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Silver lining of the water: The role of government relief assistance in disaster recovery☆

Mevlude Akbulut-Yuksel [a,b,c], Muhammad Habibur Rahman [d,e], Mehmet Ali Ulubaşoğlu [f,*]

[a] *Dalhousie University, Canada*
[b] *IZA, Germany*
[c] *HICN, Germany*
[d] *Durham University, United Kingdom*
[e] *Curtin University, Australia*
[f] *Deakin University, Australia*

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A B S T R A C T

Combining three datasets, the Australian Longitudinal Census Panel of 2006 and 2011, engineering data on flood-water height, and administrative data on government relief assistance, we investigate whether and how the government's post-disaster relief payments helped the economic recovery from riverine floods that struck the state of Queensland in Australia in 2010/11. Using a difference-in-differences methodology that compares the flooded areas with unflooded zones within Queensland whereby the flooded zones differed in their levels of flooding and the government's relief assistance, we find that the government's disaster relief assistance was effective in economic recovery, having led individuals residing in flooded areas with average flood height to experience a 3.4 percent rise in (self-reported) income following the disaster, relative to those individuals living in unflooded areas of the state. Our findings are robust to a battery of sensitivity tests, including migration, parallel trends, spatial spillovers, and possible confounders.

1. Introduction

History has demonstrated that both natural and man-made disasters, such as earthquakes, hurricanes, floods, fires, wars, and famines, can destroy cities fatally. While disasters have wiped out some cities in the past (e.g., Reimerswaal, Netherlands; Agdam, Azerbaijan; and Arkwright, United Kingdom), other cities have been able to rebound successfully (e.g., Chennai, India, from the 1943 flood; Zhumadian, China, from the 1975 Banqiao Dam flood; and Chicago, United States, from the 1871 fires). The modern era is by no means immune to city devastation owing to disasters. A formidable threat is riverine flooding, given that many major metropolitan areas around the globe are situated on riverbanks. Examples of such cities include, inter alia, London, Paris, Berlin,

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* Correspondence to: Department of Economics, Deakin University, 70 Elgar Rd, Burwood VIC 3125, Australia.
E-mail address: mehmet.ulubasoglu@deakin.edu.au (M.A. Ulubaşoğlu).

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Vienna, Budapest, Washington DC, Melbourne, Brisbane, Tokyo, Bangkok, Baghdad, Cairo, Delhi, Shanghai, Seoul, São Paulo, and Buenos Aires. These complex urban systems have become increasingly exposed to urban flood risk owing to global warming, which is argued to have ushered in a new climatic regime of torrential rainfall with increased frequency and intensity (Kocornik-Mina et al., 2020; Boustan et al., 2020).

Riverine floods pose a considerable threat not only to human lives and social order but also to economic activity and public and private infrastructure. To ensure a successful rebound, well-designed recovery and relief programs, targeted at both the public domain and individual economic well-being, are the principal way forward. Despite the availability of other market-based recovery means such as insurance payments, sovereign interventions are generally the first and essential for alleviating the disasters' financial and cognitive burdens as well as expediting economic recovery.

The central objective of this paper is to investigate whether and how the government's relief assistance helped individuals to revert to their normal economic course following extensive riverine floods that struck the Australian state of Queensland, including the major metropolis of Brisbane for two months during December 2010–January 2011. The literature on the economic consequences of natural disasters currently shows a vacuum in documenting the role played by the government's relief and recovery interventions in helping disaster-stricken areas to rebound.[1] Based on a confidential disaster relief and assistance dataset, this study aims to provide further evidence on the essence of post-disaster relief assistance in disaster recovery by assessing its effects on the local post-disaster economy. We undertake our examination by the analyzing effects of floods on individuals' income streams and how, in turn, the government's assistance affected the income levels in the post-disaster period. To estimate the average treatment effect, we compare the incomes of individuals who are in the flooded and unflooded geographic units within Queensland, whereby the flooded areas differed in both their levels of flooding and the amounts of post-disaster direct income assistance. The government's total relief and recovery expenditure amounted to AU$6 billion dollars during the 2010–11 fiscal years, of which 10% was direct income assistance.

The Queensland floods are among the most devastating floods in Australian history. Host to a population of two million, the metropolitan city of Brisbane witnessed a succession of six excessive rainfall spells from December 2010–January 2011, only to see the flood waters reach 4.46 m (14.63 ft) high on January 13, 2011, before spreading to surrounding regional cities in the following days. The floods are estimated to have caused AU$6.7 billion in direct damage, with an overall cost of AU$14.1 billion (Deloitte Access Economics, 2016). This corresponds to 5.2% of Queensland's GDP in 2011. The impact on the population was also enormous: the inundation of more than 28,000 homes and a power outage in 480,000 buildings paralyzed the economic activity in the succeeding months. One in five businesses in Queensland had to close following the floods due to either water inundation or power outage, with 48% of all businesses affected in some way (Chamber of Commerce and Industry Queensland, 2011).

The Queensland floods present an important setting in which to examine the causal effects of disasters on economic activity and the subsequent recovery because the perceived probability of a modern Australian metropolitan city being inundated with riverine waters was substantively low. Detailed urban models had estimated the risk of a major flood in Brisbane to be a 1-in-2000-year event; that is, a probability of 0.05% per annum (Queensland Government, 2014). Accordingly, the flooding event offers a novel natural experiment. The Queensland floods also provide, arguably, an exemplary case of post-disaster relief and recovery interventions by the Australian Government through the speedy mobilization of local, state, and federal means. Consequently, both the impact of the disaster and the efficacy of the government's recovery assistance can provide valuable lessons for many other developed cities around the world, especially those in the OECD countries.

Our investigation exploits three datasets with fine spatial components: the Australian Longitudinal Census Panel, engineering data on flood-water height as the measure of flood severity, and administrative data on federal relief assistance. The Australian Longitudinal Census Panel of 2006 and 2011 is a nationally representative longitudinal data of 5% of the Australian population and confidentially provides self-reported individual-level proprietary data on income, residential address, and a corpus of other personal characteristics for more than 175,000 working-age Queenslanders. The 2011 Census was conducted on 9 August 2011 and therefore constitutes a convenient 'end line survey' for analyzing the short-term effects on income of both the disaster and the relief assistance, which was mostly concluded by the census date.

We measure flood severity by constructing the flood-water height data at the Statistical Area-2 (hereafter, SA2) level.[2] As importantly for the purpose of this paper, borrowing from the engineering literature, we compute the flood-water height at a resolution of 0.0002 arc degrees (i.e., around 22 m) using a combination of earth surface elevation data sourced from the Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM v2), and the flood extent map sourced from the Department of Natural Resources and Mines, Government of Queensland, by employing the FEMA – the Federal Emergency Management Agency (2014) water surface elevation calculation methodology.

As to the administrative data on relief assistance, we obtain confidential access to the data on post-flood direct income assistance at the local government area (LGA) (i.e., municipality) level from the Attorney General's Department of Australia. This direct income

[1] Notable exceptions are del Valle et al. (2020), who study the economic effects of an indexed disaster fund program (Fonden) in Mexico, and Schneider and Kunze (forthcoming), who study the political bias in disaster allocations following hurricane strikes in the United States.

[2] Statistical Area-2 is a geographic-statistical unit analogous to zip codes in the United States, which hosts 3000-25,000 people. Out of 528 SA2s in Queensland in 2011, the Australian Census Longitudinal Dataset provides data for 526 SA2s. These granular-level geographic units enable a detailed local account of both the flood intensity and individual well-being. We further note that there was no change in the borders of these SA2s between the 2006 and 2011 Australian censuses.

assistance corresponds to the 10% of total relief and recovery expenditures.[3] The use of this administrative dataset allows us to quantify the importance of effective relief assistance in the economic recovery of the areas hit by floods. We then intersect the LGA-level relief and recovery data with the SA2-level flood-water height data and link them with the individual-level longitudinal census data.

We employ a difference-in-differences (DID) estimation that takes advantage of the variation in flood exposure and post-disaster relief assistance across geographic units.[4] More specifically, we compare the economic conditions of individuals residing in flooded and non-flooded zones of Queensland before and after the floods. As importantly, a within-state DID setting provides a strong degree of comparability between our treatment and control groups because the rules that govern the disaster assistance distribution are the same in a single state jurisdiction whereas they may differ across states. This approach accounts for any confounders in the mediating effects of disaster relief expenditures on the flood-income relationship. We further investigate not only the effects of post-disaster assistance on average income but also on sector-specific income. The longitudinal structure of the 2006–11 Australian Census allows us to extend the difference-in-differences analysis further by incorporating individual fixed effects. This estimation framework permits us to account for all time-invariant unobservable individual characteristics and to control for potential self-selection into flood-prone areas or other potential moral hazard-type concerns (e.g., locations of better public schools, lifestyle choices, and general household well-being). Further, we are able to track the geographic mobility of both affected and unaffected individuals using the residential address information in the census data, thus accounting for a potential migration bias and providing formal evidence demonstrating that migration yields minor, if any, consequences for our results.

Similar to previous studies investigating the local economic effects of natural disasters such as hurricanes, especially Hurricanes Katrina and Andrew in the US, our results show that the economic rebound in Queensland was rapid.[5] Using both individual and SA2 fixed effects analyses and novel engineering data on flood intensity across areas in Queensland, we find that individuals residing in a geographic zone with an average flood-water height (2.02 m) experienced a 3.4 percent increase in their self-reported annual income between 2006 and 2011 compared to individuals who resided in the unflooded areas of Queensland during the same period. Because the relief data are available at the SA2 level, we interpret this result as the relief assistance having assisted the economic activity in each locality, which in turn led to a positive change in income streams. We note that our results represent the short-run effects of the Queensland floods on income, while the medium-run and long-run effects could be different due to other post-disaster relief policies as shown in Deryugina (2017), and possibly the adaptation of the individuals and households to the post-disaster economy.

We also consider that disaster insurance, reconstruction efforts, and infrastructure investments are other potential mediators to explain the positive income change in the affected zones, relative to the control group. We show that the post-disaster direct income assistance that was disbursed to the affected areas in the first six months after the event is an important mediator for our findings, suggesting that the policy was effective in assisting individuals in the flooded zones with their recovery.

A battery of robustness checks, involving alternative specifications and testing for potential confounders, bolster our confidence in our baseline results. First, separately utilizing the Australian Census data of 2001 and 2006 and the annual Household, Income, and Labour Dynamics in Australia (HILDA) survey data through employing an event study approach, we show that the parallel trend assumption is satisfied. Second, we account for the potential flood-driven internal migration into or out of flooded areas. Previous studies find that, in contrast to other natural disasters, floods tend to increase the local population due to in-migration (Boustan et al., 2020). Investigating the extent of the net migration into or out of the flooded zones, we find no evidence to suggest that the flooded areas experienced a net migration either way. Third, we demonstrate that there is no evidence of bias in our key results due to Cyclone Yasi, a major concurrent shock that hit some of the control SA2s during our study period.

Our paper contributes to the body of micro-level studies of natural disasters. Notably, using administrative tax return data on Hurricane Katrina victims, Deryugina et al. (2018) demonstrate that Hurricane Katrina had only small, transitory impacts on the employment and incomes of its victims. Indeed, within a few years, the income levels of Katrina victims outperformed those of unaffected individuals in the control cities. Similarly, focusing on four states affected by Hurricanes Katrina and Rita, Groen et al. (2020) find that job separation following the hurricanes led to earnings loss in the short run but increased wages in the long term, primarily due to the decreased labor supply in the affected areas after being hit by the hurricane and increased labor demand for reconstruction. Further, Gallagher and Hartley (2017) have shown that Katrina victims experienced a significant reduction in their total debt and have better financial standing overall right after the hurricane, mainly facilitated by the use of flood insurance money to repay mortgages rather than rebuilding the damaged houses. The evidence from Hurricane Andrew and other hurricanes in Florida is similar, with worker earnings in Florida counties hit by a hurricane increasing and these workers experiencing a faster earnings growth but a smaller employment growth, relative to comparable workers in the unaffected counties (Belasen and

[3] Income and wage assistance is a direct cash injection made to the economy that is easy to measure and whose effects may be detected in the short term. While assistance other than income and wage support may have made a difference to individual incomes, we do not have data on their distribution at the SA2-level. The way in which other assistance items might have trickled down to individual incomes requires detailed theoretical and empirical modeling that is beyond the scope of this paper.

[4] Recent studies have shown that the difference-in-differences estimates could be biased due to negative weights and heterogeneous treatment effects if the design is staggered in nature (e.g., Goodman-Bacon (2021); de Chaisemartin and d'Haultfœuille (2020)). As we only have a single time period, such concerns do not pose a threat to our estimations.

[5] We also note that hurricanes and riverine flooding are different types of disasters. Hurricanes are rather extreme disasters that bring in devastation with high-wind speed, which may not be at times followed by floods. In most extreme examples like Hurricane Katrina, they cause massive out-migration too. For instance, 70 percent of the population in New Orleans had to be evacuated due to Hurricane Katrina. On the other hand, riverine flooding offers another type of natural experiment that causes damage, with economic activity paused temporarily but with a possibility to recover to pre-disaster levels.

Polachek, 2009). On the other hand, similar to our work, del Valle et al. (2020) have found that more effective and less restrictive relief assistance programs could help alleviate the burden of natural disasters. They show that the Mexican municipalities that were eligible for Mexico's indexed disaster fund (Fonden) perform significantly better in economic outcomes one year later compared to other municipalities, highlighting the importance of effective post-disaster policies.[6]

Our findings also resonate with the literature that explores the macroeconomic effects of migration responses to natural disasters using county- or city-level data. This line of inquiry generally shows that cities tend to recover quite rapidly after floods if they were already booming prior to the natural disaster, or had a strong economy, as long as the disaster is not followed by major turmoil (Kocornik-Mina et al., 2020; Cavallo et al., 2013; Vigdor, 2008). In contrast, Strobl (2011) finds that U.S. coastal counties that are hit by a hurricane witness a 0.45 percentage point lower economic growth on average, with a quarter of this effect being driven by the out-migration of rich households. Boustan et al. (2020, 2012) build a county-level data set for the more than 5,000 natural disasters that hit the United States between 1920 and 2010, and show that those counties that were hit by severe disasters experienced greater out-migration, lower home prices, and higher poverty rates. However, different types of natural disasters generated different migration responses, with counties that were hit by a flood actually experiencing net in-migration.

The remainder of the paper is organized as follows. Section 2 provides the background of the 2010–11 Queensland floods. Section 3 describes our data and presents the descriptive statistics. Section 4 lays out the estimation framework. Section 5 presents the main results. Section 6 performs some robustness checks. Section 7 presents the sources of heterogeneity and the relief and recovery mechanisms that explain our results. Section 8 concludes.

2. Background on the 2010–11 Queensland floods and the post-disaster assistance

2.1. The extent of the floods

In December 2010 and January 2011, Queensland experienced a series of flash floods and a major inundation that ran through a series of Brisbane suburbs. This event was labeled the second-most catastrophic flood of the last 100 years, after the 1974 Queensland flood (NCC: National Climate Centre, Bureau of Meteorology, 2011). A succession of six major excessive rainfalls in December 2010 and January 2011, coupled with pre-soaked catchments, resulted in low-probability but high-intensity flooding.[7] As the wettest December on record – 209.45 millimeters – for Queensland since 1900 (see, Fig. 1), the state witnessed torrential rainfalls from 23–28 December 2010, which resulted in exceptional flooding in many other parts of the state, particularly Central and Southern Queensland, with many rivers reaching record height levels. Although the north of Queensland also experienced heavy rainfall, the region had been suffering from heavy rainfall constantly throughout the years. Hence, there were already existing systems in place to avoid flooding. However, the height of the Brisbane River was even more dramatic: it reached a peak of 4.46 m at the 'city gauge' on 13 January 2011 (see Fig. 2). This caused substantial destruction of infrastructure in metropolitan Brisbane and elsewhere.

This flooding turned out to be a statewide event. Besides the state capital of Brisbane, floods inundated South-East Queensland along the Condamine, Ballone, and Mary Rivers. In addition, surprise flash flooding was triggered in the Lockyer Valley area–where 23 people died–and in the regional city of Toowoomba.[8] The flooding finally receded in early February 2011, but it was then followed by a strong La Niña weather pattern, leading to warmer waters along the northeastern coast and making Queensland fertile ground for tropical storms. On 2 February 2011, Category 5 Cyclone Yasi struck the Queensland coast with a 'maximum wind speed 30 minutes' of 89 km/h (corresponding to 'maximum sustained wind speed' of 290 km/h), becoming the worst cyclone to hit Australia since 1918 (see Appendix A1 for the timeline of 2010–11 Queensland floods). Cyclone Yasi hit the outer north of the flooded zones, affecting 78 control SA2s.

As to the human dimension, the consequences of this flooding were catastrophic. Thirty-two people died and three were reported missing, while over 2.5 million people were affected (Queensland Floods Commission of Inquiry, 2011). Further, the floods damaged approximately 9100 km of the state's roads and 4700 km of the rail networks, inundated over 29,000 homes and businesses, caused power outages to around 480,000 homes and businesses, and disrupted 54 coal mines, 11 ports, and 411 schools (World Bank, 2011). The economic consequences were also dramatic. The World Bank and the Queensland Reconstruction Authority provided a 'ballpark' estimate of US$15.9 billion in total damages and economic losses, of which the public reconstruction cost was US$7.2 billion. This left the 2010–11 Queensland floods as one of the major international disasters of the last decade (World Bank, 2011).[9] In a recent study, the Deloitte Access Economics (2016) revised these statistics to a total cost of AU$14.1 billion and an intangible cost of AU$7.4 billion.

2010–11 Queensland floods came as a complete surprise. Moreover, the major flood was followed by a series of localized flash floods that baffled many Queenslanders. The surprising effect of the 2010–11 floods is also rooted in the construction of the

[6] Karbownik and Wray (2019) also demonstrate that experiencing a hurricane in utero or during early childhood is associated with lower earnings later on without causing any change in long-term labor force participation, schooling, or migration.

[7] See van den Honert and McAneney (2011), NCC: National Climate Centre, Bureau of Meteorology (2011) for detailed accounts of the 2010–11 Queensland floods.

[8] Of 526 SA2s, the Queensland floods 2010–11 affected 140 SA2s. Of all 140 affected SA2s, 116 are urban and 24 are rural, and of all 386 control SA2s, 289 are urban and 97 are rural, providing a good mix of urban and regional SA2s, which is important to retrieve a reliable average treatment effect using DID (see Section 4).

[9] To put the Queensland floods in perspective, the combined impact of the Indian Ocean Tsunami – a disaster that hit several countries – came to US$11.5 billion. The 2002 flooding of the Elbe River in Germany had an economic cost of US$14 billion.

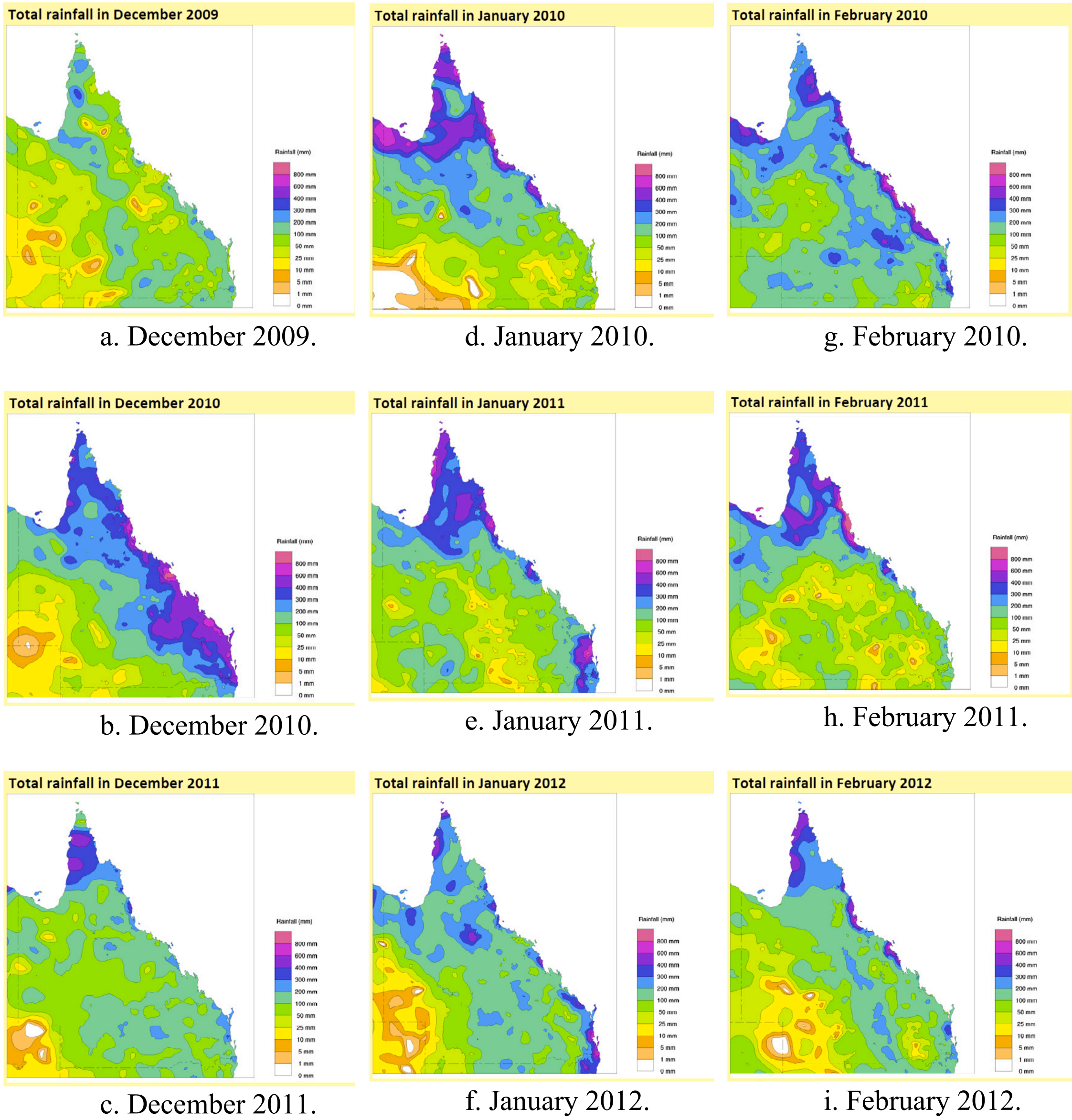

Fig. 1. Total rainfall in December–February 2009, 2010, 2011, 2012.
Note: This figure compares month-wise total rainfall in December–February during 2009–2012. Fig. 1b singles out 2010 from 2009 and 2011 Decembers showing excessive rainfall in Queensland. The rainfall during January and February 2011 further cumulated this runoff, which soaked Queensland.
Source: Various Issues of Monthly Weather Review, Queensland, Bureau of Meteorology, Australian Government; website: http://www.bom.gov.au/climate/mwr/.

'Wivenhoe Dam' across the Brisbane River after the 1974 floods as a 'flood mitigation' structure. Megastructures of this sort tend to provide the false impression that an area is flood-proof (Humphries, 2011). The extent of the rainfall and the subsequent flooding presented a puzzle to the dam hydrologists, as their modeling failed to forecast rainfall and therefore resulted in a sub-optimal water release strategy. This failure to release water from the Wivenhoe Dam was one of the primary causes of the flooding, making it a "dam release flood" (van den Honert and McAneney, 2011). Thus, it is plausible to assume that the 2010–11 floods were exogenous to economic performance, in that the pre-disaster decisions of economic agents were orthogonal to their flood expectations, and thus exploiting the variation in flood severity across geographic zones in Queensland is warranted.

2.2. Post-disaster direct income assistance

In Australia, the primary responsibility to take measures for disaster relief and recovery efforts lies with the state governments, though the funding may originate from the federal budget. The Queensland government coordinated its post-flood interventions

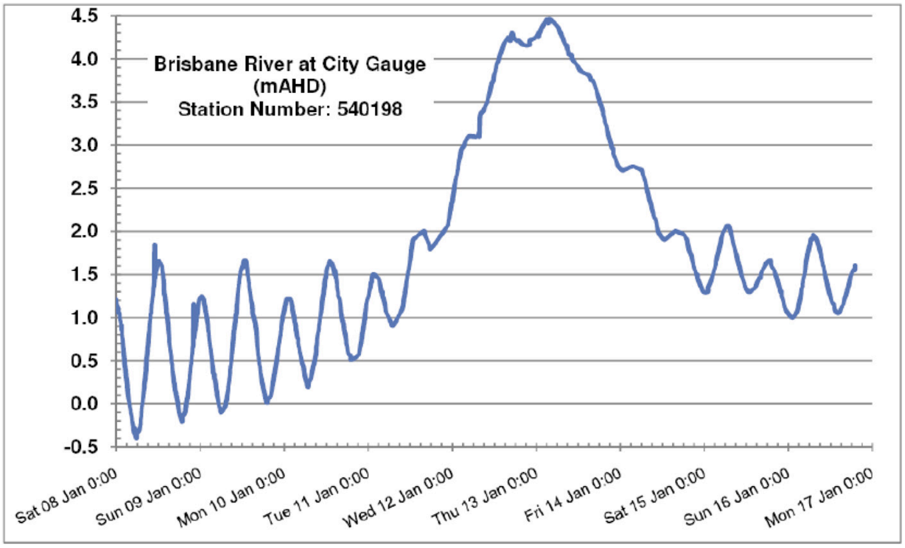

Fig. 2. Height of the Brisbane River at the city gauge 8–16 January 2011.
Source: van den Honert and McAneney (2011).

in three phases. First, emergency management departments, the Australian Army, and volunteers immediately became involved in emergency response efforts and subsequently managed the clean-up operations.[10] Second, the Queensland Government established a dedicated institution – the Queensland Reconstruction Authority (QRA) – under the 2011 Queensland Reconstruction Act, which was commissioned with the overall coordination of the relief and recovery efforts. Third, financial assistance was directed to 'needy' individuals, primary producers and small business entities in order to smooth immediate income shocks and restore individuals' livelihoods.

The funding required to finance such an enormous recovery expenditure was massive, and this was further magnified by the Queensland state government's 'no insurance' policy for its own public infrastructure.[11] The relief and recovery activities of the 2010–11 Queensland floods incurred a total cost of AU$11.8 billion, which was financed by the Federal Government,[12] the Queensland State Government, insurance corporations, and philanthropic donations (see Appendix A2). Of the Federal Government's AU$6 billion funding, AU$505,641,320 were paid to individuals as direct income assistance through two financing modalities: AU$446,272,200 for 381,036 accepted claims under the Australian Government Disaster Recovery Payment (AGDRP) (an average payment of AU$1170 per claim), and AU$59,369,120 for 51,933 accepted claims under the Disaster Income Recovery Subsidy (DIRS) (an average payment of AU$1143 per claim). These two cash payment schemes for over 430,000 claims compensated employees, small businesspersons, and farmers who were affected directly by the floods for their short-term income losses. Such income recovery payments were disbursed within the first six months after the disaster. The remaining 90% of the total funding was spent on deferral of federal and state tax liabilities, concessional loans to small businesses and non-profit organizations, clean-up assistance, and workshops to help with recovery.[13]

One may be concerned about a disaster relief bias, especially since 90% of the relief was not allocated to individuals. For instance, Gasper and Reeves (2011), Reeves (2011) as well as Schneider and Kunze (forthcoming), demonstrate how political bias may influence the issuance of disaster relief for various natural disasters in the US.[14] We acknowledge that political biases of that nature both by the SA2 level government entities as well as among individuals could be important in our setting. However, such concerns are to an extent mitigated by the fact that the 2010 Queensland Floods were an extreme one-off flooding event in Australia, thereby somewhat limiting the scope for political bias in relief allocations among different localities. Further, we also note that our

[10] Approximately 12,000 people were rescued and placed in 34 evacuation centers of the Red Cross across Queensland (see van den Honert and McAneney, 2011). Over 55,000 registered and thousands of unregistered volunteers were mobilized to assist clean up mud and flood debris, which meant the first phase of the post-flood recovery included overwhelming community involvement.

[11] Queensland was the only state in Australia without a comprehensive insurance policy.

[12] State governments in Australia have institutional arrangements with the Federal Government under the Natural Disaster Relief and Recovery Arrangements (NDRRA) whereby the Federal Government finances 75% of the overall reconstruction costs of public infrastructure in the event of a natural disaster. The NDRRA system is a formal channel through which states can request national aid following large natural disasters.

[13] The federal government financed their post-flood interventions by imposing a one-off 'flood levy' on all *flood-unaffected* Australians with a taxable income over $50,000 and who reside outside Queensland. For example, individuals with an annual income of $60,000 paid AU$1 a week for 12 months, increasing progressively, so that individuals earning over AU$100,000 paid an additional $5 a week. We further note that other states are different jurisdictions in Australia; thereby the spillover effects are unlikely to occur through institutional design.

[14] Cole et al. (2012) further find that electoral incentives may lead to governments to provide more disaster relief during election years in India.

focus is on the direct income assistance disbursed to over 430,000 claims in a state with a 4.3 million total population in 2011. Considering the sheer size of claims, the adult population, and the share of flooded areas, we believe that political bias precipitated by household behavior in applying for income assistance is unlikely to drive our results. In addition, the post-disaster recovery aid is distributed on-demand basis in that the affected individuals and families have to appeal for recovery assistance. Besides, such post-disaster aid operations are extensively managed by the state or territory government, rather than local government authorities. This transparent system of disaster recovery arrangement significantly mitigates the concerns that the differential government transfers may only be reflective of political favoritism towards certain types of households rather than the severity of flooding that could be driving our estimated effects.

3. Data and descriptive statistics

3.1. The Australian Census Longitudinal Data

We conduct our empirical analysis using the 2006 and 2011 Australian Census Longitudinal Data (Australian Bureau of Statistics, 2016).[15] The Longitudinal Census is a confidential dataset that encompasses a random 5% sample of the Australian population and provides information on a broad range of individual and household characteristics, including educational attainment, labor market outcomes such as annual income, employment, the sector of employment, and detailed information on demographic characteristics. A major advantage of the longitudinal census is its massive size and panel structure, which allows us to follow a large number of individuals over a five-year period. The Australian Bureau of Statistics combined a random 5% sample from the 2006 Census with records from the 2011 Census. The success in linking these two datasets was quite high, with over 86% of all records in the two censuses being matched in the linkage process.[16]

Essential to the purpose of this paper, the longitudinal structure of the census and the time span it covers allow us to causally estimate the local economic effects of the 2010–11 Queensland flood. Since Brisbane and surrounding suburbs were inundated between December 2010 and February 2011, the 2011 Census constitutes an convenient end-line survey for the flood, while the 2006 Census provides the baseline information. Thus, the use of the Longitudinal Census allows us to account for SA2 fixed effects or individual fixed effects in the analysis that we describe in the next section. Such controls allow us to partial out the true effects of the flood from the time-invariant locality (or individual) characteristics.

We capture the local effects of the 2010–11 Queensland flood on economic activity using several economic outcomes. One of our main outcomes of interest is the logarithm of annual income. The income variable is provided by the census question "What is the total of all wages/salaries, government benefits, pensions, allowances, and other income the person usually receives?". The interpretation of our results hinges on the assumption that surveyed people in the treated region only enter their usual income and do not add flood relief to the figure they report. The wording of the question (i.e. "usually" receives) and the one-off nature of the relief assistance could suggest that the respondents may not have the relief assistance payment in mind when answering the question.[17] Because our income measure is self-reported, measured in intervals, and given how the relevant census question is framed, we interpret income to be an indicator of economic activity, rather than taxable earnings in an administrative sense. While this measure exhibits limitations, the size of the census dataset provides an opportunity to undertake various comparability checks including the comparison of sectoral employment shares. Moreover, our analysis relies on fine geographic variation in flood height, which is a continuous measure that we believe has strong exogeneity grounds. For this flood severity variable to differentiate variations in individuals' flood exposure and economic outcomes across different geographic units, our sample must be large enough to draw a meaningful number of individuals from each SA2. This is why we set the census dataset as the benchmark for our analysis. We also present the results for other labor market outcomes such as full-time and part-time employment, unemployment, and weekly working hours. Moreover, the large census dataset allows us to delve further into the sector-specific impacts of natural disasters. Sector-specific analyses are imperative both for the effective allocation of disaster-relief assistance after natural disasters and for devising future disaster-management strategies.[18]

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[15] This dataset is accessible only by special approval, and access is granted only in designated Australian Bureau of Statistics offices, in line with confidentiality requirements. The estimation results are released after clearance.

[16] We have also excluded individuals that are residing overseas and individuals that do not provide information regarding their residing location.

[17] This census dataset provides interval-based annual income data, namely, $0, $1–$7799, $7800–$12999, $13000–$20799, $20800–$31199, $31200–$41599, $41600–$51999, $52000–$67599, $67600–$83199, $83200–$103999, and $104000 or more, as income intervals. Such intervals further limit the respondents' response being driven by relief assistance given the payments are slightly more than $1000 per claim. In our estimation, we follow the common practice in the literature and take the mid-point of the respective interval class as the actual income of individuals. The highest income value is taken to be $104000. We then adjust this income measure for inflation using the Consumer Price Index of Brisbane between 2006 and 2011. No particular surge in inflation is observed in 2011 due to floods.

[18] The specific sectors that we will analyze include 19 sectors identified in the National Accounting System of Australia, namely, Agriculture, forestry and fishing; Mining; Manufacturing; Food, beverage, and tobacco products; Electricity, gas, water, and waste services; Construction; Wholesale trade; Retail trade; Accommodation and food services; Transport, postal and warehousing; Information media and telecommunications; Financial and insurance services; Rental, hiring, and real estate services; Professional, scientific and technical services; Administrative and support services; Public administration and safety; Education and training; Health care and social assistance; and Arts and recreation services.

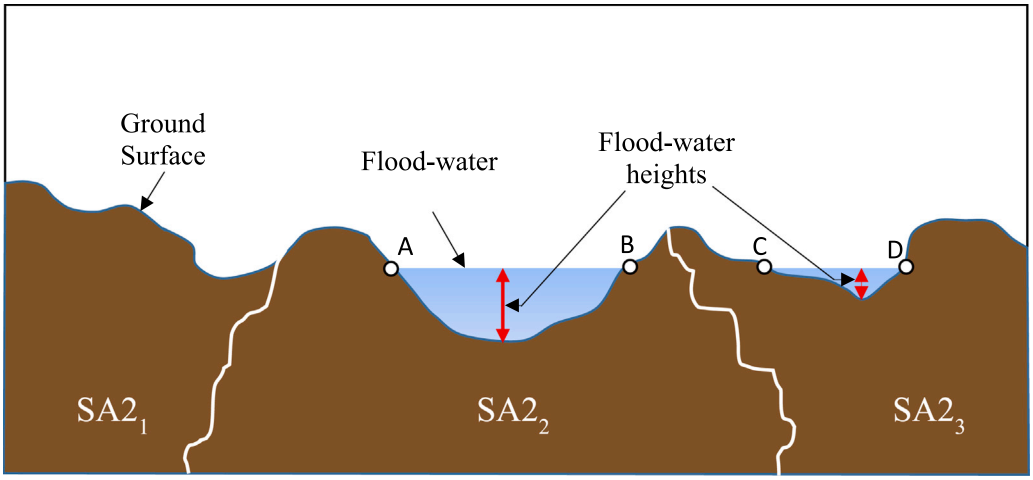

Fig. 3. Schematic of the flood-water height calculation at the SA2 level.

3.2. Flood severity measure: Flood-water height

As importantly, our analysis utilizes a unique engineering dataset on the flood-water height intensity at the SA2 level. As mentioned in Section 2, a flood severity map for 2010–11 Queensland flooding indicating spatial variations is not available from the authorities. Thus, we employ an engineering methodology to compute the flood-water height in each SA2, which enables a more precise estimate of the true economic effects of the inundation.[19] More specifically, this is FEMA – the Federal Emergency Management Agency (2014) water surface elevation calculation method whereby we calculate the flood-water height at a resolution of 0.0002 arc degrees (i.e., around 22 m) using earth surface elevation data sourced from the Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM v2) and the flood-water inundation map sourced from the Department of Natural Resources and Mines, Government of Queensland.

This process of calculating flood-water heights is depicted in Fig. 3. First, using the flood extent map, we identify two points A and B such that all areas between A and B are flooded. Second, we overlay earth surface elevation data on the flood extent map to calculate the difference in elevation between the ground surface and the level of the flood-water surface (as shown in red lines). This calculation is performed at the 0.0002 arc degree level. We then obtain flood severity data at the SA2 level by taking the average of all flood-water height values within a given SA2. Fig. 4 illustrates the flood severity map based on flood-water height for the Queensland floods.

3.3. Administrative data on post-disaster direct income assistance

We obtained confidential access to the data on post-disaster direct income assistance of the Attorney General's Department (2011). This is LGA-level data on the Australian Government Disaster Recovery Payment (AGDRP) and Disaster Income Recovery Subsidy (DIRS) schemes implemented following the Queensland floods. Because some LGAs encompass multiple SA2s in Queensland and some SA2s straddle over two or more LGAs, we apply the following formula to convert the relief assistance from the LGA level to the SA2 level:

$$Postflood\ Recovery\ Aid\ Per\ Capita\ at\ an\ SA2 = $$
$$= \sum_{i=1}^{n} \left\{ \frac{(AGDRP\ in\ LGA_i + DIRS\ in\ LGA_i)}{Population\ in\ LGA_i} \times Geographic\ Share\ of\ SA2\ in\ LGA_i \right\}$$

where i stands for LGAs. That is, we converted the post-disaster assistance to the SA2 level based on the number of SA2s in each LGA, their population, and the geographic share of a given SA2 in its LGA.

3.4. Descriptive statistics

Table 1 presents the descriptive statistics of the flood exposure indicators and the main individual-level covariates. The table reveals that around 28% of Queenslanders in our regression sample were affected by the 2010–11 flooding and that the average flood-water height in the flooded SA2s was 2.02 m. Of all individuals in our sample, 48% were female and 58% did not move across

[19] Notable exceptions are Gallagher and Hartley (2017) and Groen et al. (2020), which also utilize a similar method to ours to calculate the flood severity in the aftermath of Hurricane Katrina and Rita, respectively.

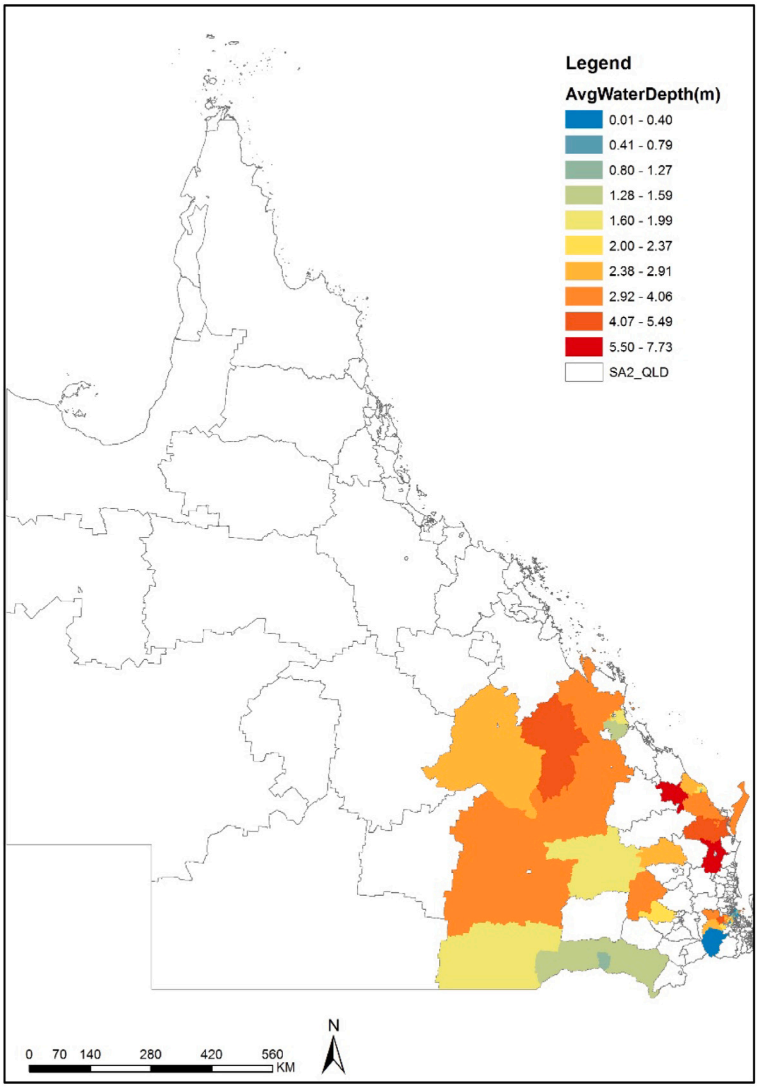

Fig. 4. The Queensland floods severity map: Dec 2010–Jan 2011.
Source: Authors' own calculations.

SA2s between 2006 and 2011.[20] Non-mover rates across treatment and control groups were 58% and 61%, respectively. About 92% were urban dwellers in the treatment group while this is 80% for the control group. Moreover, about 70% (60%) lived in major cities during the treatment (control) group. These rates remained steady between 2006 and 2011. Furthermore, educational attainment and family size are almost similar between the treatment and control groups. Taken together, these descriptive statistics provide a signal that the 2010 Queensland floods are unlikely to influence households' decisions on migration, family size, and education outcomes.

Table 1 further demonstrates that the annual average income in our census sample is AU$41,991. The SA2s with and without flooding differ somewhat in terms of several individual-level economic outcomes. For example, individuals living in the treatment SA2s had an average income of AU$41,828, while those in comparison SA2s earned AU$40,136 in 2006. Thus, we employ a DID estimation strategy in our analysis, which controls for fixed SA2 characteristics and compares individuals within the same SA2 over time. The table also shows that around 60% of people worked full-time, 24% worked part-time and 4% were unemployed. In addition, about 11% of individuals (all in the control group SA2s) experienced another natural disaster event, Cyclone Yasi, just after this flooding. We also note that we account for the potential effect of Cyclone Yasi in our analysis.

[20] Page et al. (2014) provide further formal empirical evidence demonstrating that homeowners in the flooded and unflooded areas in Queensland exhibit similar observable characteristics.

Table 1
Descriptive statistics: Treatment and demographic status.

	All	Treatment group in 2006	Control group in 2006	Treatment group in 2011	Control group in 2011
	(1)	(2)	(3)	(4)	(5)
Panel A: Treatment-related characteristics:					
The Queensland Floods 2010–11 Dummy	0.276	–	–	–	–
	(150863)				
Flood-water Height (in metre)	–	–	–	2.011	0
				(20819)	(54566)
Cyclone Yasi	0.109	–	–	0	0.150
	(150863)			(20819)	(54566)
Maximum Wind Speed in Cyclone Yasi (km/h)	7.161	–	–	0	9.869
	(150863)			(20819)	(54566)
Pop. Share in Adjacent Controls	–	–	–	–	0.198
					(54566)
Panel B: Individuals' socio-demographic characteristics:					
Female	0.480	0.480	0.480	0.479	0.480
	(146729)	(18784)	(54659)	(18720)	(54566)
Nonmovers	0.584	–	–	0.576	0.608
	(150863)	–	–	(18720)	(54566)
Urban Dwellers	0.834	0.922	0.799	0.933	0.796
	(148796)	(22918)	(53565)	(18720)	(54566)
Individuals in Major Cities	0.636	0.716	0.602	0.705	0.613
	(148796)	(22918)	(53565)	(18720)	(54566)
Individuals Below 25 Years	0.139	0.216	0.182	0.094	0.079
	(150835)	(22918)	(54659)	(18712)	(54546)
Individuals Between 25 and 44 Years	0.465	0.486	0.477	0.460	0.446
	(150835)	(22918)	(54659)	(18712)	(54546)
Individuals Above 44 Years	0.396	0.298	0.341	0.446	0.475
	(150835)	(22918)	(54659)	(18712)	(54546)
Family Size	2.822	2.694	2.948	2.680	2.799
	(150863)	(22918)	(54659)	(18720)	(54566)
Education: Year 8 or below	0.015	0.016	0.015	0.015	0.014
	(150863)	(22918)	(54659)	(18720)	(54566)
Education: Year 9 to Year 12	0.188	0.219	0.197	0.170	0.174
	(150863)	(22918)	(54659)	(18720)	(54566)
Education: Above Year 12 to Bachelor Degree	0.587	0.517	0.620	0.511	0.610
	(150863)	(22918)	(54659)	(18720)	(54566)
Education: Bachelor (Honours) Degree or Above	0.210	0.249	0.168	0.304	0.202
	(150863)	(22918)	(54659)	(18720)	(54566)
Panel C: Individuals' economic attributes:					
Annual Income (in AUD)	41991	41828	40136	45776	42619
	(150863)	(22918)	(54659)	(18720)	(54566)
Log of Annual Income	10.188	10.212	10.210	10.235	10.141
	(150863)	(22918)	(54659)	(18720)	(54566)
Weekly Working Hours	34.855	34.383	34.293	35.720	35.399
	(134759)	(21367)	(51292)	(16062)	(46038)
Full-time Workers	0.616	0.634	0.630	0.617	0.594
	(150863)	(22918)	(54659)	(18720)	(54566)
Part-time Workers	0.245	0.268	0.277	0.207	0.217
	(150863)	(22918)	(54659)	(18720)	(54566)
Unemployed Workers	0.036	0.047	0.041	0.028	0.030
	(150863)	(22918)	(54659)	(18720)	(54566)

Note: The numbers of observations are shown within the parentheses. All variables are binary indicators unless otherwise mentioned.

One of the pre-conditions for the credibility of difference-in-differences estimation is that the individual characteristics between the treatment and control groups have to be comparable during the pre-treatment period. Columns 2 and 3 of Table 1 illustrate whether there were notable differences in the mean between the treatment and control groups prior to the flood incident. It appears that almost all characteristics were well balanced in terms of their magnitudes. Besides, we take a restrictive approach in that all our regression results are guarded against time-invariant differences across individuals by controlling for individual fixed effects. Once we control for these effects, we argue that there are no systematic differences between the affected and unaffected individuals regarding their inherent characteristics related to their annual income.

To assess the comparability of the treatment and comparison groups further, Appendix Table A3 displays the sectoral shares of employment in treatment and control groups in 2006 and 2011. Employment shares of all 19 sectors range between 1% and 11%. Only two sectors seem to have somewhat disparate shares across both groups: Construction (7% in the treatment, 10% in the control group) and Professional, Scientific, and Technical Services (8% in the treatment and 5% in the control group). There is otherwise a sizeable degree of similarity among sectoral shares in the 17 remaining sectors across the treatment and control groups in both periods. Even the Agriculture and Mining sectors, the prime suspects for sectoral employment disparities given the somewhat mixed urban and regional baskets of SA2s, exhibit very similar employment patterns. These tables, therefore, indicate that the economic structure of the treatment and comparison groups in QLD are reasonably comparable.[21]

The patterns in Appendix Tables A3 and A4 also address the comparability concerns related to the presence of other possible shocks during August 2006 and November 2010 and their potential differential impacts on labor market trends by treatment status, such as that of the Global Financial Crisis 2008. Similar sectoral shares and relatively comparable sectoral income levels across treatment and control groups over time, including for major sectors like agriculture, mining, manufacturing, and construction, are suggestive of the fact that there is unlikely to be another spatial shock that would have affected the labor market outcomes differentially for the affected and comparison groups. In fact, on the contrary, differential outcomes in the Accommodation and Food; Transport and Warehousing; Health Care; and Retail Trade sectors, which are more likely to be impacted by a shock like flooding, suggest that unconditional relationships extend credibility to the comparability of the affected and control groups, except for the flood exposure.[22]

4. Estimation framework

We identify the overall and sector-specific economic consequences and the effects of post-disaster assistance of the 2010–11 Queensland floods by employing a generalized DID-type strategy. Our basic quasi-experimental design exploits the plausibly exogenous spatial variation in the flood intensity across geographical units in Queensland and the temporal variation in the timing of the flood on income after controlling for individual and census-year fixed effects. In this setting, the "treatment" variable is an interaction between the flood intensity at the SA2 level and an indicator for the post-flood period. The proposed average treatment effect of floods on income is estimated by β in the following baseline individual and census-year fixed effects equation:

$$Y_{irt} = \alpha + \beta(Flood_r \times Post_t) + \delta_i + \gamma_t + \mathbf{X}_{ir}\boldsymbol{\pi} + \varepsilon_{irt}, \tag{1}$$

where Y_{irt} is the labor market outcome for individual i in SA2 r in year t (i.e., 2006 or 2011). $Flood_r$ is a measure of the flood intensity experienced in SA2 r. We use two measures for flood intensity in each region. The first is a binary indicator which takes a value of one if the SA2 faced any inundation during the flooding and zero otherwise.[23] The second measure of flood intensity incorporates the flood-water height in each SA2 obtained by employing the aforementioned engineering methodology.[24] This finer measure of the flood intensity allows us to quantify the potential overall and sector-specific economic effects of floods more precisely since it incorporates all the available spatial variation in flood-water levels across geographic units. We also decompose the flood intensity into three percentiles (i.e., bottom, middle, and upper 33rd percentile) to investigate the potential non-linearity in the flood effects.[25] By quantifying the non-linear effects of the Queensland flood on the local economic activity, we can discern whether the potential effects of the natural disasters are felt primarily after a certain threshold, and negligible otherwise.

In our estimation framework, $Post_t$ is a dummy variable for the post-flood period and takes a value of one if the observation comes from the 2011 Census and zero otherwise. The baseline specification also controls for individual fixed effects, δ_i, which absorb the time-invariant flood intensity measures and other time-invariant SA2 characteristics. We also note that time-invariant individual characteristics are controlled for in the individual fixed effects estimations. γ_t stands for census year fixed effects, and controls for the likely secular changes between the 2006 and 2011 Censuses (which practically corresponds to $Post_t$ dummy). X_{ir} is a vector of time-invariant individual characteristics such as gender and type of residence in SA2 fixed effects models. In individual fixed effects analysis, X_{ir} is no longer included in the equation since this model can control for time-invariant observable and unobservable individual characteristics.

[21] To provide more credibility for the comparability of the affected and control groups, Appendix Figure A4 reports the mean incomes in 2006 and 2011 by economic sector. This figure illustrates that there was no systematic pattern in the descriptive statistics of flooding and incomes across a number of sectors.

[22] Appendix Table A5 shows the SA2-wise descriptive statistics for 140 flooded and 78 Cyclone Yasi-hit SA2s among all 526 SA2s. Also presented are the LGA-wise descriptive statistics of direct income assistance, both in monetary terms and the number of recipients, for 59 LGAs. Within the NDRRA context, a claim was made for each adult and child. The AGDRP disbursed AU$1000 per adult and AU$400 per child, suggesting that a family of four might have received up to AU$2800.

[23] Treatment status is fixed for each individual in 2006.

[24] One concern of this flood intensity measurement is that low elevation areas that are more likely to be hit by floods may also have more concentrated economic activity, as shown by Kocornik-Mina et al. (2020). As a result, the treatment may no longer be exogenous. In our analysis, we control for SA2 fixed effects or individual fixed effects, which significantly mitigates these concerns. We further performed a series of analyses to demonstrate that the parallel trend assumption is satisfied, which provides supporting evidence on the orthogonality of the floods on household behavior. We discuss these results in detail later on from Figs. 5 to 7 and Appendix Table A6.

[25] To do this, we estimate three different regressions by splitting the treatment group into three based on the flood percentile while keeping the control group the same across the three samples.

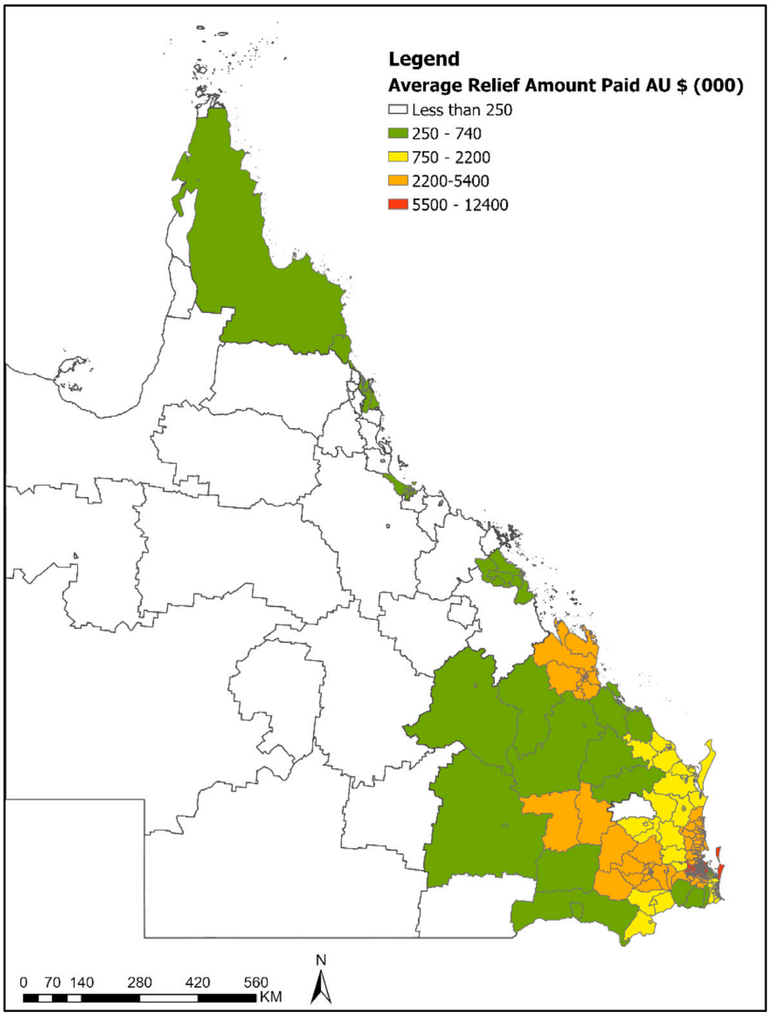

Fig. 5. The Queensland floods disaster relief payments per SA2.
Source: Authors' own calculations.

To quantify the potential effects of post-disaster assistance, we augment Eq. (1) with additional interaction terms: the interaction between the logarithm of the post-disaster direct relief assistance per capita and the post dummy, and the triple interaction between flood-water height, the logarithm of the post-disaster relief assistance and the post dummy. More specifically, we estimate the following equation:

$$\begin{aligned} Y_{irt} =& \alpha + \beta(Flood_r \times Post_t) + \lambda(IA_r \times Post_t) + \phi(Flood_r \times IA_r \times Post_t) + \\ & \delta_i + \gamma_t + \mathbf{X}_{ir}\boldsymbol{\pi} + \varepsilon_{irt}, \end{aligned} \tag{2}$$

In this equation, IA_r denotes post-flood direct income assistance at the local government area (LGA) (i.e., municipality). A three-way interaction coefficient, ϕ, captures the combined effect of the flood, post-disaster direct relief assistance, and the time period after Queensland was inundated with the floods. The other controls in this equation are the same as in Eq. (1).

We estimate our regressions with OLS given that we use the mid-point of the income brackets, but our results are robust to undertaking interval estimation (unreported). We use robust standard errors when the sample is full sample but cluster them at the SA2 level when the sample is restricted to non-movers only.[26] As the non-movers sample allows us to allay the concerns related to flood-driven migration responses and enables to the cluster the standard errors at the SA2-level, this sample is our preferred sample.

[26] As pointed out in Bertrand et al. (2004), one advantage of clustering the standard errors at the SA2 level is that we account for spatial dependence in the treatment variables – i.e., both floods and government payments – in addition to individual-specific characteristics. That is, clustering at the SA2 level accounts for the fact that individuals in the same area are likely to experience the same level of flooding and similar payouts. However, different clustering makes practically no difference to standard errors.

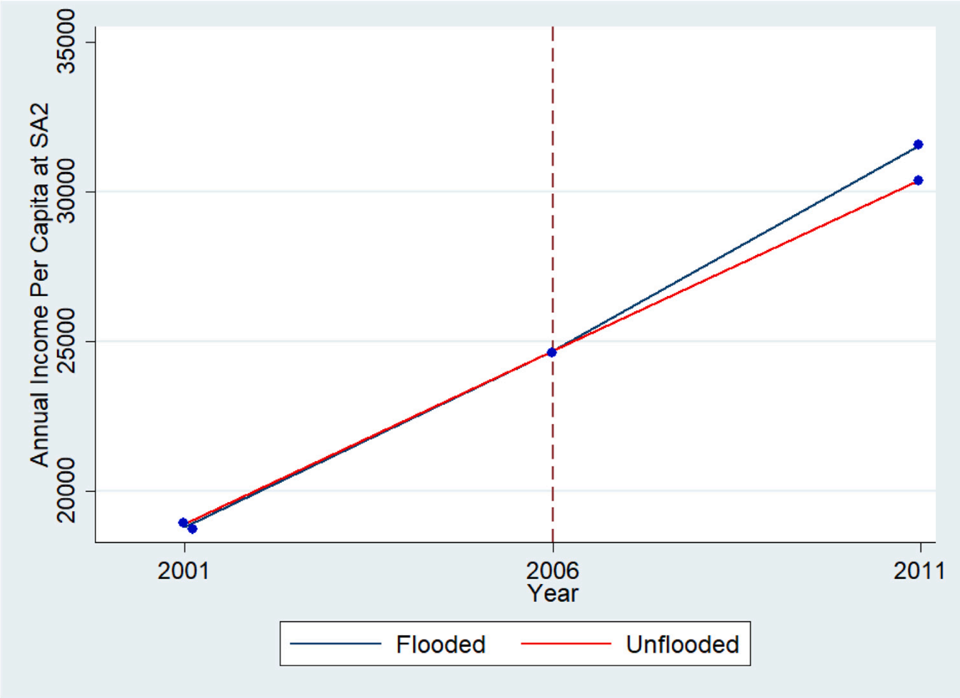

Fig. 6. Average income in flooded and unflooded SA2s (Census Dataset).
Note: Data on the average annual income per capita of SA2s are sourced from the 2001, 2006 and 2011 Australian Censuses. SA2 fixed effects are controlled. The associated regression results are provided in Table Appendix A6.

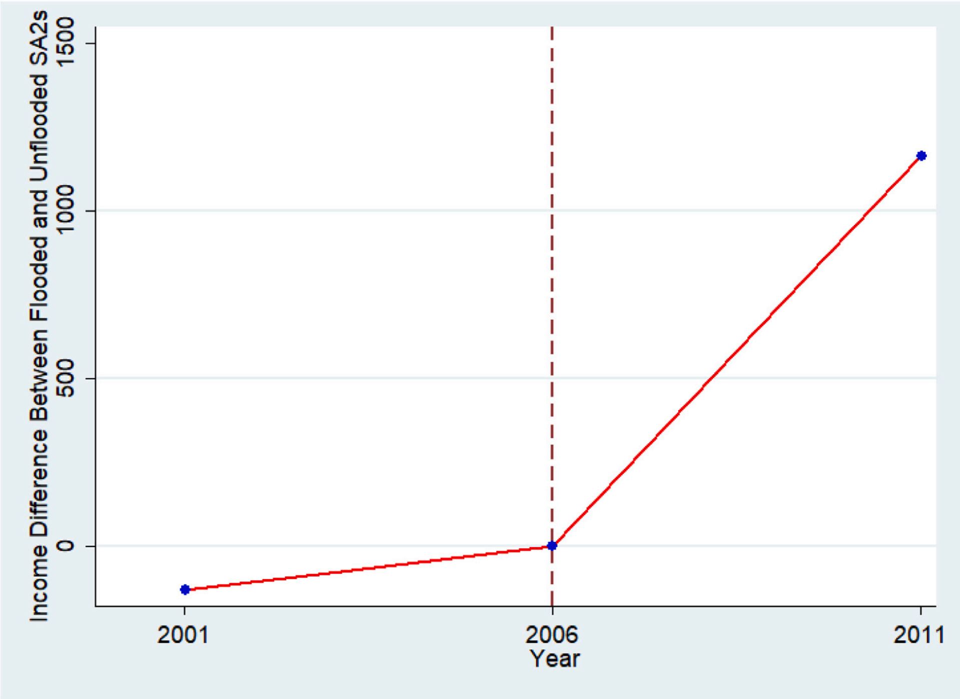

Fig. 7. Average income differences across flooded and unflooded SA2s.

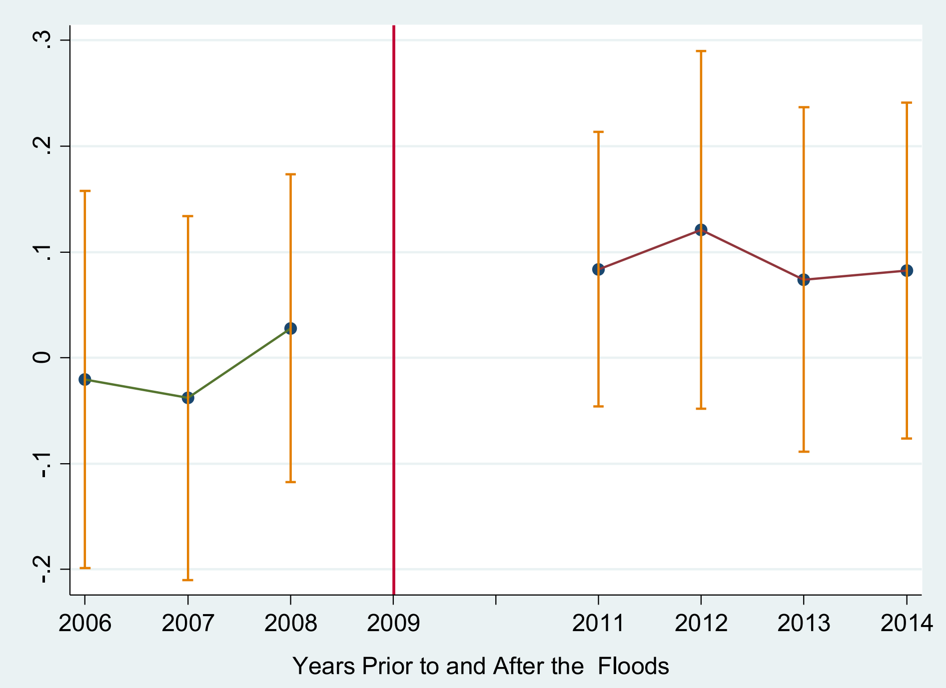

Fig. 8. Event study estimates of the income effect of the 2010–11 Queensland floods using the HILDA dataset.
Note: The figure displays coefficients and 95% confidence intervals. The outcome of interest is annual disposable income for the non-movers sample. The reference year is 2009. The year 2010 is dropped due to being the disaster year. The coefficients are the net of SA2 fixed effects. The survey for HILDA wave 10 was conducted during Aug 2010–Feb 2011, which overlapped with the timing of the 2010 Queensland floods; so, we exclude this wave from our sample. The standard errors of the 2011 and 2012 coefficients are 0.066 and 0.086, which correspond to the level of significance at 20%.

The key identification assumption for the validity of the DID estimation of Eq. (1) is the presence of parallel trends in the outcomes of interests before the floods. That is, the trends in the logarithms of the annual incomes would have been trended similarly across flooded and unflooded SA2s had the floods not occurred. We assess the plausibility of this parallel trends assumption in several ways. First, we visually plot the annual incomes in the flooded and unflooded SA2s (see Fig. 6) using 2001, 2006, and 2011 Censuses at the SA2 level (since the 2001 Census is available only at the SA2 level). The analysis presented in Fig. 6 shows that the annual incomes between the flooded and unflooded SA2s in 2001 and 2006 Censuses generally trend similarly, and the difference in incomes is amplified significantly after the floods (see also Fig. 7). Note that this approach treats income distribution as homogeneous within each SA2 and does not account for individual-level variation that might affect the parallel trends. To address this pitfall, we provide further supportive evidence on parallel trend assumption using an event study analysis based on an alternative nationally representative panel data, the Household, Income and Labour Dynamics in Australia (HILDA). While this is a survey dataset that comprises fewer observations than a census dataset, it is available annually at the individual level. As we discuss in Section 7, Fig. 8 using the HILDA dataset demonstrate that the period 2001–2006 exhibits insignificant differences in the income trajectories of flooded and unflooded areas, extending support to the parallel trend assumption.[27]

Further, consistent with visual evidence in Figs. 6 and 8, Appendix Table A6 provides additional evidence for the parallel trends assumption through regression-based estimates using the SA2-level variation in 2001, 2006, and 2011 ABS Censuses. This alternative specification acts as a control experiment to illustrate whether the annual income per capita in 2006 is indeed significantly different from 2001 and 2011. If they turn out to be similar, it reinforces our parallel trends assumption in that the flooded and unflooded SA2s in Queensland prior to the floods exhibit similar trends in outcomes. Likewise, in the same specification, if our estimates suggest that the post-flood income in 2011 is higher than the pre-flood income in 2006 only for the flood-affected SA2s, our results are likely to be credible. Our estimates in Appendix Table A6 demonstrate that the annual income per capita in 2001 and 2006 does not vary between the flooded and control SA2s using both binary flood dummy (Panel A) and flood-water height measures (Panel B), whereas they do differ noticeably between 2006 and 2011 at 5% level in Panel A and at around 15% in Panel B. Taken together, these analyses provide strong evidence of the validity of the parallel trends assumption and provide supportive inference of the DID estimates that we discuss in the next section.

[27] In an unreported analysis, we plot average family income from the HILDA Dataset and find similar patterns as those in Fig. 6. In addition, we plot mortgage paid and average rent paid in the same way. The mortgage and rent paid did not differ across flooded and unflooded SA2s after the disaster. We do not present these results for brevity.

Table 2
The effects of the 2010–11 Queensland floods on annual income.

	Full sample	Full sample: Controlling for migration	Non-movers sample	Full sample	Full sample: Controlling for migration	Non-movers sample
	Individual fixed effects			SA2 fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Whole Queensland						
A. Flood-water Height (in	0.017**	0.021***	0.017**	0.020**	0.015*	0.011
Metre) × 2011	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
N	150863	150863	88056	150863	150863	88056
B. Flood dummy × 2011	0.078***	0.058***	0.051**	0.096***	0.045*	0.039*
	(0.020)	(0.021)	(0.023)	(0.021)	(0.023)	(0.023)
N	150863	150863	88056	150863	150863	88056
Panel 2: Urban Dwellers in Queensland						
A. Flood-water Height (in	0.030***	0.027***	0.020***	0.036***	0.024**	0.018**
Metre) × 2011	(0.009)	(0.009)	(0.007)	(0.009)	(0.010)	(0.008)
N	125558	125558	72299	125558	125558	72299
B. Flood dummy × 2011	0.085***	0.060***	0.054**	0.12***	0.055**	0.049**
	(0.022)	(0.022)	(0.021)	(0.022)	(0.025)	(0.021)
N	125558	125558	72299	125558	125558	72299
Panel 3: Major Cities in Queensland						
A. Flood-water Height (in	0.029***	0.027***	0.021**	0.035***	0.024**	0.019**
Metre) × 2011	(0.010)	(0.010)	(0.0088)	(0.011)	(0.011)	(0.0087)
N	94687	94687	54009	94687	94687	54009
B. Flood dummy × 2011	0.083***	0.059**	0.057**	0.120***	0.052*	0.052**
	(0.025)	(0.025)	(0.026)	(0.025)	(0.028)	(0.026)
N	94687	94687	54009	94687	94687	54009

Notes: The method of estimation is difference-in-differences using ordinary least squares. In parentheses are the robust standard errors in Columns 1, 2, 4 and 5 and clustered standard errors at SA2 level in Columns 3 and 6. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

We have also undertaken additional robustness checks of the baseline results to test whether they are sensitive to different specifications and potential confounders. First, similarly to Belasen and Polachek (2009), we estimate Eq. (1) using SA2 fixed effects instead of individual fixed effects. However, we note that the estimates with individual fixed effects are superior empirically to the estimates with SA2 fixed effects since the former allows us to account for all the observed and unobserved heterogeneity across individuals residing in the same SA2, and to estimate more precisely how individuals' income trajectories have changed after their flood exposure. Moreover, individual fixed effects allow us to account for potential self-selection into flood-prone areas or other potential moral hazard concerns, which might be related to better public schools, lifestyle choices, or general household well-being. These results are presented alongside our main results in Table 2.

5. Estimation results

5.1. Logarithm of annual income

Table 2 reports the results of Eq. (1), where the dependent variable is the logarithm of the annual individual income. Each cell in Table 2 is from a separate regression and presents the generalized DID estimate, β. We note that our DID estimates demonstrate the net economic effects of the Queensland floods, which incorporate disaster-relief assistance and the stimulus package. We begin by presenting the effects of floods on income with individual fixed effects in the first three columns of Table 2, where we also control for census-year fixed effects. We use two measures of flood intensity: the flood-water height in metres in segment A and a flood dummy in segment B of each Panel in Table 2. The analysis with flood-water height is our preferred specification since this finer engineering-based measure allows us to incorporate all the available spatial variation in flood-water intensity across fine geographical units.

Panel 1 of Table 2 includes all Queenslanders in the sample. In segment A, we find that individuals residing in an area with an average flood-water height experienced a 3.4 percent increase in their annual income between 2006 and 2011 relative to individuals residing in the unflooded areas during the same period (see column (1)). This is the difference-in-differences coefficient β (0.017) multiplied by the average flood height in metres of the affected SA2s (2.02 m) in Table 1. Considering the average annual income in our treatment group in 2006, $41,828, the 3.4 percent rise in income corresponds to a positive change in income by $1422. This amount is not far from the average relief assistance per claim ($1170 and $1143). Assuming one claim per family (or its head, thereof), this means that the disaster income assistance traveled through the economic channels to support the individual incomes. Columns (2) and (3) account for the potential flood-driven internal migration responses. Column (2) investigates whether internal migrants were affected differentially by the flood by interacting the DID estimate with the migrant dummy. We define individuals as migrants if the SA2 that they report residing in 2011 differs from their SA2 of residence in 2006. In this specification, we also control for the two-way interactions of the flood-water height with the migration dummy, and $Post_t$. It is comforting that the DID estimate of the flood-water height retains its statistical significance and magnitude in this specification, indicating that our results are not merely an artifact of internal migrants. However, we do find that migrants experienced somewhat smaller income boosts than non-movers, which may suggest that they probably had limited access to the post-flood relief assistance or other government transfer payments that were distributed locally.

Column (3) of Table 2 restricts the analysis to non-movers only. An analysis with non-movers allows us to provide further supportive evidence regarding the concerns related to flood-driven migration responses. Indeed, column (3) shows that the DID estimates for non-movers are similar to those for the entire sample, lending credence to our main DID results. Columns (4) to (6) control for SA2 fixed effects instead of individual fixed effects where the specifications remain the same otherwise; our estimates in these cases are statistically and quantitatively analogous to the baseline specification. We note that our estimates in columns (5) and (6) are somewhat smaller than those in column (4); however since the DID estimates in all three columns share the same confidence intervals, they are statistically similar to each other.

The second segment of Panel 1 presents the estimation results using the flood dummy as a measure of flood exposure. When we utilize the flood dummy as an indicator of inundation, we happen to be treating all the affected SA2s similarly, while the flood-water height measure allows flood severity at the SA2 level. The results with the flood dummy continue to indicate that individuals who resided in flooded areas experienced larger income increases between 2006 and 2011 than the control groups, after controlling for individual and census-year fixed effects. Similarly to the first segment, our results in segment B are statistically and quantitatively analogous to the baseline specification when we include the interaction between the DID estimate and the migration dummy in the baseline specification (columns 2 and 5), or when we restrict our analysis to non-movers (columns 3 and 6).

Panel 2 of Table 2 replicates the specifications in Panel 1 except that it tests the flood effects across different geographies, in particular, restricting the sample to urban dwellers in Queensland only. This approach produces slightly larger estimates while it improves the levels of statistical significance consistently. This provides an inference that the 2010–11 Queensland floods affect urban dwellers more than their rural counterparts. In Panel 3 of Table 2, we estimate the same specification with yet another spatial change in the sample, which is the major cities in Queensland. Our estimates provide a similar finding that the 2010–11 Queensland floods affect the major cities in Queensland more than its outer areas. Taken together, our findings of similar estimates across different samples indicate that the income effect of floods in Queensland is robust.

Consistent with the previous studies investigating the local economic effects of natural disasters, including both hurricanes, especially Hurricane Katrina and Andrew in the US, and floods, our results demonstrate that the recovery was relatively quick. Indeed, Vigdor (2008) and Cavallo et al. (2013) postulate that if cities are already booming and have a strong economy, or if the disaster is not followed by any major turmoil, the potential effects of natural disasters on cities are generally temporary. Using global county-level inundation maps over the last thirty years, Kocornik-Mina et al. (2020) provide supportive evidence of this proposition by showing that cities tend to recover rather rapidly after being hit by floods and that economic activity does not relocate to less flood-prone regions. Groen et al. (2020), Deryugina et al. (2018), Gallagher and Hartley (2017) and Belasen and Polachek (2009) provide similar evidence for hurricanes in the United States, including Hurricane Katrina, Hurricane Rita and Hurricane Andrew, and various hurricanes in Florida. Using administrative tax return data on Hurricane Katrina victims, Deryugina et al. (2018) show that Hurricane Katrina had only small and transitory impacts on the employment and income of Katrina victims. Similarly, Gallagher and Hartley (2017) show that Katrina victims experienced a significant reduction in their total debt and have better financial standing overall after the hurricane, mainly facilitated by the use of flood insurance money to repay their mortgages.

5.2. The role of post-disaster assistance

Post-disaster direct income assistance, other government transfer payments, disaster insurance, reconstruction efforts, and infrastructure investments targeted towards the most affected areas and industries may all be potential interventions through which to explain the positive income change in the flooded areas, relative to unflooded areas in Queensland. In the Queensland case, the total relief expenditure by the Australian government during the 2010–11 fiscal years amounted to AU$6 billion dollars, of which 10% was direct income assistance.

We now estimate the effects of the post-disaster direct income assistance, which is potentially the main underlying mechanism for the income increase experienced after floods (Boustan et al., 2020). Focusing on the non-movers sample, column (1) of Table 3

Table 3
The effect of post-disaster direct income assistance.

	All	Indiv'ls living in SA2s with flood-water height below 33rd percentile	Indiv'ls living in SA2s with flood-water height between 33rd–66th percentile	Indiv'ls living in SA2s with flood-water height above 66th percentile	All	Indiv'ls living in SA2s with flood-water height below 33rd percentile	Indiv'ls living in SA2s with flood-water height between 33rd–66th percentile	Indiv'ls living in SA2s with flood-water height above 66th percentile	Indiv'ls living in SA2s with flood-water height below 33rd percentile	Indiv'ls living in SA2s with flood-water height between 33rd–66th percentile	Indiv'ls living in SA2s with flood-water height above 66th percentile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Flood-water Height (in Metre) × 2011	−0.019	−0.19	−0.0019	−0.059	0.010	0.020	0.033*	0.0060	0.031	0.042**	0.012
	(0.071)	(0.78)	(0.25)	(0.081)	(0.007)	(0.039)	(0.018)	(0.0066)	(0.044)	(0.021)	(0.009)
Log DIA per capita × 2011	0.026**	0.024**	0.024**	0.025**	0.027***	0.024**	0.024**	0.025**			
	(0.010)	(0.0100)	(0.0100)	(0.0100)	(0.010)	(0.0100)	(0.010)	(0.0099)			
Flood-water Height (in Metre) × Log DIA per capita × 2011	0.005	0.044	0.0066	0.012							
	(0.013)	(0.16)	(0.049)	(0.014)							
N	88056	73746	73521	73701	88056	73746	73521	73701	73746	73521	73701

Notes: Each column corresponds to a separate regression; dependent variable is income. The method of estimation is difference-in-differences using ordinary least squares. We limit the samples to non-movers only, and all models control for individual fixed effects. In parentheses are the clustered standard errors at SA2 level. The 33rd and 66th percentiles of flood-water height across the affected SA2s correspond to 1.166 and 2.560 metres, respectively *Significant at 10% level;**significant at 5% level; ***significant at 1% level.

shows that the DID estimate on flood-water height ceases to be statistically significant after controlling for the post-disaster assistance interacted with the post-disaster dummy, meaning that the positive income changes are likely to be driven by the post-disaster direct income assistance. To shed more light on the assistance dynamics, columns (2) to (4) decompose the flood severity (i.e., bottom, middle, and upper 33rd percentile). One may expect the effect of natural disasters to be non-linear, e.g., when the inundation surpasses a certain level, otherwise modest or negligible effects become especially large. The analysis reported in columns (2)–(4) shows that the role of flood assistance is not different across different levels of inundation.[28] In addition, columns (1)–(4) of Table 3 show that the triple interaction is insignificant, which is probably because a wide range of individuals claimed income assistance regardless of the level of their flood exposure.[29] Thus, irrespective of the flood severity, the affected population has received disaster payment invariably. This supports our reasoning that a wide range of people benefited from post-disaster assistance. Columns (5) to (8) repeat the analysis in the previous columns by dropping the triple interaction term, and the results remain quite analogous. For the sake of completeness, Columns (9) to (11) report the flood effects on income for each percentile group and without disaster assistance and show that the individuals that faced the middle 33rd percentile of flood severity drive the income effects. Overall, the results in Table 3 suggest that post-disaster direct income assistance contributes significantly to the recovery of the local economy and that the broad population has benefited from the disbursed income assistance.

It remains to clarify how the remaining assistance might have affected individual incomes. Of all the AU$6 billion assistance, the top six disaster assistance schemes are: deferral of state and federal tax liabilities (32.8%), small business special disaster assistance grant (up to $25,000 per grant) (23.9%), income and wage assistance (10.4%) (which is the subject of this study), back to business workshops (7.5%), Operation Clean up assistance (7.5%), and online tools (6%). While assistance other than income and wage support may have made a difference to individual incomes, we do not have data on their distribution at the SA2-level. Even if we had the data, the way in which this assistance item might have trickled down to individual incomes requires detailed theoretical and empirical modeling that is beyond the scope of this paper. In addition, it might have taken more than six months for the potential effect of these schemes to appear on income. On the other hand, income and wage assistance is a direct cash injection made to the economy that is easy to measure and whose effects may be detected in the short term. Nonetheless, we note that most of the other assistance was state-wide, so assume that they are likely to be canceled out in our DID setting across treatment and control groups. We also acknowledge the limitations related to being unable to measure other types of assistance.

Another potential mediator that may explain our results is disaster insurance, as shown for Katrina victims in Gallagher and Hartley (2017). Most homes in Australia, if not all, are covered by disaster insurance. In particular, homeowners who mortgage their homes are generally required by the lending-financial institution to purchase disaster home insurance. While we do not fully rule out the possible contribution of disaster-related insurance claims to the income increase in the flooded zones, we argue that individuals are less likely to receive their full insurance payments within the first six months after the event. For example, according to the Queensland Floods Commission of Inquiry 2011, only 47% of total insurance claims were paid within the first six months of the floods by the largest insurance corporation, Suncorp. Besides, the number of insurance policyholders is not substantial compared with the flood-affected individuals; only 19,833 insurance claims were made to the leading eight direct insurers, of which 27% were accepted.[30] Therefore, insurance claim payments are more likely to induce income in the medium term through creating multiplier opportunities in the economy rather than short-term income changes.[31]

An alternative factor to increase the economic activity in the flooded areas, relative to unflooded areas, is the post-disaster reconstruction projects and infrastructure investment through the generation of new employment opportunities by either increasing the demand for labor or fostering the earnings of the existing workers. In addition, the post-disaster reconstruction projects might have aimed at areas with outdated infrastructure or inefficient use of resources, thereby potentially mobilizing idle resources and improving the updated infrastructure through creative destruction. Indeed, Boustan et al. (2020) postulate that American counties that were prone to flooding received new infrastructure, which probably contributed to the new use of previously idle resources such as land. Post-WWII Germany and Japan also provide good examples of such a phenomenon (Davis and Weinstein, 2002; Brakman et al., 2004). We do not have direct evidence to speak to the construction and recovery mechanism, however, as we will see in the sectoral analysis below, there is indirect evidence to rule out this explanation because the income of those employed in the construction sector is estimated to have gone down by about 4% (though with a t-statistic of about 1). This outcome is not surprising because in the short-run, normal construction activity would pause during the flooding period, and we expect any construction boost to increase the incomes following the end-line census in August 2011.

5.3. Sector-specific income

To shed more light on how the income assistance navigates through the economy and who benefited from post-disaster relief assistance, Tables 4 and 5 present the sector-specific income effects of the 2010–11 Queensland floods. We identify the sector in which an individual is primarily employed by utilizing the census question that asks respondents to report the industry or business

[28] The log of direct income assistance per capita coefficient, in Table 3, yields consistent results for individuals living across the flooded percentiles. This indicates that differences in disaster heterogeneity do not affect our results.

[29] In unreported regressions we run the model with triple interaction term across different age groups and income levels, and the triple interaction continues to be similar to the baseline specification for the entire sample. We interpret this as further evidence for the wide range of individuals benefiting from direct income assistance and lack of political bias.

[30] The leading eight direct insurers in Queensland are Allianz, CGU, NRMA, RACQ, QBE, Suncorp, AAMI and CommInsure.

[31] Insurance payment recipients are also likely to have spent their payments on repairing/rebuilding their houses.

Table 4
Sector-specific effects of the floods.

	Full sample	Full sample: Controlling for migration	Non-movers sample
	(1)	(2)	(3)
Accommodation and Food Services	−0.084*	−0.093*	−0.094
	(0.050)	(0.054)	(0.064)
N	*7467*	*7467*	*3661*
Transport, Postal and Warehousing	0.014	0.018	0.025**
	(0.013)	(0.012)	(0.012)
N	*7082*	*7082*	*4375*
Rental, Hiring and Real Estate Services	0.077**	0.071**	0.078**
	(0.032)	(0.029)	(0.033)
N	*2582*	*2582*	*1417*

Notes: Each cell represents a separate regression. The method of estimation is difference-in-differences using ordinary least squares. The coefficients reported are those of flood-water height (in Metre) x 2011. All models control for individual fixed effects. In parentheses, robust standard errors are shown in Columns 1 and 2; we cluster standard errors at SA2 level in Column 3. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 5
The effect of post-disaster recovery aid on sectoral economic activity.

	Flood-water Height (in Metre) × 2011	Log relief per capita × 2011	*N*
	(1)	(2)	(3)
Accommodation and Food Services	−0.094*	−0.001	3661
	(0.053)	(0.028)	
Transport, Postal and Warehousing	0.031**	−0.023	4375
	(0.013)	(0.029)	
Rental, Hiring and Real Estate Services	0.092*	−0.041	1417
	(0.047)	(0.071)	

Notes: The method of estimation is difference-in-differences using ordinary least squares. We limit the samples to non-movers only, and all models control for individual fixed effects. Each row represents a separate regression. In parentheses, clustered standard errors at SA2 level are shown. *Significant at 10% level; **significant at 5% level; *** significant at 1% level.

of the employer at the location where the person works. Using this information, as described in the data section, we focus on 19 sectors identified in the National Accounting System of Australia. Each cell in Table 4 is from a separate regression and reports the changes in annual income of individuals working in the sector indicated due to floods. Of all 19 sectors, only three are estimated to have a net income effect of floods and our discussion focuses only on those sectors that are significantly affected. Individuals working in the Accommodation and Food Services sectors experience a significant income decline of about 16–20 percent, which is most probably because of the closure or reduced activities of cafes, restaurants, and hotels during floods if they were residing in an SA2 with an average flood-water height of 2.02 m, as reported in Table 1. Employees working in the Rental, Hiring, and Real Estate Services sector experienced a 14–15 percent increase in annual income after the floods. Our results also indicate that affected individuals employed in Transportation, Postal, and Warehousing have higher incomes after the flood too, suggesting that relocation from the damaged properties and the increased post-disaster demand for new accommodation might be responsible for the boost in economic activity in both the Rental, Hiring and Real Estate Services and Transportation, Postal, and Warehousing sectors.[32]

Table 5 presents the results related to the post-disaster assistance mechanism for each economic sector, focusing on the non-movers sample. Each row corresponds to a regression for a particular sector. Importantly, our estimated effects suggest that comparing the estimates in the first and second columns, the assistance does not reverse the adverse income effect of floods for the employees of Accommodation and Food Services. More to the point, the positive income effects initially identified in the Transport, Postal, and Warehouse and the Rental, Real Estate, and Hiring sectors seem to be unrelated to the direct income assistance. Hence, our findings suggest that the post-disaster income effect on the overall population does not seem to be working through sectoral economic activity.

6. Heterogeneities

6.1. Gender, age, and income level

We now turn to the segments of the population that are affected the most. Using the non-movers sample, Table 6 presents potential sources of heterogeneities in gender, age, and income distribution dimensions. As there is no clear-cut policy or regulation

[32] We acknowledge that these estimated effects on annual income for each sector are closely intertwined with the share of each sector after the flood. The sector-specific descriptive statistics presented in Appendix A3 demonstrate that the change in sector shares over the five-year period covered by our data is quite comparable across the flooded and control SA2s, suggesting that the observed differences in annual income across sectors are likely to be due to existing individuals earning higher incomes in excess of the secular increases in annual income over time, rather than to a change in the sector shares.

Table 6
The heterogeneous effects of floods on economic activity.

	By gender		By age group			By income		
	Female sample	Male sample	Indiv'ls below 25 years	Indiv'ls between 25 and 44 years	Indiv'ls above 44 years	Indiv'ls with income below 33rd percentile	Indiv'ls with income between 33rd–66th percentile	Indiv'ls with income above 66th percentile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood-water Height (in Metre) × 2011	0.028***	0.006	−0.024	0.021*	0.022*	0.016	0.004**	−0.001
	(0.009)	(0.010)	(0.048)	(0.011)	(0.012)	(0.025)	(0.002)	(0.002)
R^2	0.007	0.001	0.049	0.004	0.022	0.029	0.056	0.011
N	42402	45654	9536	41368	37152	30387	33590	32316

Notes: The method of estimation is difference-in-differences using ordinary least squares. We limit our samples to non-movers only, and all models control for individual fixed effects. In parentheses are the clustered standard errors at SA2 level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 7
The effects of floods on other economic activity.

Dependent Variable:	Weekly Working Hours	Full-time Status (Yes = 1)	Part-time Status (Yes=1)	Unemployed Status (Yes = 1)	Employed to Unemployed Transition (Yes = 1)	Unemployed to Employed Transition (Yes = 1)	Fully Employed to Part-time Employed Transition (Yes=1)	Part-time Employed to Fully Employed Transition (Yes = 1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood-water Height (in Metre) × 2011	0.130*	0.005*	−0.002	−0.001	−0.0004	0.001	−0.003*	−0.002*
	(0.069)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
N	80638	90034	90034	90034	90034	90034	90034	90034

Notes: The method of estimation is difference-in-differences using ordinary least squares. We limit our samples to non-movers only, and all models control for individual fixed effects. In parentheses are the clustered standard errors at SA2 level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

about lodging disaster-related claims with respect to age, gender, or income-level differences, in this section we focus on only the effects of floods on economic activity. It is well-documented that men and women act differently in times of hardship. For instance, the labor force participation rates of women with children increased during the Great Recession, and families have become increasingly dependent upon women's labor and earnings (US Bureau of Labor Statistics, 2018). The first two columns of Table 6 report similar gender-specific results for the 2010–11 Queensland floods. It appears that primarily women experienced increases in their incomes, while men's incomes remained virtually the same. This finding is consistent with the potential gender composition of the sectors positively affected by floods such as Rental, Hiring, and Real Estate Services.[33]

Columns (3)–(5) of Table 6 further explore whether there is heterogeneity by individuals' age. For instance, Deryugina et al. (2018) have shown that Katrina victims who were of 25–44 years of age and had above-median incomes before Katrina reported over $5000 more labor income in the post-Katrina period than in the pre-Katrina period. The results in columns (4) and (5) of Table 6 reveal similar results, suggesting that prime-age individuals generally experienced increases in their annual incomes after the floods, while younger individuals did not experience a similar increase, and hence, were potentially at a disadvantage. Next, we investigate whether non-linear effects are present by either individuals' income levels (columns (6)–(8)). An analysis allowing for non-linearity in individuals' annual incomes indicates that the estimated positive income effects of the flood are driven primarily by the individuals with incomes close to the median (i.e., income between the 33rd and 66th percentiles), while the annual incomes of those in the low- and high-income classes remained unchanged. Such differential effects by income levels may have been driven by an increase in employment rates among the median-income group.

6.2. Other economic outcomes

Finally, Table 7 investigates other potential mechanisms related to the labor market, such as the type of employment, unemployment, and the transition dynamics from unemployment to employment. Again, because there is no rule or regulation to differentiate between different employment profiles in disbursing disaster aid, we focus on only the direct effects of floods on employment conditions. Using the non-movers sample, the result in column (1) of Table 7 demonstrates that weekly working hours have increased among individuals in the flooded areas, an effect significant at 10%. Similarly, columns (2) to (4) indicate a higher

[33] However, we acknowledge that there might be other gendered effects of the floods in other economic outcomes our study fails to capture and could be of interest for future research.

probability of full-time employment among individuals in the flooded areas, which is significant at 10%, while we find no evidence of the increased probability of either part-time employment or unemployment. However, the magnitudes of the increase in working hours and transitions to full employment are negligible. Next, we find evidence in columns (5) to (8) suggesting a decreasing transition from full-time employment to part-time employment and vice versa; floods somewhat slow down employment transitions, but once again these effect magnitudes are relatively small. Taken together, results presented in Table 7 indicate that weekly working hours and transitions to full employment are unlikely to boost incomes due to small effect magnitudes. Another interpretation of all these results is that the post-disaster direct income assistance channel is empirically the strongest mechanism to explain our benchmark findings.

7. Validity and robustness checks

In this section, we revisit the robustness of the estimation of Eq. (1).

7.1. Parallel trends revisited

As was mentioned in the estimation strategy section, the key assumption underlying the DID analysis is the presence of parallel trends in the outcomes of interest before the geographical units were hit by natural disasters. We reiterate the plausibility of the parallel trends assumption visually using 2001, 2006, and 2011 Australian Censuses. Plotting the average annual income per capita over time in flooded and unflooded SA2s, respectively, the analysis presented in Figs. 6 and 7 indicates that the annual income differences between the flooded and unflooded SA2s are significantly greater after the floods, with negligible differences in annual income between the pre-flood years of 2001 and 2006.

Further evidence of the parallel trends assumption is obtained using an alternative dataset, HILDA. Despite the starkly reduced sample size, the HILDA dataset also enables us to check the robustness of our main results to alternative data. Moreover, HILDA provides continuous income data (both gross and disposable), hence allowing us to test the robustness of our interval regressions.[34] Fig. 8 provides an event study analysis comparing individuals' income trajectory in flooded areas compared to unflooded areas using 2009 as a reference period. We find that the period 2006–2008 exhibits insignificant differences in the income trajectories of flooded and unflooded areas, extending significant support to the parallel trend assumption. In addition, the income trajectory in the flooded areas is higher by about 10% in the period 2011–2014. While the confidence intervals of the point estimates include zero, this is possibly due to the small sample size. As noted above, our flood severity variable is a continuous measure across different geographic units, so the HILDA dataset may capture fewer observations from each SA2 to differentiate variations in individuals' flood exposure and economic outcomes. Nonetheless, it is clear that the pattern of findings is consistent with the Census results. These findings further support our parallel trends assumption in that our DID estimates are likely to be causal rather than mere statistical correlations.

7.2. Migration

One of the challenges in the interpretation of the DID estimates is the flood-induced migration response and the possibility that it was non-random. If the flood-induced migration was temporary, with most of the population returning to their homes after the initial shock of the floods had passed, our results would remain unaffected. However, if the migration was permanent for a considerable fraction of the population in the heavily flooded areas and the population composition of the flooded areas subsequently changed dramatically, our results might be biased, depending on the selection in migration. This would introduce a potential measurement error to our treatment variable that might bias our estimates towards zero. The direction of the migration-induced selection in the flooded and controlled SA2s is not clear a priori, since people residing in the geographical units that were affected heavily by inundation may have been displaced to unflooded SA2s or other states, while, on the other hand, as was demonstrated by Boustan et al. (2020), the flooded regions might have attracted large numbers of economic migrants who were seeking to take part in the reconstruction efforts and new investment projects after the floods had passed.

However, the extent of the selective migration is limited due to the fact that our estimation controls for individual fixed effects. Nonetheless, we carry out several robustness checks to address the potential concern of flood-induced migration. As was discussed in the previous section, our DID estimates remain virtually unchanged when we allow the effects of the floods to differ for individuals who report residing in a different SA2 in 2011 from 2006. Moreover, we focus exclusively on non-movers and reassuringly find that the DID estimates for the sample of non-movers are quantitatively and statistically similar to those for the entire population. In Appendix Table A7, we further explore whether the migration decision between flooded and unflooded SAs is associated significantly with the flood intensity in a given SA2. In addition, we also investigate whether selective migration is present based on individual characteristics such as age, education, and annual income. Appendix Table A7 reveals that neither the flood dummy nor the flood-water height seems to be related to the decision to migrate between flooded and control SA2s. We also find no evidence of selective migration by annual income or educational attainments. Consistent with Boustan et al. (2020) and Deryugina et al. (2018), we find that younger individuals were more likely to migrate after the floods, which may stem from age-specific differences in perceptions of

[34] We consider the total disposable income in our analysis. The exact question asked in the HILDA dataset is "What was the total amount of your most recent pay after tax was taken out?".

future disaster risks, the availability of other job opportunities elsewhere, and temporary changes in amenities in the affected areas. Since we control for individual fixed effects in our analysis, age-specific migration responses do not pose a threat to our identification. Taken together, it is unlikely that our results are driven by a potential flood-induced migration. This result is consistent with the riverine flooding not being an extreme disaster, but one that causes a temporary-but-full pause, with a kickstart to follow after a certain period.

7.3. Restricted sample, potential spillover effects and Cyclone Yasi, and other robustness checks

One potential concern of our analyses is that the treatment and control groups might be different in various aspects as our sample consisted of the whole of Queensland. Thus, the results obtained could be due to other factors other than relief payment. Hence, in the subsequent analysis, we limit our sample to only Brisbane and its suburb to ensure both treatment and control groups are similar. Our results are summarized in Appendix Table A8. The sign of all coefficients remains positive but the level of statistical significance has reduced. This outcome is likely because we have a restricted sample. The results obtained are likely downward biased due to the potential spillover effect, which we discuss further in the next analysis.

We examine the potential spillover effects of the floods in Appendix Table A9. In times of natural disasters, adjacent areas may potentially bear some of the costs of the disaster. The analysis of potential spillover effects is essential not only to obtain a complete picture of the effects of the natural disaster on local economic activity and to better assess the effects of the disasters on the larger landscape but also to assist in devising comprehensive disaster management policies for the natural-disaster-prone agglomerations in the future. In the presence of such spillover effects, the DID analysis would also yield lower bound estimates of flood exposure. Moreover, many individuals are likely to commute between flooded and nearby unflooded SA2s for jobs. This phenomenon particularly holds for SA2s within the Central Business District areas (i.e., Downtown). That is, even if an individual reports an unflooded SA2 as a residence, they might be working in a flooded SA2, hence they may be economically affected by the floods. Such selection of individuals is likely to bias our estimates downward if floods affect incomes adversely (and upward in case of the positive income effect of floods). Thus, dropping these individuals from the comparison group and focusing on distant SA2s (which are likely to be beyond reasonable daily commuting distance) would alleviate, if not entirely eliminate, the commuter-related biases.

We, therefore, assess the potential spillover effects of 2010–11 Queensland floods by classifying the comparison-group SA2s as either nearby or distant, depending on their proximity to the flooded SA2s. More specifically, we categorize the SA2s that share a border with flooded SA2s as nearby controls and those that do not share a border with the flooded SA2s as distant SA2s. One would assume that distant SA2s would constitute a better control group and provide more reliable causal estimates in the presence of spillovers. The results in columns (1) and (2) of Appendix Table A9 indeed show that the effects of the flood for all sectors combined are larger in magnitude when the control group is restricted to the distant SA2s, pointing to the existence of potential spillover effects of the flood across adjacent geographical units.

Furthermore, we test the robustness of our DID estimates for Tropical Cyclone Yasi, which hit SA2s on the Queensland coastline in February 2011. As Cyclone Yasi only affected some of the comparison SA2s, our baseline DID analysis is likely to yield lower bound estimates, if anything. Nonetheless, we control for the interaction between the 'maximum wind speed of 30 min observed in each SA2 during Cyclone Yasi and the Post dummy in order to ensure that the difference-in-differences estimates truly capture the causal economic effects of the flood. An analysis that partials out the potential effects of Cyclone Yasi are reported in columns (3) to (5) of Appendix Table A9 using all SA2s as controls as well as nearby and distant SA2s as controls. As is evident from columns (3) and (5), we continue to find that the affected individuals in the full sample experienced an increase in their incomes in the aftermath of the floods as well as with the distant SA2s as control, suggesting that our results are not confounded by differential exposures to Cyclone Yasi.

Last but not least, we check for the relationship between flood severity and post-disaster relief assistance. As Fig. 5 shows, some of the unflooded areas received relief assistance, albeit minor amounts, which is because the NDRRA does not stipulate any threshold of flood severity for assistance. Accordingly, a household residing in the northeastern corner of the state (Fig. 5) may, for example, receive assistance even if our flood severity measure does not pick any severe flooding in that area. Checking the statistical relationship between our measure of flood severity and relief assistance, Appendix A10 indeed shows a positive and significant relationship across 520 SA2s where the relevant data are available.

8. Conclusions

Although cities have been destroyed throughout history – sacked, shaken, burnt, flooded, starved, irradiated, and poisoned – in many cases, they have risen again like the mythical phoenix. Between the years 1100 and 1800, only 42 cities worldwide were abandoned permanently following their destruction (Chandler and Fox, 1974). After circa 1800, resilience became a nearly universal fact of urban settlements around the globe. San Francisco recovered from the earthquake and fires of 1906, and Chicago emerged stronger than ever from the 1871 fires. This latter reconstruction process transformed Chicago into the United States' second-largest metropolis, after New York City, by 1890. Equally dramatic is Tangshan, in northeast China, which was struck by a massive earthquake in 1976 that killed at least 240,000 of its one million people. Within a decade, the Chinese government had rebuilt the city in a maze of six-floor concrete housing projects (Chen, 1988).

The core objective of this paper has been to examine the local economic effects of extensive urban floods that struck a major Australian metropolis, Brisbane, Queensland, during December 2010 and January 2011 and whether and how the government's relief and recovery efforts assisted economic conditions to return to normal. Although the Queensland floods were not as fatal as the global anecdotes cited above, they nonetheless enable us to offer a rigorous investigation in the literature into the economic impacts of riverine flooding that afflicts a sprawling metropolitan area. Moreover, we propose one of the first pieces of evidence for the effectiveness of the recovery and relief mechanism sparked by sovereign intervention following a catastrophe. As such, our analysis of the Queensland floods not only fills an important gap in the literature but also offers valuable lessons for recovery from modern city devastation in a developed country and the potential pathways for a return to normalcy.

We undertook our inquiry by bringing together three datasets that exhibit extensive spatial variation: the Australian Longitudinal Census Dataset of 2006 and 2011, engineering flood-water height data, and administrative data on federal relief assistance. The Census provides panel data on income, residential zone, and an array of other individual characteristics for more than 175,000 working-age Queenslanders. Critically, the date of the 2011 Census, August 9, 2011, makes it a convenient 'end-line survey' for the short-term income effects of the disaster, as well as for the relief assistance, which was mostly concluded by then. Equally importantly, we compute flood-water height at the SA2 level (corresponding roughly to zip codes in the United States) using a flood inundation map and earth surface elevation data. Finally, we have been granted confidential access to data on the post-flood relief assistance available in each local government area. Our rich dataset permits us not only to trace individuals' locations so as to account for potential biases due to migration but also to isolate individual fixed effects, thus neutralizing a myriad of personal unobservable traits that might otherwise plague our results.

Taking advantage of the difference-in-differences strategy, our findings show that the economic recovery in Queensland was rapid. Our estimates demonstrate that individuals residing in a geographic zone in Queensland with an average flood-water height (2 m) experienced a 3.4 percent increase in their (self-reported) annual income between 2006 and 2011, relative to individuals who resided in the unflooded zones of Queensland. This finding is in accord with the burgeoning literature that has reported positive economic impacts of Hurricanes Katrina and Andrew (Deryugina et al., 2018; Gallagher and Hartley, 2017; Belasen and Polachek, 2009) in the United States. While the positive income effect is not equivalent to the positive utility of the flood (Deryugina, 2017), our findings offer important lessons for the design of relief and recovery management in the wake of disasters. Australian government exhibited a good example of post-disaster management by allocating an A$6 billion budget to the disaster zone, which included individual income payments as well as loans and concessions to businesses and firms. Our results suggest that this practice assisted the economy to remain afloat, which in turn supported individual incomes. This practice is akin to recent sovereign interventions during the COVID-19 pandemic where the governments assisted the economic actors with large budgets such that in the aftermath of the pandemic, the economies rebounded. A series of robustness tests firmly endorse the credibility of our estimates. One must also keep in mind that a large literature exists on the adverse effects of post-disaster relief on individuals' likelihood to purchase private flood insurance or invest in self-protection measures against future events (i.e., the Samaritan's dilemma and charity hazard), so such costly endeavors may not always result in correct incentives (Raschky and Schwindt, 2016).

This study is not without limitations. While the census dataset offers a large sample size where individuals reside over a large geographic area, the longitudinal dimension only includes two data points. In addition, the income variable is self-reported and available in intervals. We address these concerns by undertaking a separate analysis with the HILDA dataset and obtaining results in a similar direction (i.e., a positive change in income). Another limitation of the analysis is that the whole state of Queensland was declared a disaster zone after the floods even if large parts of it were not flooded. If the control group was also somehow affected economically by the floods, then our estimates could be downwardly biased. Nonetheless, because our interest is centered on the role of disaster relief assistance in economic recovery, it makes sense to focus on a within-Queensland comparison. For another research question, it might be more appropriate to use other control groups outside Queensland, and that question requires a different research design.

Overall, our study combining three datasets with substantial spatial components fills a major void in the literature on the economic consequences of natural disasters: investigating the relief and recovery mechanism instigated by government intervention in the aftermath of a disaster. We show that the latter has resulted in a successful rebound of economic activity. Thus, given the increased prevalence and intensity of natural disasters that are attributed to global warming, our findings highlight the importance of successful disaster management policies, and in particular, effective post-disaster relief assistance.

Declaration of competing interest

The authors report there are no competing interests to declare.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ejpoleco.2023.102436.

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