7%). Economic losses for the sectors below the top three are less than 10% of the loss incurred by the Real estate sector alone (\$28 million), indicating the criticality of Real Estate when the economic impact of drought is considered as a priority for Massachusetts. The economic loss of the Real Estate sector is also twice that of the Utilities sector despite the disproportionately large inoperability of the latter compared to the former (shown in Fig. 15.2). Note that manufacturing industries are again well represented in the top ten. Sector rankings have also changed markedly, and new sectors that were not in the top rankings for inoperability are introduced to the list. In particular, the Military sector is no longer in the top ten while service sectors (Professional, S53; Management, S54; and Administrative, S55) are new additions to the rankings. These changes in rankings as well as in levels of economic losses provide insights on the economic value of the sectors to the entire economy. The operation of a sector may be less disrupted by water reduction, but if the economic value of its product is high, the sector can have comparatively greater economic losses than other sectors.

The total economic loss of each county throughout the 180-day drought timeline is plotted for the Real estate sector in Fig. 15.5. Suffolk and Middlesex counties in the Northeast drought region incur the highest economic losses; their combined losses account for 49.3% of the total losses incurred by the Real Estate sector in the entire state. Interestingly, the peak inoperability values of both counties were much lower than those for the critical counties of Franklin, Hampden, Worcester, Bristol, and Plymouth (see Fig. 15.2). Further, Suffolk, has a slightly higher economic loss than Middlesex (25.9% vs. 23.4% of sector total) despite its significantly smaller land area. This is not entirely unexpected; Suffolk encompasses metropolitan

Boston, which has the ninth highest GDP among all metropolitans in the entire US (US Census Bureau 2016).

The results of this case study provide critical insights to the risk analyst on how to formulate strategies for building resilience against the adverse impacts of drought. Inoperability and economic loss can be used as metrics of vulnerability and resilience to varying drought severity and duration, at the sector level or for the region as a whole. Strategies for drought management can be designed based on sector or geographic prioritization, or a combination of both. Where water resources are extremely limited, intervention measures can also be phased over time depending on the level of vulnerabilities and recovery rates of the sectors. The differences in rankings for the inoperability and economic loss metrics indicate that when operations are disrupted during drought events, the resulting economic loss may not be as severe if the value of the product output is comparatively low, or it can be significant if the product has high economic value. In the latter case, even small disruptions in operation can yield high economic loss. It must be emphasized that the rankings alone should not be the sole basis for prioritization. Economic sectors are inherently interdependent due to their economic linkages. Disruptions in the operation of non-prioritized sectors will have ripple effects on the entire economy, even on the prioritized sectors.

15.5 Conclusions

In this research, we have developed a drought risk analysis framework that integrates various modeling components including economic IO modeling, dynamic inoperability analysis, and visualization using GIS. This decision support tool enables the spatio-temporal assessment of the impacts of drought on the regional economy while accounting for the inherent linkages across economic sectors. It also provides policymakers a visual and quantitative tool for evaluating the resilience of economic sectors to varying drought severity and duration over time and across locations, from the onset of drought and through the ensuing recovery phase. The case application to the state of Massachusetts demonstrates the utility of the framework in performing drought risk analysis for a region and for its individual components. As measures of drought resilience, the inoperability and economic loss metrics provide insights on critical sectors and sub-regions, and their ripple effects on the regional economy. Research findings can guide policies and strategies for enhancing drought resilience across sectors and the entire regional economy.

References

Addams L, Boccaletti G, Kerlin M et al (2009) Charting our water future: economic frameworks to inform decision-making. McKinsey, New York

Albala-Bertrand JM (2013) Disasters and the networked economy. Routledge, Oxford
Anderson C, Santos JR, Haimes YY (2007) A risk-based input-output methodology for measuring the effects of the August 2003 northeast blackout. Econ Syst Res 19:183–204
Avelino AFT (2017) Disaggregating input–output tables in time: the temporal input–output framework. Econ Syst Res 29:313–334
Blignaut J, Heerden JV (2009) The impact of water scarcity on economic development initiatives. Water SA 35(4):415–420
CA Exec. Order No. B-29-15 (April 1, 2015), https://www.gov.ca.gov/docs/4.1.15_Executive_Order.pdf
Cazcarro I, Duarte R, Choliz JS (2013) Multiregional input-output model for the evaluation of Spanish water flows. Environ Sci Technol 47:12275–12283
Dietzenbacher E, Lahr ML (2004) Wassily Leontief and input-output economics. Cambridge University Press, Cambridge, UK
Dietzenbacher E, Miller RE (2015) Reflections on the inoperability input–output model. Econ Syst Res 27:478–486
Executive Office of Energy and Environmental Affairs and Adaptation Advisory Committee (2011) Massachusetts Climate Change Adaptation Report. 128 pp
Haimes YY (1991) Total risk management. Risk Anal 11(2):169–171
Haimes YY, Jiang P (2001) Leontief-based model of risk in complex interconnected infrastructures. J Infrastruct Syst 7(1):1–12
Holling C (1973) Resilience and stability of ecological systems. Annu Rev Ecol Syst 4:1–23
Horridge M, Madden J, Wittwer G (2005) The impact of the 2002–2003 drought on Australia. J Policy Model 27(3):285–308
Howitt RE, MacEwan D, Medellín-Azuara J et al (2005) Agricultural and environmental policy models: calibration, estimation and optimization. University of California Davis, UC Davis
Hubacek K, Sun L (2005) Economic and societal changes in China and their effects on water use: a scenario analysis. J Ind Ecol 9:187–200. https://doi.org/10.1162/1088198054084572
Jones RN, Whetton PH, Walsh KJE et al (2002) Future impacts of climate variability, climate change and land use change on water resources in the Murray Darling Basin: overview and draft program of research. Murray-Darling Basin Commission, Canberra
Kaplan S, Garrick BJ (1981) On the quantitative definition of risk. Risk Anal 1:11–27
Leontief W (1936) Quantitative input and output relations in the economic system of the United States. Rev Econ Stat 18(3):105–125
Lian C, Haimes YY (2006) Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input-output model. Syst Eng 9:241–258
Lowell Water Utilities. Personal communication, 31 October 2016
Martín L, Justo JB (2015) Análisis, prevención y resolución de conflictos por el agua en América Latina y el Caribe. Serie Recurso Naturales e Infraestructura. United Nations Economic Commission for Latin America and the Caribbean, Santiago. Available via http://repositorio.cepal.org/bitstream/handle/11362/37877/S1500220_es.pdf. Accessed 9 March 2017
Martin-Carrasco F, Garrote L, Iglesias A, Mediero L (2013) Diagnosing causes of water scarcity in complex water resources systems and identifying risk management actions. Water Resour Manage 27:1693–1705. https://doi.org/10.1007/s11269-012-0081-6
Massachusetts Executive Office of Energy and Environmental Affairs and Massachusetts Emergency Management Agency (MA EEA) (2013) Massachusetts Drought Management Plan, 41 pp
Massachusetts Office of Water Resources (MAOWR). Personal communication, 25 October 2016
MATLAB version 2017a (2017) MathWorks, Inc. Natick, Massachusetts
Miller RE, Blair PD (2009) Input-output analysis: foundations and extensions, 2nd edn. Cambridge University Press, Cambridge
National Drought Mitigation Center (2017) U.S Drought Monitor Massachusetts. http://droughtmonitor.unl.edu. Accessed 19 Feb 2017

Okuyama Y (2007) Economic modeling for disaster impact analysis: past, present and future. Econ Syst Res 19(2):115–124
Oosterhaven J (2017) On the limited usability of the inoperability IO model. Econ Syst Res 29:452–461
Organization for Economic Co-operation and Development (2012) Environmental outlook to 2050: the consequences of inaction. OECD, Paris. https://doi.org/10.1787/9789264122246-en
Orsi MJ, Santos JR (2010) Probabilistic modeling of workforce-based disruptions and input-output analysis of interdependent ripple effects. Econ Syst Res 22:3–18
Pagsuyoin SAT, Santos JR (2015) Modeling the effects of drought in urban economies using input-output analysis. Br J Environ Clim Change 5(2):134–146
Paulson RW, Chase EB, Roberts RS, Moody DW (1991) National water summary 1988-89: hydrologic events and floods and droughts. United States Geological Survey Water-Supply Paper 2375
Perrings C (2001) Resilience and sustainability. In: Folmer H, Gabel HL, Gerking S, Rose A (eds) Frontiers of environmental economics. Edward Elgar, Cheltenham, UK, pp 319–341
Postel SL (2000) Entering an era of water scarcity: the challenges ahead. Ecol Appl 10(4):941–948
Resurreccion JZ, Santos JR (2013) Uncertainty modeling of hurricane-based disruptions to interdependent economic and infrastructure systems. Nat Hazard 69:1497–1518
Rockstrom J, Steffen W, Noone K et al (2009) A safe operating space for humanity. Nature 461:472–475
Rose A (2009) Economic resilience to disasters: community and Regional Resilience Institute (CARRI) Research Report 8. CARRI Institute, Oakridge, TN
Rose A, Liao SY (2005) Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. J Reg Sci 45(1):75–112
Rowland M (2005) A framework for resolving the transboundary water allocation conflict conundrum. Ground Water 43(5):700–705
Roy SB, Chen L, Girvetz EH, Maurer EP, Mills WB, Grieb TM (2012) Projecting water withdrawal and supply for future decades in the U.S. under climate change scenarios. Environ Sci Technol 46(5):2545–2556. https://doi.org/10.1021/es2030774
Santos JR, Haimes YY (2004) Modeling the demand reduction input-output inoperability due to terrorism of interconnected infrastructures. Risk Anal 24:1437–1451
Santos JR, Pagsuyoin SA, Herrera LC, Tan RG, Yu KDS (2014) Analysis of drought risk management strategies using dynamic inoperability input-output modeling and event tree analysis. Environ Syst Decis 34(4):492–506. https://doi.org/10.1007/s10669-014-9514-5
Schlosser CA, Strzepek K, Gao X et al (2014) The future of global water stress: an integrated assessment. Earths Future 2:341–361. https://doi.org/10.1002/2014EF000238
Seung CK, Harris TR, Englin J, Netusil N (2000) Impacts of water reallocation: a combined computable general equilibrium and recreation demand model approach. Annu Reg Sci 34:473–487
Shiklomanov I (1993) World fresh water resources. In: Gleick P (ed) Water in crisis: a guide to the world's fresh water resources. Oxford University Press, New York
Strategic Environmental Research and Development Program (2018) Treatment of Wastewater and Drinking Water. https://www.serdp-estcp.org/Program-Areas/Environmental-Restoration/Wastewater-and-Drinking-Water. Accessed 17 Jan 2018
UN (2016) Global sustainable development report 2016. Department of Economic and Social Affairs, New York. Available via https://sustainabledevelopment.un.org/globalsdreport. Accessed 19 Feb 2017
UN Framework Convention on Climate Change (UNFCCC) (2015) Adoption of the Paris Agreement. http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf. Accessed 20 Feb 2017
UN World Water Assessment Program (UNWWAP) (2016) The United Nations World Water Development Report 2016: water and jobs. UNESCO, Paris. Available via http://unesdoc.unesco.org/images/0024/002439/243938e.pdf. Accessed 19 Feb 2017

US Bureau of Economic Analysis (2015) National Economic Accounts. http://www.bea.gov/itable. Accessed 20 Feb 2017
US Census Bureau (2016) QuickFacts Beta: Massachusetts. https://www.census.gov/quickfacts/table/PST045215/25. Accessed 4 Mar 2017
US Government Accountability Office (2014) Supply concerns continue, and uncertainties complicate planning (GAO Publication No. 14-430). U.S. Government Printing Office, Washington, DC
US Intelligence Community Assessment (2012) Global water security. https://www.dni.gov/files/documents/Newsroom/Press%20Releases/ICA_Global%20Water%20Security.pdf. Accessed 17 Jan 2018
Virginia Department of Environmental Quality (2017) Drought assessment and response plan. Available at http://www.deq.virginia.gov/Portals/0/DEQ/Water/WaterResources/vadroughtresponseplan.pdf. Accessed 21 Feb 2017
Ward FA, Michelsen A (2002) The economic value of water in agriculture: concepts and policy applications. Water Policy 4(5):423–446
Ward F, Pulido-Velazquez M (2012) Economic costs of sustaining water supplies: findings from the Rio Grande. Water Resour Manag 26(10):2883–2909
Webb G, Tierney K, Dahlhamer J (2000) Business and disasters: empirical patterns and unanswered questions. Nat Hazard Rev 1:83–90
World Wildlife Fund (WWF) (2017) Water scarcity. http://www.worldwildlife.org/threats/water-scarcity. Accessed 19 Feb 2017

Sheree Pagsuyoin is an assistant professor at the University of Massachusetts Lowell, USA. Her primary research interests are in the areas of emerging micropollutants' fate and transport, water treatment, and water resources management. She received her doctoral degree in civil and environmental engineering from the University of Virginia in 2010.

Joost Santos is an associate professor at the George Washington University. His research focuses on systems engineering, disaster risk management, and economic input-output modeling. He obtained his BS/MS degrees in industrial engineering at the University of the Philippines and PhD degree in systems engineering at the University of Virginia.

Gustavo Salcedo is a graduate student at the Department of Civil and Environmental Engineering, University of Massachusetts Lowell. He holds a bachelor's degree in Civil Engineering from Pontificia Universidad Javeriana Cali in 2014.

Christian Yip graduated from the George Washington University with a Master of Science in Engineering Management and a Bachelor of Science in Systems Engineering. He applies his business management and technology literacy skills at a major consulting firm in Washington, DC.

Chapter 16
The Game-Theoretic National Interstate Economic Model: Economically Optimizing U.S. Aviation Security Policies Against Terrorist Attacks

Ha Hwang and JiYoung Park

Abstract The study proposes an approach to assessing airport and aviation security policies, which incorporates terrorist attack behaviors with economic impacts stemming from disruption of U.S. airport systems. Terrorist attacks involve complicated strategic behaviors of terrorists, while various defenders need to consider the degree of negative impacts that may occur via complicated paths. Simultaneous attacks will make this situation more complicated, because defending entities must secure airports and aviation systems with more tightly integrated inter-governmental collaborations. This study, for the first time, suggests a dynamic method to design the complicated micro-level behavioral strategies with macro-level economic impacts. In terms of game strategies, the current study only considers a competitive game situation between a defender and an attacker. In terms of the macro-level economic model, the National Interstate Economic Model (NIEMO) is introduced, which is a spatially disaggregated economic model used for the U.S. By combining these two approaches, a new framework is called the Game Theoretic National Interstate Economic Model (G-NIEMO). G-NIEMO, then, can be used to assess probabilistic costs of airport closure when potential terrorist attacks occur under the circumstance of considering the allocation of a government' resources for designing airport security optimally by event location and industry type. NIEMO has been widely applied through a variety of empirical studies, but the competitive game model has not yet combined successfully. Based on the basic algorithm applied in the "attacker-

H. Hwang
Division of Disaster and Safety Research, Korea Institute of Public Administration, Seoul, Republic of Korea
e-mail: hahwang@kipa.re.kr

J. Park (✉)
Department of Urban and Regional Planning, University at Buffalo, The State University of New York, Buffalo, NY, USA

Regional Information Program, Seoul National University, Seoul, Republic of Korea
e-mail: jp292@buffalo.edu; jiyoungp@snu.ac.kr

Y. Okuyama, A. Rose (eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts*, Advances in Spatial Science,
https://doi.org/10.1007/978-3-030-16237-5_16

defender game," this chapter explains how G-NIEMO could be achieved. Further, establishing a cooperative coordination system and collective countermeasures against terrorism is necessary to cope with much more complicated forms of terrorist attacks such as simultaneous attacks and cyber-attacks. G-NIEMO can meet these needs through a collaborative gaming model. When applying G-NIEMO practically to simulate comprehensive defense strategies, for example, for urban critical infrastructure systems, corresponding estimated probabilistic impacts can be prepared. Therefore, G-NIEMO can be used to establish equilibrium strategies for protecting U.S. territory, creating general guidelines and assessing government resource allocations.

16.1 Introduction

Major U.S. airports are still exposed to terrorist attacks, despite border security enhancements of the United States (U.S.) especially since September 11, 2001. Due to tight connections between domestic and international airports, disruptions of any airport may cause direct and indirect economic impacts across the nation and worldwide. Ripple economic impacts caused by inter-regional and inter-industrial relationships between industries and regions should be taken into account. Assessing the economic impacts of a terrorist attack is now operational using the National Interstate Economic Model (NIEMO) for the U.S. Still, determining the level of resource allocation for defenses, which successfully protects airports and aviation systems targeted by attackers, remains as a difficult task. Because both terrorists and governments are intelligent, once strategic action begins, either decision could influence each other's decision. Resolving the complicated situations of interdependent strategic competitions needs to be established for government security policies.

As airport security risk increases, it is imperative to offer state-of-the-art policy solutions that combine the probability of terrorist attacks and the corresponding economic damages. Because terrorist attacks on aviation systems include both complicated game situations of both micro-level behavioral decision making process and macroeconomic analysis for sizable potential economic consequences, an integrated approach requires interactive communication between the game situation with an economic impact model. Therefore, this approach must take into account both the micro-level strategic behaviors among the relevant groups involved in the attack situation and the macro-level economic impacts stemming from successful attacks.

So far, any previous approach has never attempted to combine the two different scales that interactively work while Park et al. (2016, 2018) provide two conceptual frameworks recently. From this perspective, an innovative, theoretical approach to developing extended economic impact models coupled with game-based simulations is mathematically proposed in this chapter. The proposed model, called game theoretic NIEMO (G-NIEMO), will advance our understanding of how uncertain attack behaviors are associated with the local and neighbor economies of the U.S. when an aviation system is disrupted, which usually impact beyond one region where an airport is located.

Among many game theoretic models, this chapter only considers a competitive game-theory model as an operational case. A competitive game runs iteratively on the basis of continuous strategies. Also, it refers to a dynamic game that uses the previous game results for the information of the current game. Although spatially disaggregated models have widely been applied to empirical studies of terror events, game theoretical processes have not been explicitly included in the multiregional economic impacts. Various economic impact models combined with micro-level simulation models do not demonstrate the dynamic process connecting the two different approaches. Synthesizing fundamental components and algorithms of "attacker-defender games" can contribute to improving the dynamic integration mechanism of the combined model. The new methodology developed herein can contribute to the literature on methodologies combining both micro-level simulation approaches with various economic impact models.

The following sections are organized as follows. Section 16.2 discusses contemporary terrorist threats at major airports. Section 16.3 explains the outline of G-NIEMO and the competitive game situation between terrorists and governments. Section 16.4 provides a comprehensive discussion about each procedure of G-NIEMO. Section 16.5 concludes the chapter with brief discussions.

16.2 Threats of Terrorists' Attacks on Major Airports

Since September 11, 2001, the U.S Customs and Border Protection (CBP 2008) agency has made it a priority "to keep terrorists and their weapons from entering the United States." As a result, security enhancements have been implemented at the U.S. border to block physical aggression across borders. Unfortunately, it appears that the Department of Homeland Security does not effectively prevent physical invasions at the U.S. border (Tirman 2006).

Yet, this raised security level does not prevent terrors on an airport effectively. The Los Angeles International Airport (LAX) was paralyzed due to a shooting on November 1, 2013. The shutdown at LAX has had a ripple effect throughout the U.S. air network, cancelling more than 400 domestic flights on the day (ABC 2013). While this case was not a big enough event to cause social disruption, it has shown that a less important event could seriously destroy domestic and international air networks. If one of the LAX terminals were shutdown, for example, it may affect airports as far away as JFK and ripple across the nation for several days or more after the incident.

A terrorist's attack on U.S. airports is complex and strategically challengeable. It involves ill-structured multiple criteria, multiple participant decision processes characterized by extreme uncertainty, multi-faceted negotiations, and high decision stakes. The risk of simultaneous attacks is another criterion to be considered. It causes another difficulty for defending entities to secure the airport systems. While aviation security decisions must often be made under pressure and high uncertainty,

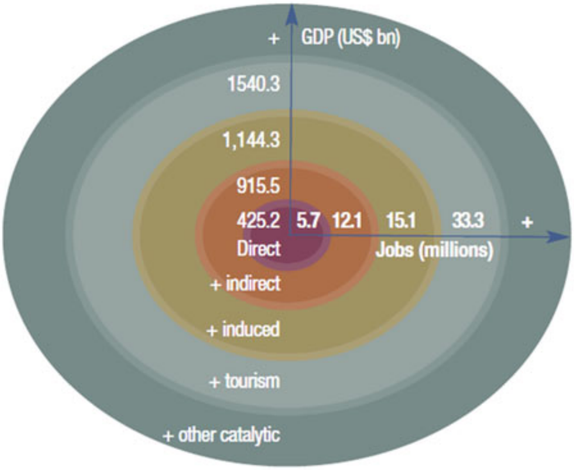


Fig. 16.1 Contributions of air transport to the global economy. Source: Oxford Economics (2009)

moral and ethical values held by stakeholders may be as important as technical issues.

This highlights the need for improved and integrated collaboration among local and regional governments, state and federal agencies, and enhanced international collaboration to cope with the risk of threats. As found in Fig. 16.1, air transport substantially contributes more than $1.5 trillion and 33 million jobs to the global economy. Because of the intricate interactions of worldwide aviation systems, terrorist attacks from any airport can have a worldwide impact.

Recent experiences report the global impacts. For example, when Bangkok International Airport was closed for 8 days in 2008, economic impacts exceeded $8.5 billion (ARTBA 2010). This includes tourism losses and disruptions to exports and tourists. Associated with this event, the U.S. aviation industry experienced $1.4 billion in losses after 9/11 (ARTBA 2010). Also, the 2010 volcanic eruption in Iceland led to large losses for the aviation industry (approximately $1.5 billion in direct losses), forcing to cancel more than 100,000 flights over a 6-day period (Oxford Economics 2010). The total economic impacts resulting from the crisis were estimated at approximately $4.7 billion. They are much greater than the direct impacts of $1.5 billion on air transportation systems. Further, according to the recent American Institute of Aeronautics and Astronautics (2013), aviation's global economic impacts that include direct, indirect, induced and tourism catalytic reach at $2.2 trillion, approximated as 3.5% of global GDP.

16.3 The Game-Theoretic National Interstate Economic Model

16.3.1 A Competitive Game Between Terrorists and Governments

A terrorist attack on a country usually begins with complex strategic actions by terrorists who try to sneak across the border. At the same time, the governments associated must take into account the complex processes involved, including the terrorist's strategic actions, in order to prevent terrorists' threatening attempts that could have made catastrophic consequences. Terrorists and governments simultaneously respond to each other's strategic decisions to achieve their goals. The competitive game theory has been widely applied in the study of strategic interactions between attackers and defenders (Daniel et al. 2003). Based on strategies evolved from Dawkins' "Selfish Gene," competitive and evolutionary dynamic game processes are most effective in finding the best solution under limited conditions (Benkler 2011b).

Terrorists are intelligent and adaptable. The national border security aims at preventing any physical terrorist invasion. Terrorists are trying to find places where border security measures are weak and use a variety of illegal network channels to transport money, weapons, and manpower across borders. The game theoretical situation begins with terrorists creating action strategies that can cross borders. The government should develop a response strategy to prevent it. However, it is a question of how much resources should be allocated to prevent anticipated terrorist attacks (Zhuang and Bier 2007). From this point of view, policy makers need a G-NIEMO type tool to solve the problem of optimal resource allocation for effective anti-terrorism policies.

16.3.2 Attacker-Defender Games

The defense of terrorism is not easy because strategic agents including terrorists and governments interact to the mechanisms responding along with opponents' decisions. Among a number of approaches, a game theory has been widely applied to solve this complicate issue. Scholars have especially focused on the ways of deterring terrorism via building a mechanism of strategic interactions between terrorists and governments. Since Sandler et al. (1983) applied negotiation game process between the terrorists and the policy makers, the economists and political scientists have kept developing "attacker-defender games." The study greatly boomed after al-Qaida's four skyjackings on September 11, 2001 (Sandler and Siqueira 2009). Even though both the competitive (or non-cooperative) and the cooperative game theory can be used to study terrorism, most analyses only involved the competitive game theory so far. For more details of "attacker-defender games," see Brown et al. (2005).

Game-theoretic models are classified into several dimensions according to game settings. First, when players have only binary strategies (yes or no), the game becomes a binary choice game. The game will advance to a continuous choice game when they decide the level of strategic intensity. While binary choice models are intuitive and conveyable to decision makers, these games do not fully describe the game mechanisms. This is because players' binary choices are outputs of continuous choices as well (above or below threshold). For more examples of binary choice attacker-defender games, see Sandler and Lapan (1988), Sandler (2003), Bier (2007), Dighe et al. (2009), Zhuang (2010), and Zhuang and Bier (2011).

Continuous choice games provide the level of strategies to defenders. Continuous choice games are more preferable to decision makers who have to efficiently allocate limited resources (Guan and Zhuang 2016). For example, the optimal payoff of a defender is generated based on how much effort an attacker would use for its target and how much defense resources should be invested to deter the attack. Zhuang and Bier (2007) set the effort level of attackers and defenders as continuous variables, creating the probability of a successful attack as a function of them. For more examples of attacker-defender games with continuous choice, see Major (2002), Lakdawalla and Zanjani (2005), De Mesquita (2005a, b), and Sandler and Siqueira (2006) and more.

Second, games are classified into simultaneous games and sequential games based on information secrecy and disclosure. Action orders exist in any "attacker-defender games." For example, an attacker invades first and then a defender response the target. Alternatively, a defender behaves first to protect facilities, but an attacker invades the protected target. While a simultaneous occasion of attack and defense rarely happens, the games without information of opponents' decisions can be regarded as a simultaneous game. In the game, both players make their decisions without knowing their opponents' strategies in advance. In this game situation, players' decisions are independent to their opponents' decisions while they are interdependent to each other's decisions in the succeeding games. Otherwise, the games are classified into sequential games. In the sequential games, players' choices are interdependent to each other.

Lastly, there are additional dimensions of game situations. Some of them were briefly introduced here. Games are classified into symmetric or asymmetric games based on the amount of strategies available to each player. Based on players' knowledge of opponents' available strategies and payoff functions, games are classified into perfect information games and imperfect information games. When the sum of players' payoff amount is constant, it is classified into a zero-sum game; otherwise, non-zero-sum games. Competitive games and cooperative games can be classified based on centralized or decentralized decisions. For more game dimensions and their features, see Osborne (2004) and Gibbons (1992).

All game-theoretic situations assume that the game players are intelligent, who move strategically. Players should be able to utilize their best strategies to achieve their goals. In attacker-defender games, an attacker will choose the best strategy to devastate targets, maximizing the expected damages on targets. A defender will try the best to deter attacks, minimizing the expected damages. Based on these basic assumptions, we can infer the attacker-defender game is comprised of three main elements: (1) a set of players; (2) a set of strategies; and (3) conflicting goals of players (Muggy and Heier Stamm 2014). In game-theoretic models, the goals of players are conceptualized in mathematic expressions. They combine each player's strategies that determine their payoffs. These mathematic expressions are called "utility functions" or "payoff functions." More details will be discussed in Sect. 16.4 of this chapter.

There are various topics to be discussed such as information disclosure and secrecy, deceptions, centralized and decentralized decisions and so on. The current chapter only discusses "Best Response Functions (BRF)" and "Contest Success Functions (CSF)" that are essential mechanisms of an "attacker-defender game." These functions reflect players' strategic and intelligent features and their interdependent decisions.

16.3.3 The National Interstate Economic Model

The ideal, spatially disaggregated IO model was first suggested by Isard (1951). Early efforts to apply this idea were made by Chenery (1953) and Moses (1955). Based on Isard's idea, they developed a multiregional input-output model (MRIO) by applying a simpler dataset. Since then, many economists and regional scientists have applied an input–output (I–O) analysis to measure the socioeconomic impacts caused by diverse disasters. The National Interstate Economic Model (NIEMO) is an economic MRIO model covering 50 states and the District of Columbia (D.C.). This is the first operational MRIO model covering the entire US area since 1990 (Park et al. 2007). NIEMO applied Commodity Flow Survey (CFS) data to estimate interstate trade flows (Park et al. 2009) and IMPLAN data (from the Minnesota IMPLAN Group; MIG, Inc.) for inter-industrial transaction flows by state. Most of the NIEMO-based studies have been focused on measuring the impact of various man-made and natural disasters on regional and national economies. The findings provide useful information to propose effective public policy alternatives useful for disaster mitigation.

NIEMO has been applied to various empirical studies that include hypothetical terrorist attacks (Park et al. 2007; Park 2008; Richardson et al. 2014). The various economic impact studies using NIEMO are summarized in Table 16.1. As a primary tool of application to regional and national security problems, NIEMO has been applied to various security threat situations to quantify the costs of national security. They include a temporary closure of major U.S. seaports (Park et al. 2007, 2008a), a closure of U.S. theme parks (Richardson et al. 2007), temporary U.S. border closures (Gordon et al. 2009a), foreign export bans resulting from mad cow disease outbreak in the State of Washington (Park et al. 2006), a bio-terrorism and Foot-and-Mouth disease (Lee et al. 2012), the Gulf Oil Spill impacts (Park et al. 2013) and the Joplin tornado impacts (Richardson and Park 2014).

Table 16.1 Various economic impact studies using NIEMO

Nature of events	Targets	Type of economic impact	Total economic impacts ($M)	Citations	Note
Explosives	LA/LB, Houston, and NY/NW ports	Ports shut down	23,258	Park et al. (2007)	Direct/Indirect state-by-state impacts
Dirty bomb	LA/LB ports	Ports shut down	26,905	Park (2008)	Direct/Indirect state-by-state impacts
9/11	U.S. airports	Loss of air passengers	214,347–420,455	Gordon et al. (2007)	Direct/Indirect/Induced U.S. impacts
Mad cow disease	U.S. bovine animals	Cessation of foreign exports	13,681	Park et al. (2006)	Direct/Indirect state-by-state impacts
Explosives	13 U.S. theme parks	Consumer losses	20,747–24,921	Richardson et al. (2007)	Direct/Indirect state-by-state impacts
Hurricanes Katrina and Rita	PADD III	Disruption of oil refinery industries	4849	Park et al. (2017a)	Direct/Indirect state-by-state and month-to-month impacts
International avian influenza epidemic	U.S. border closures	Loss of Air passengers, U.S. seaports closing, loss of cross-border shopping, loss of legal and illegal labors	1,734,075–5,408,796	Gordon et al. (2009a)	Direct/Indirect state-by-state or U.S. impacts
2002 West Coast Ports Shutdown	LA/LB	LA/LB Ports shutdown	Loss: 3000 Gain: 579	Park et al. (2008a)	Direct/Indirect state-by-state for 5 months
Hurricane Sandy	Residents in 12 U.S. states	Temporary losses of income	10,380	Park et al. (2017b)	Direct/Indirect state-by-state and day-by-day impacts for 4 days
Panama Canal Expansion	12 South and East Coast states	Losses and gains in US port states stemming from the change in shipping routes and modes	Loss: 8206 Gain: 15,522	Park and Park (2016)	Direct/Indirect state-by-state impacts

(continued)

Table 16.1 (continued)

Nature of events	Targets	Type of economic impact	Total economic impacts ($M)	Citations	Note
Tornado	Joplin	Mortality, residential, housing services and business losses	5757	Richardson and Park (2014)	Direct/Indirect/Induced U.S. impacts for 1 year
Gulp oil spill	Three industries in two states	Oil production and seafood industry in Louisiana; tourist industry of Florida	47,562	Park et al. (2013)	Direct/Indirect/Induced U.S. impacts for 6 months
Hurricanes Katrina and Rita	Louisiana customs district	Seaports shut down	44,374	Park et al. (2008b)	Direct/Indirect state-by-state impacts

Notes:
1. This table was updated from Table 1 in Park et al. (2018)
2. All economic impacts except for the cases of '2002 West Coast Ports Shutdown' and 'Panama Canal Expansion' indicate total economic losses

16.3.4 A Combined Approach

Terrorists are more likely to attack an airport when anticipating the damage larger. Governments want to increase the security level when the expected damage in the target airport increases. The probability of a successful attack on the target airport is the result of a complex mechanism involving positive and negative utilities of terrorists and governments when the target airports are disrupted. If this success probability is high, terrorists will attempt to attack; accordingly, governments must invest more resources to strengthen airport security and prevent the attacks. Terrorists will reexamine the increased levels of expense used for enhancing airport security, and re-attack if the re-evaluated success probability is still attractively high; otherwise, they will abandon the attack. In this situation, governments need to find out the level of the attack success probability where the terrorists abandon the attack and build an airport security system satisfying this level. In general, this is the terrorists' indifferent utility point where the probability of successful attack is set to 0.5. Governments may set a higher security level for the lower successful attack probability if a target airport is considered important. In a multi-target game, a different security level in each target airport becomes a critical parameter to allocate investment of a government's resource.

Paralytic disruption of aviation systems stemming from terrorism causes further extensive economic damages. Direct damages include costs due to cancellation and rebalancing of airline schedules, restoration costs of aviation systems, damage from logistics delays, reduced benefits for customers, and so on. The indirect damages caused by these is much more varied and difficult to measure. The extent to the degree that terrorists and governments will include in the range of damages is an important factor to decide the behavior needed for the interaction of the two agents. The bottom line is that a government has a duty to protect citizens and properties in their jurisdictions and possess a more inclusive and comprehensive scope of damages than terrorists do.

In order to develop an analysis tool that takes into account both the expected economic damages and the likelihood of a successful attack, it needs to clearly understand the terrorist attack decision mechanism and the economic consequence process resulting from the successful terror attacks. Two processes that need to be considered are (1) an understanding of the interdependence of strategic behaviors between attackers and defenders at a micro-level; and (2) direct impacts generated from the airport disruptions along with the successful incident and any indirectly associated consequences associated with the direct impacts at the macro-level. Either direct or combined impacts may be what terrorists expect as a return from their attacks, while both impacts are transferred to losses to governments due to unblocking of terrorist attacks. The target valuation is an important parameter in deciding a level of attack or defense resources needed to terrorists and governments, respectively. If governments could prevent the attack attempts via sufficient airport security investment, the behaviors can be understood as an effective counter-terrorism policy.

The distinctive feature of the proposed G-NIEMO involves the combination process of both a competitive game model and NIEMO. To build a new model toward an aviation security enhancement strategy, it is necessary to resolve a competitive game situation via economic outcomes. As presented in Fig. 16.2, the general concept of calculating the expected economic costs of a successful terrorist attack is straightforward; it is to multiply the probability of a success attack on the target airport and aviation system with the corresponding economic losses stemming from the airport closure and the system shutdown. The probability of an attack success is the result of an attacker-defender game, and the economic losses associated with the attach behaviors can be obtained via NIEMO. Although NIEMO has been validated and applied to various empirical cases (see Table 16.1), a competitive game algorithm has not yet been successfully combined.

The dual-methodologically applied model of G-NIEMO can be used to identify the probabilistic costs of an infrastructure shutting-down such as airport closure and provide the economic importance of airport security by location and by industry type. Also, general guidelines assessing the allocation of security resource are developed via the balancing strategies identified by G-NIEMO. These guidelines will help airport administrators and aviation security agencies understand the optimal level of security needed for U.S. airports.

Combining the two models requires a dynamic combination process in which the result of one model is used for input information to the other model; this is different from such a static method that simply multiplies both results of a game model and results of an economic model. Other micro-level models such as an agent based model (ABM) combined with macro-approaches with computable general equilibrium (Dixon et al. 2010) still have not reached to the dynamic process. Except

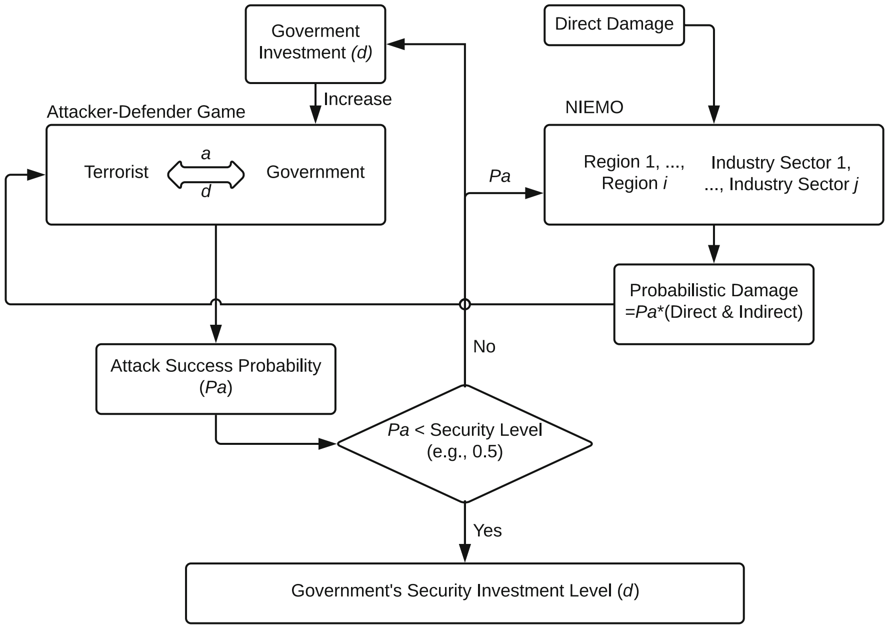


Fig. 16.2 G-NIEMO system to measure economic impacts

G-NIEMO, macroeconomic models only depend upon a couple of simulation results of the micro-level approaches. Hence, as an integrated economic model that keeps updating game results, G-NIEMO allows that the game players consider the updated information generated by the economic model in succeeding games. The game is being repeated until a certain equilibrium condition is met (refer to the level of *Pa* written below for this repeating process).

NIEMO considers a damage to the local industry directly caused by the event to direct damage and regards the damage caused by the inter-regional industrial relations as indirect damage. NIEMO could capture the ripple effect on various economies in the U.S. on the case of airport closures (Park 2008; Park et al. 2007, 2009, 2011, 2013). The direct and indirect damage generated by NIEMO is used as initial input information for the initial competitive game. Whether or not terrorists and governments have the same level of information about economic damage can be varying depending on the circumstances. However, as mentioned earlier, the government should at least consider the same or wider range of damage than terrorists. Based on the given conditions, if the competitive game derives the probability of a successful terrorist attack, this result can be used as input information to NIEMO. The initial value of success probability of an attack shows a security level in the targeted airport without any government investment. This probability is multiplied by the result of NIEMO and becomes the probabilistic damage. The probabilistic economic losses derived by NIEMO are again used as input information for competitive games and change the probability of a successful terrorist attack. As the government gradually increases its investment to raise the level of aviation security, the likelihood of success in terrorism will gradually decline. As a result, the input value of probabilistic damage in iterative competitive games will also decrease. This feedback procedure is repeated until the probability falls below a threshold set by governments. Through this dynamic and repetitive mechanism, G-NIEMO can determine the level of government investment that prevents terrorist attacks.

A review of related literature demonstrates that few studies have used economic impact analysis models that combine game-based simulation processes. This G-NIEMO approach is innovative because it combines a multiregional economic impact model and behavioral simulations between terrorists and governments. This model allows governments to determine the level of airport and aviation security or the appropriate level of budget allocation. The level of airport security is conceptually opposite to the probability of a successful terror attack. While several factors can affect the level of this probability value, the physical and non-physical value of the target airport is a key factor to be considered. For example, if a damage on a target airport is unexpected when causing extreme turmoil, governments will set this level at 0.5 that indicates indifferent to terrorists. Their attack effort will be fully compensated by the expected utility from the successful attack on the target airport. If the airport targeted is highly valued, the damage on the airport may result in enormous socio-economic losses. Governments should have allocated sizable and other visible and invisible resources including increased budget in order to raise the level of security.

G-NIEMO, therefore, suggests equilibrium strategies to enhance the readiness of U.S. aviation systems including airports against terrorist attacks by assisting the following goals:

- Determining optimal allocation of airport management resources;
- Increasing the communication and cooperation within the aviation community, with the active participation of relevant industry players;
- Leveraging, extending, and applying to the aviation industry best practices;
- Improving research and education efforts;
- Identifying short-, mid-, and long-term security actions; and
- Establishing a governmental and industrial network coordinating national aviation security strategies, policies, and plans.

16.4 G-NIEMO Process

16.4.1 Generating Direct and Indirect Economic Damage

To establish possible individual or cooperative defense strategies for a terrorist attack, the costs of direct damage when the attack is successful should be measured based on virtual or actual historical data. Diverse historical data can be found from sources such as the Bureau of Economic Analysis (BEA), the Office of Travel and

Tourism Industries (OTTI), the Travel Industry Association (TIA), the Bureau of Transportation Statistics (BTS), and the Bureau of Labor Statistics (BLS). These data can be used to calculate costs of direct damage caused by airport closure due to hypothetical invasion scenarios. Direct damage costs classified by industry are used as input variables of NIEMO and are used to estimate indirect damage costs by industry in each region.

NIEMO has been updated from its original version by several scholars (Gordon et al. 2009b; Park et al. 2011; Park and Park 2016). A mathematical representation of the latest version of NIEMO is shown as below:

$$X^s(t) = A(t)X^s(t) + F(t) \tag{16.1}$$

where

$X^s(t)$ = the total input row vector;
$F(t)$ = total final demands;
$A(t)$ = a $X^s(t)$-based requirement matrix (i.e. NIEMO coefficients) composed of a technical flows matrix for industries within a region, Z(t), and a block diagonal matrix of interregional trade flows, $C^s(t)$, and defined as

$$A(t) = \Gamma_t[Z(t), C^s(t)] \tag{16.2}$$

Where Γ_t = a matrix function that includes the requirement matrices of technical flows and trade flows.

16.4.2 Defining Interdependent Utility Functions

In an attacker-defender game, objectives of both players can be achieved by allocating a suitable level of attack effort and defense resources, respectively. Both an attacker and a defender aim to maximize their expected utilities in this game. Interestingly, one player's strategic decision depends on the other player, just like a ping-pong game. These repeated simultaneous or sequential interactions increase both a terrorist's attack effort and a government's defense investment up to certain levels. They will devote more effort until their marginal utility payoffs reach zero. This "strategic" compliment and iterative decision game results in an arms race. In this perspective, Sandler and Lapan (1988) noted earlier that counterproductive can be caused by agents' intelligence in this kind of games. However, the goal of an attacker-defender game tries to find the best solution in preventing terrorism upon inevitable counter-productivity.

The "strategic" concept denotes that choices of players are interdependent to each other. They have to react their opponents' decisions. Governments who concern terror attacks should decide a level of resource allocation for defense in response to terrorists' choice variables (Sandler and Siqueira, 2009). Bier et al. (2007) and

Zhuang and Bier (2007) provided similar forms of game settings where both players' strategies are entangled. In these games, an attacker's or defender's payoff depends on attack effort, $a = (a_1, \ldots, a_N)$, and defense resources, $d = (d_1, \ldots, d_N)$. Both a defender and an attacker try to maximize their expected utilities, $U_D(a, d)$ and $U_A(a, d)$, respectively, simultaneously considering attack effort and defense resources. These expected utilities are the product of target valuation for target i and the probability of damage (p_i) that depends on a_i and d_i. Also, U_A and U_D include disutilities that are defined as an attacker's total effort and a defender's total investment over all sites.

Zhuang and Bier (2007) provided these strategic and conflicting utility maximization behaviors as mathematical expression. The basic structure of payoff functions comprises of expected total utility ($E(u_A)$, $E(u_D)$) and disutility (g_A, g_D) functions as shown below:

$$\max_{a \in \mathcal{A}} U_a(a, d) = E\{u_A[w(a, d)]\} - g_A(a) \tag{16.3}$$

$$\max_{d \in \mathcal{D}} U_d(a, d) = E\{u_D[v(a, d)]\} - g_D(d) \tag{16.4}$$

where,

a = a terrorist's attack effort;
d = a government's defense level;
$\mathcal{A} = (a_1, a_2, \ldots, a_m)$;
$\mathcal{D} = (d_1, d_2, \ldots, d_n)$;
U_a = a terrorist's total expected utility;
U_d = a government's total expected utility;
w = a terrorist's valuation of a target;
v = a government's valuation of a target;
u_A = a terrorist's utility when secceeding an attack;
u_D = a government's utility when defensing an attack ;
g_A = a government's disutility, cost of defense investment; and
g_D = a terrorist's disutility, cost of attack effort.

To solve an equilibrium of these payoff functions, we should know two functions BRF and CSF as defined in Sect. 16.3.2. BRF is a player's level of attack or defense effort to maximize his or her total expected utility. Since the first-mover advantage is already proven in "attacker-defender games" (Bier 2007; Zhuang and Bier 2007), we need an attacker's BRF to compute a defender's utility function.

16.4.3 Formulating Best Response Functions

BRF is defined to maximize total expected utilities of attackers and defenders. Mathematically, the utilities are defined as follows (Zhuang and Bier 2007):

$$\hat{a}(d) \equiv \arg max_{a \in \mathcal{A}} U_A(a, d) \tag{16.5}$$

$$\hat{d}(a) \equiv \arg max_{d \in \mathcal{D}} U_D(a, d) \tag{16.6}$$

where, $\hat{a}(d)$ and $\hat{d}(a)$ are the best responses of an attacker and a defender, respectively. As Eqs. (16.5) and (16.6) denote, these functions are used to find the levels of players' strategies that maximize their utilities in response to their opponents' strategies (d and a). The attacker's BRF is obtained by a partial differential of an attacker's total expected utility by an attacker effort (a_i). Equation (16.7) describes this:

$$\hat{a}(d) = \begin{cases} 0, & if\ U_A^{(a_i)}(0, d_i) \leq 0 \\ \left\{a_i : U_A^{(a_i)}(a_i, d_i) = 0\right\}, & if\ U_A^{(a_i)}(0, d_i) > 0 \end{cases} \tag{16.7}$$

where a_i = continuous level of attack effort, and d_i = continuous level of defense investment.

A defender's payoff function is decided by an attacker's best response in sequential games. It is based on the first-mover advantage. A defender moves first under the assumption that the attacker's best choice $(\hat{a}(d))$ will be made in respond to the defender's first-move. In other words, a defender confines the attacker's best response by allocating defense resource prior to any attacker's decision. This mechanism for a single target case is described in Eq. (16.8) (Zhuang and Bier 2007):

$$\max_{d \in \mathcal{D}} U_d(\hat{a}(d), d) = E\{u_D[v(\hat{a}(d), d)]\} - g_D(d) \tag{16.8}$$

The payoff function is comprised of several parameters. They reflect both players' attributes. Based on Zhuang and Bier (2007), the function includes: (1) technologies available to an attacker and a defender that comprise of a probability of successful attack; (2) an attacker's and a defender's valuation on potential targets; (3) an attacker's and a defender's utilities caused by an attack; and (4) an attacker's and a defender's disutility for an attack effort and a defensive resource, respectively.

16.4.4 Computing Success Attack Probability

CSF represents strategic interactions between intelligent agents (Hausken et al. 2009). CSF has been widely used in the literature of conflict solving and rent seeking (Hirshleifer 1995; Skaperdas 1996). In "attacker-defender games," both players' decisions are interdependent to each other. In game-theoretic models, the interdependency is conceptually set by CSF. It is a probability function of a successful attack in "attacker-defender games," which captures essential relationships among a defensive investment (a), an attack effort (d) and an inherent defense level of a target (c) (Guan and Zhuang 2016). A "successful attack" can be interpreted as either a proportion of target damage (in partial damage) or a probability of total destruction of a target caused by any threat (Hausken et al. 2009).

Zhuang and Bier (2007) made several assumptions to define CSF of attacker-defender games. The first assumption is:

$$P_i(0, d_i) = 0 \textit{ and } \log_{d_i \to \infty} P_i(a_i, d_i) = 0. \tag{16.9}$$

This assumption defines conditions when a successful attack probability is zero. These conditions include an extreme case either that an attacker does not make any effort to attack a target i, or that a defender allocates infinite resource to protect a target i regardless of their opponents' effort or resource investment. The second assumption is:

$$P_i^{(a_i)}(a_i, d_i) \equiv \frac{\partial P_i(a_i, d_i)}{\partial a_i} > 0 \textit{ and } P_i^{(a_i, a_i)}(a_i, d_i) < 0 \tag{16.10}$$

This defines a probability of successful attack function as a concave-increasing curve. This function increases when an attack effort increases while a marginal probability decreases. The third assumption is:

$$P_i^{(d_i)}(a_i, d_i) \equiv \frac{\partial P_i(a_i, d_i)}{\partial d_i} < 0 \textit{ and } P_i^{(d_i, d_i)}(a_i, d_i) > 0. \tag{16.11}$$

This defines a probability of successful attack function as a convex-decreasing curve. This function decreases when a defensive level increases while a marginal probability increases (marginal returns to investment level decreases). Decreasing marginal returns to both players satisfies most situations of continuous resource investments. However, this assumption is not always true, and increasing marginal returns can be considered in some situations. For this CSF with increasing marginal returns, see Skaperdas (1996) and Hirshleifer (1989).

CSF has various forms based on different assumptions. In general, CSF is assumed to be a continuous function. Hirshleifer (1995) and Skaperdas (1996) introduced a ratio form and an exponential form of CSF, which were applied to the fields of rent seeking, tournaments, and conflict. These forms are also applicable to "attacker-defender games." In the exponential-form of CFS, the probability of successful attack decreases exponentially when the defender's effort increases. However, it does not depend on the level of attack effort. For more details of the exponential-forms of CSF, see Bier et al. (2008), Wang and Bier (2011) and Shan and Zhuang (2013).

In CSF with ratio-forms, a probability of the successful attack decreases convexly when a level of defender's effort increases and an inherent defense level is large. A probability increases concavely when an attacker's effort increases. For more details of this ratio-form type CSF, see Zhuang and Bier (2007) and Hausken and Zhuang (2011, 2012). Nikoofal and Zhuang (2012) combined both the ratio and exponential

Table 16.2 Examples of CSFs in the literature of "attacker-defender games"

Functions	References	$\partial P/\partial D$	$\partial P/\partial A$	$\partial^2 P/\partial D^2$	$\partial^2 P/\partial A^2$
e^{-kD}	Bier et al. (2008) Hao et al. (2009) Wang and Bier (2011) Shan and Zhuang (2013)	≤ 0	NA	≥ 0	NA
$\frac{A}{k(A+D+C)}$	Zhuang and Bier (2007)	≤ 0	≥ 0	≥ 0	≤ 0
$\frac{A}{A+D+C}$	Hausken and Zhuang (2012)	≤ 0	≥ 0	≥ 0	≤ 0
$1 - e^{-kA/D}$	Nikoofal and Zhuang (2012)	≤ 0	≥ 0	≥ 0	≤ 0
$\frac{\beta(A-W_A)}{\beta(A-W_A)+\alpha(D-W_D)+C)}$	Guan and Zhuang (2016)	*if* $D > W_D$ ≤ 0	*if* $A > W_A$ ≥ 0	CP	CP

Source: Guan and Zhuang (2016, p. 777), modified by the author
Note: A, D, and C represent the attacker effort, defense effort, and the inherent defense level, respectively. CP denotes "*complicate*." For details, see Guan and Zhuang (2016)

forms of CSF. In these functions, a probability of a successful attack decreases when a defender's effort increases while the probability increases when an attacker's effort increases. Marginal returns of a probability diminish in both sides of the attacker and defender. Guan and Zhuang (2016) raised a practical problem of these continuous shapes of CSF. They argued the property of diminishing marginal returns may hold only when each player's investment is sufficiently high. the investment of first several dollars made by either player may neither increase nor decrease the probability of a successful attack. They define this condition as "warmup effects," and proposed a new functional form of CSF to address this issue. Table 16.2 summarizes various forms of CSF discussed above.

Because CSF is built on numerous assumptions, instead of empirical data, traditional CSF approach requires a validation process using empirical data. An issue is to find or collect the empirical data to be applied for CSF. This makes an empirically applied study difficult. While G-NIEMO applies NIEMO's results that are empirical, still the current G-NIEMO approach requires more empirical information for behavioral parameters of players as the limitation of CSF.

16.4.5 Deciding the Optimal Security Investment Level

G-NIEMO helps to establish government strategies that allow terrorists to abandon attacks based on the level of economic damage information if the target airport collapses. For this, G-NIEMO simulates iterative competitive games between terrorists and governments as the level of government investment (d) increases. As the government increases the security level of the aviation system (as d increases), terrorists lose their willingness to attack (as Pa decreases). If the government increases the security level further, the attack success probability will decrease accordingly. At this point, the government should decide the degree of the security level to lower *Pa*. As mentioned earlier, the level of *Pa* set to 0.5 is where the terrorists' utility reaches zero. In the case of "rational" terrorists, where factors such as religion and belief do not work, there is no reason to attack if the probability of success is low. However, if intangible value of the target is high, or if combined with "non-rational" elements, governments may have to lower *Pa* below 0.5. The repeated game situation continues until the probability of attack success is less than the security level set by the governments. The level of government investment (d) obtained through this mechanism is the minimum investment level needed to protect the target airport by deterring terrorist attacks.

16.5 Discussions

G-NIEMO can be applied to simulate various terrorist attack trials at major airports and useful to improve aviation safety, contributing to assessing aviation security policy. The integrated methodology presented in this study allows local, state, regional and national governments to seek ways of effectively allocating limited resources in order to improve the security of airport operating systems. G-NIEMO can provide a list of priority airports and appropriate resource allocation levels that are used to protect our aviation systems against terrorist attacks; it takes the importance of major airports in the U.S. into account, potentially preventing terrorism. The results of this G-NIEMO run will advance our understanding of how terrorist attacks affect U.S. economies in a dynamic process. This research is expected to provide the basis for communication between policy makers and local economic organizations involved in aviation security and policy.

Terrorist attacks are becoming increasingly organized and intelligent. Terrorists try to increase socioeconomic turmoil by attacking multiple targets rather than one target. Terrorists also paralyze social infrastructure systems through cyber-attacks rather than physical attacks. Cyber terrorists can attack any target anywhere via internet, easily attacking multiple targets at the same time. In order to prepare such attacks, a collective counter-terrorism strategy should be established through cooperation strategies between inter-governmental and cross-institutional organizations. Our society is in such a situation, unfortunately, that there is a lack of preparation for the diversification and advancement against terror attacks.

The G-NIEMO approach can be a cornerstone for building such a cooperation system. To do so, G-NIEMO needs to add the cooperative game process that considers governments of various locations and hierarchies. In establishing a counterterrorism strategy, agreements among various governmental organizations with different interests may be unstable. For this reason, there is a need to provide mechanisms for inter-agency collaboration and collective interdependences. This is an indispensable factor when facing cyber-threats (Benkler 2011a; Nowak and Highfield 2011). To ensure cooperative and collective actions between local

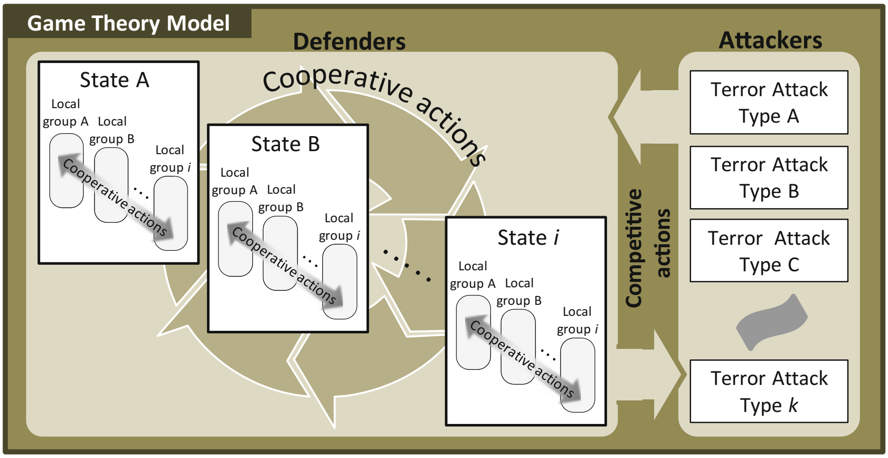


Fig. 16.3 Cooperative and competitive game situations between various agencies

governments, state governments, federal governments and international organizations, a horizontally and vertically balanced strategy establishment mechanism should be preceded. Strategies derived through cooperative games influence the strategy of terrorists through competitive game processes again; and hence, a recurrent structure will be regenerated in which the renewed terrorist strategies re-affect the cooperative game process. Figure 16.3 demonstrates a strategic approach to the integrated structure of cooperative and competitive behaviors of defenders.

G-NIEMO can encompass competitive and cooperative games. If then, it will have another potential to be used for a wider range of applications. In addition to airports and aviation systems, it is also applicable to a number of critical infrastructure systems. For example, nuclear power plants, large dams, and communication server buildings are obviously potential targets of terrorists. If one of these facilities is damaged by a terrorist attack, the secondary damage of the associated systems will result in the chained failures. Terrorist attacks invading several infrastructures that are functionally and geographically related or stopping these systems simultaneously through cyber-attacks, are difficult to predict. Hence, it is difficult to completely prevent the attacks. If preventing such attacks without cooperating tightly among the related entities is almost not possible, it would be important to apply this G-NIEMO to the entire urban critical infrastructure systems. Via G-NIEMO, we can prepare equilibrium strategies needed for protecting U.S. territory, constructing general guidelines that assess government resource allocations.

References

ABC (2013) Article available at https://www.abc15.com/news/national/lax-airport-shooting-shots-fired-at-lax-airport-evacuated
American Institute of Aeronautics and Astronautics (2013) A framework for aviation cybersecurity. An AIAA decision paper
ARTBA (2010) The 2010 U.S. Transportation Construction Industry Profile. ARTBA Transportation Development Foundation, available at: http://www.artba.org/Economics/Econ-Breakouts/04_EconomicImpactInterruptedService.pdf. Accessed November 2012
Benkler Y (2011a) The penguin and the leviathan: the triumph of cooperation over self-interest. Crown, New York
Benkler Y (2011b) The unselfish gene. Harv Bus Rev 89(7–8):76–85
Bier VM (2007) Choosing what to protect. Risk Anal 27(3):607–620
Bier V, Oliveros S, Samuelson L (2007) Choosing what to protect: strategic defensive allocation against an unknown attacker. J Public Econ Theory 9(4):563–587
Bier VM, Haphuriwat N, Menoyo J, Zimmerman R, Culpen AM (2008) Optimal resource allocation for defense of targets based on differing measures of attractiveness. Risk Anal 28 (3):763–770
Brown G, Carlyle M, Salmerón J, Wood K (2005) Analyzing the vulnerability of critical infrastructure to attack and planning defenses. In: Greenberg HJ, Smith JC (eds) Tutorials in operations research: emerging theory, methods, and applications. INFORMS, Hanover, pp 102–123
CBP (2008) About border security. Available at http://www.cbp.gov/xp/cgov/border_security/bs/. Accessed September 2008
Chenery HB (1953) The structure and growth of the Italian economy: United States of America, Mutual Security Agency
Daniel G, Arce M, Sandler T (2003) An evolutionary game approach to fundamentalism and conflict. J Inst Theor Econ JITE 159(1):132–154
De Mesquita EB (2005a) Conciliation, counterterrorism, and patterns of terrorist violence. Int Organ 59(01):145–176
De Mesquita EB (2005b) The terrorist endgame: a model with moral hazard and learning. J Confl Resolut 49(2):237–258
Dighe NS, Zhuang J, Bier VM (2009) Secrecy in defensive allocations as a strategy for achieving more cost-effective attacker deterrence. Int J Performability Eng 5(1):31–43
Dixon PB, Lee B, Muehlenbeck T, Rimmer MT, Rose A, Verikios G (2010) Effects on the US of an H1N1 epidemic: analysis with a quarterly CGE model. J Homel Secur Emerg Manag 7(1)
Gibbons R (1992) Game theory for applied economists. Princeton University Press, Princeton, NJ
Gordon P, Moore JE II, Park JY, Richardson HW (2007) The economic impacts of a terrorist attack on the US commercial aviation system. Risk Anal 27(3):505–512
Gordon P, Moore JE II, Park JY, Richardson HW (2009a) The economic costs of border closure: a state-by-state analysis. In: Richardson HW, Gordon P, Moore JE II (eds) Global business and the terrorist threat. Edward Elgar, Cheltenham, pp 341–374
Gordon P, Park JY, Richardson HW (2009b) Modeling input-output impacts with substitutions in the household sector: a numerical example. Econ Model 26(3):696–701
Guan P, Zhuang J (2016) Modeling resources allocation in attacker-defender games with "warm up" CSF. Risk Anal 36(4):776–791. https://doi.org/10.1111/risa.12502
Hao M, Zhuang J, Jin S (2009) Robustness of optimal defensive resource allocations in the face of less fully rational attacker. In: Proceedings of the 2009 industrial engineering research conference, Miami, FL, pp 886–891
Hausken K, Zhuang J (2011) Governments' and terrorists' defense and attack in a T-period game. Decis Anal 8(1):46–70
Hausken K, Zhuang J (2012) The timing and deterrence of terrorist attacks due to exogenous dynamics. J Oper Res Soc 63(6):726–735

Hausken K, Bier V, Zhuang J (2009) Defending against terrorism, natural disaster, and all hazards. In: Bier VM, Azaiez MN (eds) Game theoretic risk analysis of security threats. Springer, New York, pp 65–97
Hirshleifer J (1989) Conflict and rent-seeking success functions: ratio vs. difference models of relative success. Public Choice 63(2):101–112
Hirshleifer J (1995) Anarchy and its breakdown. J Pol Econ 103:26–52
Isard W (1951) Interregional and regional input-output analysis: a model of a space economy. Rev Econ Stat 33:318–328
Lakdawalla D, Zanjani G (2005) Insurance, self-protection, and the economics of terrorism. J Public Econ 89(9):1891–1905
Lee B, Park JY, Gordon P, Moore JE II, Richardson HW (2012) Estimating the state-by-state economic impacts of a foot-and-mouth disease attack. Int Reg Sci Rev 35(1):26–47
Major JA (2002) Advanced techniques for modeling terrorism risk. J Risk Finance 4(1):15–24
Moses LN (1955) The stability of interregional trading patterns and input-output analysis. Am Econ Rev 45:803–832
Muggy L, Heier Stamm JL (2014) Game theory applications in humanitarian operations: a review. J Humanitarian Logist Supply Chain Manag 4(1):4–23
Nikoofal ME, Zhuang J (2012) Robust allocation of a defensive budget considering an attacker's private information. Risk Anal 32(5):930–943
Nowak M, Highfield R (2011) SuperCooperators: altruism, evolution, and why we need each other to succeed. Simon and Schuster, New York
Osborne MJ (2004) An introduction to game theory. Oxford University Press, New York
Oxford Economics (2009) Aviation: the real world wide web. Onward, Oxford
Oxford Economics (2010) The economic impacts of air travel restrictions due to volcanic ash. Available at: http://www.oxfordeconomics.com/FREE/PDFS/OEAVIATION09.PDF. Accessed November 2012
Park JY (2008) The economic impacts of a dirty-bomb attack on the Los Angeles and Long Beach Port: applying supply-driven NIEMO (National Interstate Economic Model). J Homel Secur Emerg Manag 5(1)
Park C, Park JY (2016) Panama canal expansion, U.S. trade diversion from west coast seaports and urban innovation. J Open Innov 2(12)
Park JY, Park CK, Nam S (2006) The state-by-state economic impacts of mad cow disease on the United States. In: A proceeding paper of 2006 American Agricultural Economic Association (AAEA) annual meeting, Long Beach, CA, July 23–26
Park JY, Gordon P, Moore JE II, Richardson HW, Wang L (2007) Simulating the state-by-state effects of terrorist attacks on three major U.S. ports: applying NIEMO (National Interstate Economic Model). In: Richardson HW, Gordon P, Moore JE II (eds) The economic costs and consequences of terrorism. Edward Elgar, Cheltenham, pp 208–234
Park JY, Gordon P, Moore JE II, Richardson HW (2008a) The state-by-state economic impacts of the 2002 shutdown of the Los Angeles-Long Beach ports. Growth Change 39(4):548–572
Park JY, Gordon P, Moore JE II, Richardson HW, Kim S, Kim Y (2008b) Estimating the state-by-state economic impacts of hurricane Katrina. In: Richardson HW, Gordon P, Moore JE II (eds) Natural disaster analysis after hurricane Katrina. Edward Elgar, Cheltenham, pp 147–186
Park JY, Gordon P, Moore JE II, Richardson HW (2009) A two-step approach to estimating state-by-state commodity trade flows. Ann Reg Sci 43(4):1033–1072
Park JY, Cho J, Gordon P, Moore JE II, Richardson HW, Yoon S (2011) Adding a freight network to a national interstate input-output model: a TransNIEMO application for California. J Transp Geogr 19(6):1410–1422
Park JY, Gordon P, Moore JE II, Richardson HW (2013) The interregional and interindustry impacts of the gulf oil spill: applying the National Interstate Economic Model (NIEMO). J Homel Secur Emerg Manag 10(1):231–244
Park JY, Son M, Hwang H, Cho D, Park C (2016) A new framework to quantifying the economic impacts of cyberattacks on aviation systems: a Korean game-theoretic interregional economic

model. In: Kim E, Kim BH (eds) Quantitative regional economic and environmental analysis for sustainability in Korea (New frontiers in regional science: Asian perspectives). Springer, Singapore, pp 153–168
Park JY, Son M, Park C (2017a) Natural disasters and deterrence of economic innovation: a case of temporary job losses by hurricane Sandy. J Open Innov 3:5
Park JY, Gordon P, Moore JE II, Richardson HW (2017b) A new approach to quantifying the impact of hurricane-disrupted oil refinery operations utilizing secondary data. Group Decis Negotiation 26(6):1125–1144
Park JY, Levy J, Son M, Park C, Hwang H (2018) Advances in cybersecurity design: an integrated framework to quantify the economic impacts of cyber-terrorist behavior. In: Masys AJ (ed) Security by design: innovative perspectives on complex problems. Springer, Cham, pp 317–339
Richardson HW, Park JY (2014) The Joplin tornado of 2011. In: Richardson HW, Park JY, Moore JE II, Pan Q (eds) National economic impact analysis of terrorist and natural disasters. Edward Elgar, Cheltenham, pp 192–203
Richardson HW, Gordon P, Moore JE II, Kim SJ, Park JY, Pan Q (2007) Tourism and terrorism: the national and interregional economic impacts of attacks on major U.S. theme parks. In: Richardson HW, Gordon P, Moore JE II (eds) The economic costs and consequences of terrorism. Edward Elgar, Cheltenham, pp 235–253
Richardson HW, Park JY, JE Moore II, Pan Q (2014) National economic impact analysis of terrorist and natural disasters. Edward Elgar, Cheltenham
Sandler T (2003) Terrorism & game theory. Simulat Gaming 34(3):319–337
Sandler T, Lapan HE (1988) The calculus of dissent: an analysis of terrorists' choice of targets. Synthese 76(2):245–261
Sandler T, Siqueira K (2006) Global terrorism: deterrence versus pre-emption. Can J Econ/Revue canadienne d'économique 39(4):1370–1387
Sandler T, Siqueira K (2009) Games and terrorism recent developments. Simulat Gaming 40 (2):164–192
Sandler T, Tschirhart JT, Cauley J (1983) A theoretical analysis of transnational terrorism. Am Polit Sci Rev 77(4):36–54
Shan X, Zhuang J (2013) Cost of equity in homeland security resource allocation in the face of a strategic attacker. Risk Anal 33(6):1083–1099
Skaperdas S (1996) Contest success functions. Econ Theor 7(2):283–290
Tirman J (2006) Immigration and insecurity: post-9/11 fear in the United States. MIT Center for International Studies Audit of the Conventional Wisdom, 06–09
Wang C, Bier VM (2011) Target-hardening decisions based on uncertain multiattribute terrorist utility. Decis Anal 8(4):286–302
Zhuang J (2010) Impacts of subsidized security on stability and total social costs of equilibrium solutions in an n-player game with errors. Eng Economist 55(2):131–149
Zhuang J, Bier VM (2007) Balancing terrorism and natural disasters-defensive strategy with endogenous attacker effort. Oper Res 55(5):976–991
Zhuang J, Bier VM (2011) Secrecy and deception at equilibrium, with applications to anti-terrorism resource allocation. Defence Peace Econ 22(1):43–61

Ha Hwang is an Associate Researcher Fellow at the Division of Disaster and Safety Research of the Korea Institute of Public Administration, Republic of Korea. Dr. Hwang earned his doctoral degree in urban and regional planning from the University at Buffalo, the State University of New York in 2017. His primary research interests center on measuring socio-economic impacts stemming from disasters by developing game-theoretic economic models; transportation-combined economic models; resilience of new transportation system such as autonomous vehicles.

Dr. Park is an Associate Professor in the Department of Urban and Regional Planning at the University at Buffalo (UB) and Adjunct Associate Professor at Seoul National University. His main research areas include various economic, transportation, and environmental modeling works related to disasters and other external impacts. He theoretically advances input-output models including spatio-temporal extensions and game theoretic applications. Before joining his current department at UB, he was employed as a post-doctoral scholar developing applied economic models for national and regional security issues at the Center for Risk and Economic Analysis of Terrorist Events at the University of Southern California (USC). He also earned his Ph.D. from USC's School of Policy, Planning, and Development in 2007.