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Journal of Policy Modeling 45 (2023) 90–102

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Containment measures during the COVID pandemic: The role of non-pharmaceutical health policies

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Received 12 June 2022; Received in revised form 27 September 2022; Accepted 9 October 2022
Available online 12 December 2022

Abstract

Many countries have imposed a set of non-pharmaceutical health policy interventions in an effort to slow the spread of the COVID-19 pandemic. The objective of this paper is to examine the effects of the interventions, drawing on evidence from the OECD countries. A special feature here is the mechanism that underlies the impact of the containment policies. To this end, a causal mediation analysis decomposing the total effect into a direct and an indirect effect is conducted. The key finding is a dual cause-effect channel. On the one hand, there is a direct effect of the non-pharmaceutical interventions on the various health variables. Beyond this, a quantitatively dominant indirect impact of non-pharmaceutical interventions operating via voluntary changes in social distancing is shown.

JEL classification: C23; C26; C54; I18

Keywords: COVID-19 pandemic; non-pharmaceutical interventions; mediation analysis; causal effects

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https://doi.org/10.1016/j.jpolmod.2022.12.001

1: Introduction

To contain and mitigate the novel coronavirus (SARS-CoV-2), most countries have implemented a wide range of non-pharmaceutical health policy interventions. These interventions vary between countries and over time but include social distancing restrictions, bans of large gatherings, business closures, national border closures, partial or complete kindergarten and school closures, measures to isolate symptomatic individuals and their contacts, rules for wearing a mask, enhanced surveillance, comprehensive testing and advising the population to self-isolate voluntarily and preferably meet only the same people in 'social bubbles.'[1] Beyond these containment measures, governments have taken a multitude of fiscal and social safety net responses limiting the human and economic impact of the COVID-19 pandemic.[2] Understanding whether these interventions have had the desired effect of controlling the pandemic, and which interventions are successful in maintaining control, is critical given their large economic and social costs.

Countries vary in their capacity to surveil and enforce laws and regulations. Government interventions, entailing rigorous implementation of mobility restrictions throughout China, appeared to be effective in stemming the outbreak in Wuhan (Kraemer et al., 2020; Prem et al., 2020). In countries where a similar level of enforcement may not be feasible, people must comply voluntarily with mobility restrictions for them to be effective (Reluga, 2010). People may then choose not to comply because they perceive the risk of the pandemic or the benefits of mobility restrictions for themselves to be low. Of particular relevance in this context is the compliance with social distancing measures, in particular (not) meeting friends and acquaintances.[3] On the other hand, agents respond to the health hazards and voluntarily change their behavior to less risky activities. One can also put it this way: de jure interventions are only part of the story; de facto compliance and voluntary social distancing matter as well. In the case of recurrent outbreaks, this distinction is particularly relevant, as this leads people to be less respectful of rules and less careful about their behavior.

The overall impact of the various measures to "flatten the curve" thus depends on two transmission channels. The first impact channel consists of the mobility changes evoked by the imposition of mitigation policies - the rigor element of governmental stringency measures - and voluntary social distancing - the fear element.[4] Stated differently, this channel is mediated by changes in mobility. All the other treatment effects belong to the second non-mobility-mediated impact channel. The causal importance of these two containment channels will be quantified

[1] Since the onset of the pandemic, multiple modeling approaches have been used to analyze disease dynamics and shed light on the impact of physical distancing and other public health measures (Alfano et al., 2022, Anderson et al., 2020, Bonfiglio et al., 2022, Kumar et al., 2021). For a review of this literature analyzing the effect of containment measures, see the IMF (2020, pp. 65–84).

[2] For an overview of the country-specific fiscal responses, see https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

[3] The compliance with governmental strictness measures has been attributed to factors such as personal attitudes, risk-taking behavior, political orientation, social norms, trust in the government, trust in media sources and belief in science (Allcott et al., 2020; Bargain & Aminjonov, 2020, Malmandier & Nadler, 2011; Simonov et al., 2020, Webster et al., 2020).

[4] See Van Bavel et al. (2020) for several of these behavioral interventions. Their overview of knowledge in social and behavioral science explored the potential avenues and channels through which these disciplines can support the management of the pandemic crisis.

below. This unpacking exercise is called causal mediation analysis.[5] The exclusive focus of impact assessments on *whether* and *how much* a policy measure works has been repeatedly criticized (Deaton, 2010). Instead, there should be a stronger focus on the question of *why* a policy intervention works. Statistical framework for the analysis of such causal mechanisms will not only enhance the understanding of causal mechanisms behind non-pharmaceutical policy interventions, but may also enable policymakers to prescribe better policy designs.[6] The remainder of the paper is organized as follows. We start by presenting the data and some stylized facts in Section 2. In Section 3, we present the econometric causal mediation methodology and the estimation results. With this retrospective cross-country analysis, we provide estimates regarding the effectiveness of different mandatory non-pharmaceutical interventions versus voluntary social distancing during the first three pandemic waves. To close, we conclude and present some policy implications in Section 4.

2: Data and variables

In this section, we describe the data that we use in our empirical analysis and the variables that we construct to study the effects of non-pharmaceutical interventions.

For our analysis, we assemble a panel dataset comprising 36 OECD countries (all the OECD countries except Iceland, for which mobility data are not available) and five variables: (i) COVID-19 infections; (ii) COVID-19-related fatalities; (iii) the COVID-19 effective reproduction rates; (iv) government non-pharmaceutical interventions; and (v) country-level mobility data. The health data are reported with a daily frequency. To investigate their potential impact, weekly data are considered.[7] Our sample period covers February 26, 2020 to July 27, 2021. Overall, 2280 data points are available, implying a sufficiently high number of degrees of freedom.

We use the number of COVID-19 cases and fatalities as a proxy for the severity of the pandemic in each country. We gather daily data on confirmed new cases and new fatalities from Roser et al. (2020). As an alternative indicator for the time course of the pandemic we also look at the real time reproduction rate, R_t, as constructed by Arroyo-Marioli et al. (2021).[8] The time-varying reproduction rate R_t mirrors the infection dynamics due to the decline in susceptible individuals (intrinsic factors) and the implementation of control measures (extrinsic factors). If $R_t < 1$, it suggests that the pandemic is in decline and may be regarded as being under control at time t (vice versa if $R_t > 1$). Not surprisingly, all COVID-19 waves started with a value of $R_t$above 1 and ended with a value below 1. The time-varying growth rate is estimated using the Kalman filter from data on the number of infected individuals, and their specification can be

[5] Mediation analysis moves beyond calculation of average treatment impacts and instead seeks to quantify the impact of a treatment that operates through a particular causal mechanism. In other words, the mediator can be interpreted as an intermediate outcome. Nontechnical surveys to causal mediation analysis are provided by Imai et al. (2011) and Celli (2021).

[6] The review article of Ludwig et al. (2011, p. 20) has highlighted how understanding mechanisms in policy analyses plays a "crucial and underappreciated role".

[7] A drawback of daily data is that the reported infection numbers exhibit irregular fluctuations due to reporting delays and varying test incidence due to local holidays and weekends. In other words, weekly data overcome time delays from alternative reporting bodies. Another reason for using weekly data is that, in many countries, a time lag exists between the federal government's lockdown decision and its effective implementation at the regional level.

[8] The daily R_t data are available for download at http://www.globalrt.live/. We have converted the R_t data into a weekly series, so that the frequency matches that of the other data.

assessed by standard statistical test procedures. The advantage of the time series approach is that it can adapt very quickly to the most recent information and hence produce timely real-time estimates. This flexibility enables the effects of changes in policy, virus mutations and human behavior to be tracked.[9] Since the fraction of detected COVID-19 cases changes rapidly over short windows of time, statistical filtering techniques are employed by Arroyo-Marioli et al. (2021) to obtain a smoothed version of R_t.

In order to evaluate the impact of government policies and thus the treatment effect on the above variables, we employ data from the Oxford COVID-19 Government Response Tracker (OxCGRT) for containment measures.[10] The OxCGRT collects and quantifies information on government policy responses across fourteen dimensions, namely: (i) school closures; (ii) workplace closures; (iii) public event cancellations; (iv) gathering restrictions; (v) public transportation closures; (vi) stay-at-home orders; (vii) restrictions on internal movement; (viii) international travel bans; (ix) facial coverings; (x) testing policy; (xi) contact tracing; (xii) public information campaigns; (xiii) cash unemployment payments; and (xiv) freezing of households' financial obligations. The stringency indices in the database are rank scaled, depending on whether the measure is a recommendation or a requirement and whether it is targeted or nationwide. To exploit the information from the various sub-indices optimally, we calculate the first principal component instead of simple averages, allowing some measures to be less weighted than others.[11] Increasing values of the index imply stricter regulations.

To review behavioral responses to the containment policies, de facto mobility measures are needed. A straightforward and useful set of high-frequency social distancing indicators is based on the location history of mobile devices, which was exceptionally made available by Google due to the COVID-19 pandemic. It provides a daily pulse of economic activity, proxied by the extent to which people frequent recreational spots and their workplaces. In addition to their timeliness, an advantage of the mobility indices is their standardized format and availability for a large group of economies, allowing cross-country comparisons. The availability of de-identified and aggregated Google mobility data divided into different categories opens up the possibility to quantify the effectiveness of the compliance with the measures decreed. The mobility data of people with smartphones and with "location history" turned on in their phones' settings are available for six location categories (grocery and pharmacies, parks, residential, retail and recreation, transit stations and workplaces). Google has constructed these data by comparing visits to and lengths of stays in certain places compared with a baseline using information from Google Maps.[12] This study works with the first principal component of the various categories.[13]

9 The simple and transparent methodology is data driven and so are different from the structural models used by epidemiologists which rely on assumptions about transmission and behavior (see, e.g. Avery et al., 2020).

10 See https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

11 Another justification for the aggregate intervention variable is the multicollinearity problem as many containment measures have often been introduced simultaneously or very close together.

12 According to Google's mobility report, the baseline day represents a normal value for that day of the week, so the baseline day is the median value from the five-week period January 3 to February 6, 2020. A growing literature has provided evidence of the usefulness of now-casting mobility data to assess the impact of the COVID-19 pandemic containment policies (see, e.g., Buckee et al., 2020 and Chen et al., 2020).

13 A drawback is that that the mobility data only measure intra-national mobility. In other words, cross-border mobility is not recorded. For the cross-border mobility effects, data on international passenger volumes and flight routes have been used in the literature; see, for example, Keita (2020) and Wu et al. (2020).

In the following section, we will present the instrument variables mediation estimation results. The mediator that we consider is the first principal component of the actual Google mobility measures. The goal is to find causal treatment effect; and the IV mediation analysis is an important econometric tool to achieve this objective. In particular, the mediation analysis unpacks the black box of causality and allows researchers to assess the relative importance of direct and indirect effects.

3: Estimation methodology and estimation results

This section describes the empirical methodology used to examine the causal effect of mandatory and voluntary social distancing on COVID-19 infections and fatalities. To investigate this subject, we employ a causal mediation instrumental variable setup. To identify the fraction of the total health impact Y_{it} in country i in period t that is explained by the behavioral response M_{it}, we conduct a mediation analysis that decomposes the total effect of the mandatory interventions T_{it}on Y_{it} into (i) the mediated indirect effect of T_{it} on Y_{it} that operates via mandatory and voluntary social distancing M_{it} and (ii) the intervention effects that do not work via M_{it}. The outcome variable $Y_{it}$is allowed to be any type of random variable (continuous, binary or categorical). Among others, examples are health system measures like mandates for wearing masks, mass testing and contact tracing. In Figure 1, we illustrate the formal mediation framework for decomposing an overall effect into interventional direct and indirect impacts.

The key quantity of interest is the calculation of how much of the treatment variable T_{it} is transmitted via the focal mediation variable M_{it}. In other words, causal mediation analysis decomposes the total effect into its indirect and direct components. The indirect component represents a posited explanation for why the treatment works, while the direct component represents all other possible explanations. The interest focuses on what proportion of the total effect is indirect.

An obvious problem is that in most real-world applications the treatment T_{it} is systematically nonrandom and therefore needs to be instrumented by a variable Z_{it} which is a reasonable strong predictor of T_{it}. Given a scalar instrument variable with these properties, Figure 1 shows that M_{it} mediates the effect of the treatment T_{it} on Y_{it}, as indicated by the $T_{it} = f_T(Z_{it}, \varepsilon_{T,it}) \rightarrow M_{it} = f_M(T_{it}, \varepsilon_{M,it}) \rightarrow Y_{it} = f_Y(T_{it}, M_{it}, \varepsilon_{Y,it})$ path. This is the indirect effect of the treatment T_{it} on Y_{it}. Another arrow indicates that there is also a direct impact of the treatment $T_{it} = f_T(Z_{it}, \varepsilon_{T,it}) \rightarrow Y_{it} = f_Y(T_{it}, M_{it}, \varepsilon_{Y,it})$ that does not work via M_{it}. For

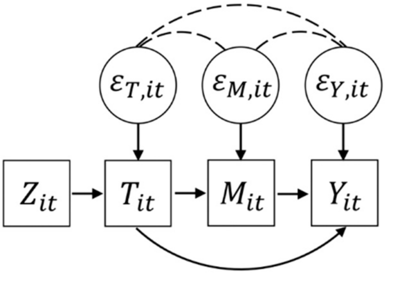

Fig. 1. Direct and Indirect Treatment Effects in the Mediation Analysis. *Note*: Solid arrows between nodes represent causal effects. The diagram is a customized panel data version reprinted from Dippel et al. (2020).

identification, we require the validity of $Z_{it} \perp (\varepsilon_{T,it}, \varepsilon_{M,it}, \varepsilon_{Y,it})$, where $\perp$ denotes statistical independence (VanderWeele, 2015).

Establishing causality in the pandemic is difficult because countries' decision to implement containment measures crucially depends on the evolution of the virus. In other words, the non-pharmaceutical interventions (treatments) T_{it} are an endogenous policy variable. This implies that addressing causality requires us to control effectively for this endogenous response, which would otherwise lead to biased estimates of the treatment effect. To identify the causal effect, we instrument the interventions of each OECD country $i = 1, \cdots, 36$ with the weighted average of the interventions of all other OECD countries $j = 1, \cdots, 36, j \neq i$. In other words, the instrument represents the non-own interventions. The results below explore the validity of the instrument.[14]

Formally, given the anticipated endogeneity of the treatment variable, the standard instrumental variables estimation approach for T_{it} and M_{it} at the country–week level is

$$T_{it} = \beta_T^Z \times Z_{it} + \mu_i + \varepsilon_{T,it} \quad (1)$$

$$M_{it} = \beta_M^T \times \hat{T}_{it} + \mu_i + \varepsilon_{M,it}, \quad (2)$$

where $\hat{T}_{it}$ is the estimated value of T_{it} in the first-stage regression (1), Z_{it} is a reasonably strong scalar instrument (predictor) for the endogenous COVID-19 treatment variable T_{it}, μ_i are country fixed effects, $\varepsilon_{T,it}$ and $\varepsilon_{M,it}$ are the unobserved error terms in the first- and second-stage regressions and the indices i and t refer to the country and the week. The country fixed effects allow for idiosyncratic but persistent differences across countries. Dippel et al. (2020) showed that the total effect, the indirect causal mediation effect and the direct treatment effect can be estimated as follows:

$$M_{it} = \beta_M^Z \times Z_{it} + \beta_M^T \times T_{it} + \mu_i + \varepsilon_{M,it}, \quad (3)$$

$$Y_{it} = \beta_Y^M \times \hat{M}_{it-k} + \beta_Y^T \times T_{it-k} + \mu_i + \varepsilon_{Y,it}, \quad (4)$$

where $\hat{M}_{it}$ is the estimated value of M_{it} in the first-stage regression (3) and k is the number of lags. Dippel et al. (2020) have shown that the total treatment effect (non-pharmaceutical interventions enacted against the COVID-19 virus) is then given as the sum of the indirect causal mediation effect $\beta_M^T \times \beta_Y^M$ and the direct treatment effect β_Y^T.[15] The overall total impact $[(\beta_M^T \times \beta_Y^M) + \beta_Y^T]$ is expected to be negative.

In order to decompose the total policy impact into a direct and an indirect effect, the chosen instrument must satisfy two conditions. The first condition is that the instrument is informative and thus the problem of weak instruments does not exist. The reason is that weak instruments can produce biased IV estimators and hypothesis tests with large size distortions. To test for informative instruments, we report in Table 1 the Kleibergen and Paap (2006) statistic, which is a robust version of the Cragg and Donald (1993) test for weak instruments. The finding is that we can reject the weak instrument hypothesis and thus the chosen instrument is relevant. The second identification assumption underlying the causal mediation analysis is that the instrument is weakly exogenous. One possible objection to the instrument inspired by Autor et al. (2013) is

[14] The instrument choice parallels the procedure followed by Autor et al. (2013) who instrument trade exposure from China with the trade exposure that a set of other countries face. The identifying assumption is that this set of countries is unlikely to be subject to the same (correlated) demand shocks such that the instrument identifies increasing trade exposure due to exogenous productivity increase in China and not changes in domestic demand conditions.

[15] In contrast, the alternative causal mediation estimator of Frölich and Huber (2017) requires separate instruments for the treatment and the mediation variable.

Table 1
IV Mediation Estimation Results for the Number of New Infections, the Number of New Pandemic-Related Fatalities, and the Reproduction Rate.

Outcome variable	Weekly new infections	Weekly new pandemic-related fatalities	Average weekly reproduction rate
Total Impact	-0.31***	-0.28***	-0.26***
	(0.02)	(0.02)	(0.02)
Direct Non-pharmaceutical Policy Impact	-0.08**	-0.08**	-0.08**
	(0.04)	(0.03)	(0.03)
Indirect Mediation Mobility Impact	-0.23***	-0.20***	-0.18***
	(0.04)	(0.04)	(0.04)
Causal Mediation Effect in %	74.02	72.55	70.39
F-Stat One (T on Z)	270.98	147.28	172.56
F-Stat Two (M on Z|T)	40.47	44.12	45.57

Notes: The significance level is denoted by two asterisks (5 percent) and three asterisks (1 percent), respectively. Standard errors clustered by country are given in parentheses below the coefficient estimates. The Kleibergen and Paap (2006) F-statistic for excluded instruments in the first stage one regression (T on Z) and the first stage two regression (M on Z|T) are denoted as F-Stat One (T on Z) and F-Stat Two (M on Z|T), respectively.

that neighboring OECD countries might have a similar cultural background (individualism, libertarian) or like-minded governments which could violate the exclusion restriction. The countries may even have coordinated interventions internationally. This possible objection requires to discuss the instrument validity with care. To verify the logic of the instrument we present a heat map of the stringency of country-specific containment measures over time in Figure 2. The heat map uses a dark-to-light color spectrum to highlight country differences in the timeline of containment measure stringency. What does the visual storytelling reveal? During the sample period, governments have enforced different on-pharmaceutical interventions, under rapidly changing, unprecedented circumstances. The OECD government responses included the laissez-faire strategy, which implies doing little to nothing, the herd immunity strategy, which implies a few measures only or measures relying on voluntary compliance, and more aggressive approaches based on the implementation of a wide range of stringent measures, sometimes even limiting civil rights and liberty. The heat map illustrates that the containment policies of the OECD countries differed substantially in the stringency, timing and sequencing of non-pharmaceutical interventions. This cross-country dissimilarity and variation thus supports the choice of the chosen instrument.[16]

Table 1 presents our baseline estimation results for the 36 OECD countries. The estimates decompose the total impact into direct and indirect effects. The mandatory non-pharmaceutical interventions have a causal effect on the health variables, but part of this effect occurs through voluntary social distancing. This causal indirect effect occurs because the mandatory measures influence voluntary social distancing, which in turn influences the future course of the pandemic. The indirect and direct effects together form the total effect. The key quantity of interest

[16] Sebhatu et al. (2020) have analyzed the speed of adoption of the different COVID-19 policies across OECD countries. The diffusion analysis shows two characteristics. On the one hand, significant country-specific heterogeneity exists. Certain policy measures have not been adopted at all by individual countries. Furthermore, countries differed in the speed of implementation. The econometric analysis reveals that economic, demographic, political, and public health-related characteristics help explaining these cross-country differences. On the other hand, government policies are also driven by the policies initiated in neighboring countries - all else being equal. These two properties indicate that the chosen instrument is correlated with the endogenous variable, while satisfying the exclusion restriction.

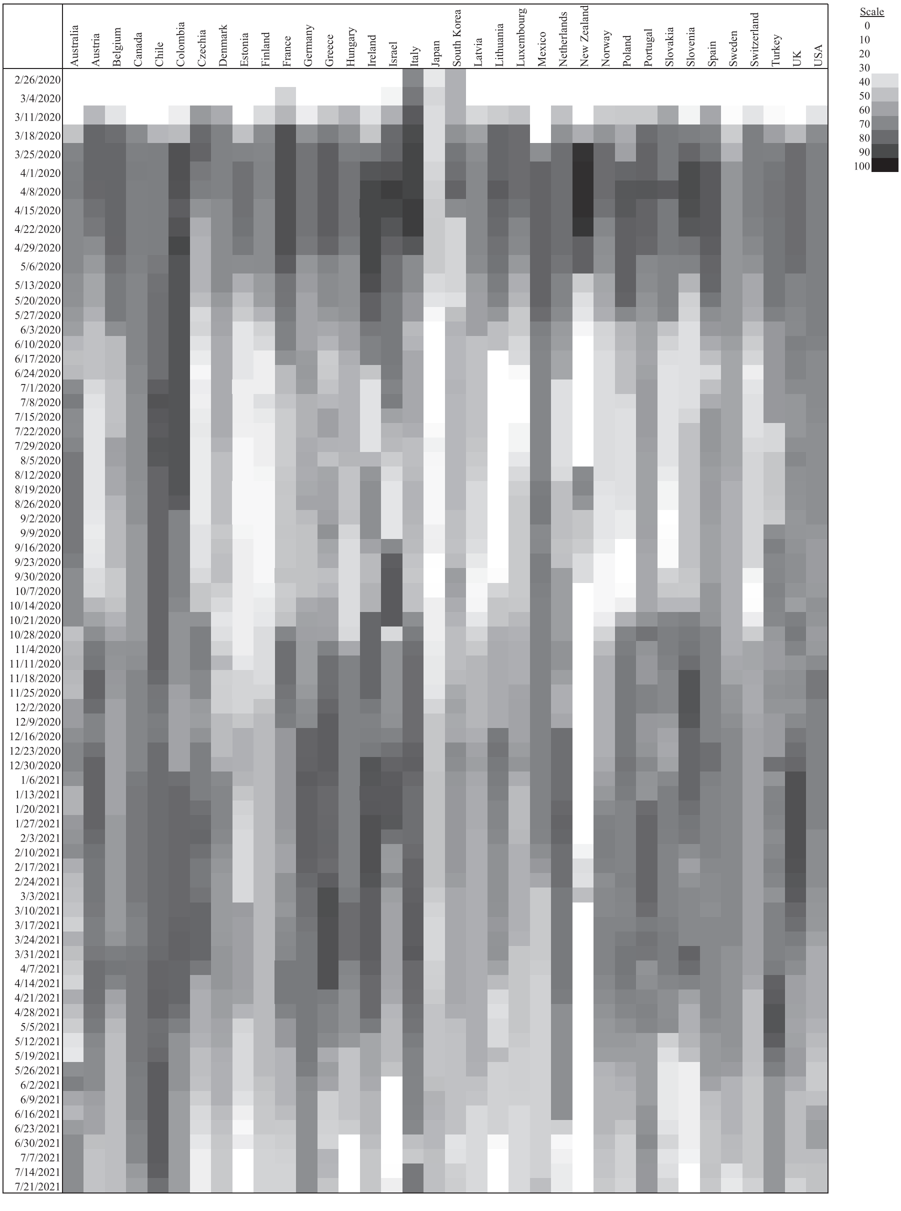

Fig. 2. Heat Map of the Non-pharmaceutical Interventions in the OECD Countries. Note: The chart shows the weekly-average strength of the OxCGRT non-pharmaceutical stringency index for 36 OECD countries which is based on a hierarchical coding scheme. Source: OxCGRT.

is the calculation of how much of the treatment variable is transmitted by the mediating variable.

The sample period is February 26, 2020 to July 27, 2021. The three dependent variables are the log-difference of the new confirmed COVID-19 cases per million population, the log-difference of the new confirmed COVID-19 fatalities per million population, and the weekly reproduction rate R_t.[17] All the specifications include country fixed effects to control for omitted factors. Prior to the actual estimation, the appropriate lag structure in (4) needs to be determined. In the estimates for the infection rate and the reproduction rate, the policy and mobility variables T_{it} and M_{it} are lagged by one week, respectively.[18] In the estimates for fatalities, the lag is two weeks.

The estimation results for the various health policy metrics in the first three columns of Table 1 show a consistent pattern. Several findings are worth noting. First, according to the Kleibergen and Paap (2006) test statistics, the null hypotheses that the instrument is weak is comfortably rejected. Second, all coefficients generally have the expected sign. Third, the direct intervention effects are significant and thus contribute to the containment of the pandemic. Fourth, the indirect mediation variable “de facto mobility” has paramount importance for the evolution of the pandemic across countries and over time. In the case of new COVID-19 infections, the causal explanatory proportion is 74 %. In the case of new pandemic-related fatalities and the reproduction rate, it is 73 % and 70 %, respectively. Finally, the flip side of the coin is that the direct public health policies, like mandating mask wearing, test-and-trace policies, restricting visits to care/elderly/retirement homes and specific testing in such homes, have a subordinate impact as can be seen from the smaller coefficients.[19]

Overall, our estimates for the three health policy metrics enable us to reach an important conclusion. For the purpose of modeling the impacts of non-pharmaceutical intervention on the health policy metrics, the de facto mobility index is the pivotal causal mediation variable as it captures the ultimate impacts of both the rigor element of government policies and the behavioral changes that they trigger. In other words, the mobility indices can be interpreted as the all-encompassing societal response to the imposed lockdown measures rather than that of the government alone. This conclusion is supported by Chen et al. (2020). It is also consistent with Maloney and Taskin (2020), showing that mandatory social distancing policies matter less than voluntary demobilization in reducing mobility and enabling social distancing. Similarly, the great significance of induced cautious behavior was shown by Goolsbee and Syverson (2021). They found that visits to businesses declined by up to 60 % because of the pandemic but that legal restrictions explained only 7 percentage points of this drop. Finally, the results in Golstein et al. (2021) also match this finding. Their results indicate that a fading effect of non-pharmaceutical interventions can be attributed to an increasing non-compliance with mobility restrictions. In other words, lockdown fatigues diminish the effectiveness of de jure containment policies.

4: Conclusion and policy implications

In program evaluations, analysts tend to focus solely on the study of health policy impact. Policymakers may, however, demand deeper explanations for why interventions matter. Causal mediation analyses are able to shed light on such causal mechanisms.

[17] The testing of the appropriate functional form of the dependent variable is performed using the Box–Cox statistic. The test decisively favors the logarithmic form.

[18] Askitas et al. (2021) found that the COVID-19 infections started to drop with a time lag of about 1 week after the containment policies were introduced. The 2-week lag for fatalities confirms the well-known fact that particularly severe disease progressions become apparent after 10–14 days.

[19] To be effective, test-and-trace policies require testing on a truly mass scale and the ability to carry out testing swiftly, which many OECD countries have struggled to implement (OECD, 2020).

Our analysis contributes to the body of work that is trying to understand the effectiveness of different measures to control the spread of COVID-19. Coupling the data of confirmed COVID-19 cases, fatalities and the COVID-19 reproduction rate with non-pharmaceutical interventions and Google mobility data, we employ a causal mediation instrumental-variable approach, using as instrument for each country a jackknife (leave-one-out) mean of the other countries' interventions. Thus, we decompose the total effect into direct and indirect impacts. The methodology reveals the mechanism through which non-pharmaceutical health policy interventions affect the future course of the pandemic. Ideally, such studies could inform public health policy in the onset of the COVID-19 pandemic.

The underlying idea is that health policy stringency and actual mobility are distinct concepts. The effectiveness of additional policy measures depends on their adherence. Conversely, relaxing restrictions does not guarantee an increase of economic activity if the general public remains concerned about the virus and therefore exercises voluntary social distancing. Therefore, the mobility index reflects both government policies and preferences of the general public, and it can thus be thought of as the society's policy choice rather than that of the government alone.

Two main findings are prominent. First, the estimation results indicate that the de facto mitigation effort reflected in the mobility data plays the key role in safeguarding people's health and lives. Given that governments can only influence mobility behavior to a certain extent, this is corroborative of recent work modeling an endogenous agent response to health risks. The underlying proposition of this work is that significant voluntary social distancing will be practiced regardless of the presence of non-pharmaceutical interventions.[20] Second, the estimation results highlight effective and convincing communication as a critical component of the management of the COVID-19 pandemic. Furthermore, to achieve compliance, governmental legitimacy is needed.[21] The relevance of the results is obvious. COVID-19 could reappear in further waves, especially when highly contagious mutations occur. Returning to pre-pandemic routines may be impossible until mass vaccinations have taken place. In addition, future virus mutations must not call into question possible vaccination achievements. Until then, the above conclusions apply. To flatten the curve and contain the repeated infection waves, a reduction in de facto mobility is imperative and the key to success.

Acknowledgement

We would like to thank the editor and the anonymous referees for helpful comments and suggestions on an earlier draft of the paper. All remaining errors are our own.

[20] Several models integrating social distancing decision making into canonical epidemiology models have been developed. Examples include the work by Eichenbaum et al., (2020a, 2020b, 2020c) and Krueger et al. (2020). These modeling frameworks underline the role of voluntary social distancing, which is important for delaying and flattening the COVID-19 infection curve, and thus help to design policies that improve the trade-off between economic and health outcomes during the pandemic.

[21] Christensen and Lægreid (2020) defined government legitimacy as the belief that the government does what is desirable, appropriate and fair. They hypothesized that Norway's success in handling the pandemic and the compliance with stay-at-home orders were mostly due to its government's legitimacy.

Appendix: List of OECD Countries included in the regressions

Country	ISO Code	Country	ISO Code	Country	ISO Code
Australia	AUS	Greece	GRC	New Zealand	NZL
Austria	AUT	Hungary	HUN	Norway	NOR
Belgium	BEL	Ireland	IRL	Poland	POL
Canada	CAN	Israel	ISR	Portugal	PRT
Chile	CHL	Italy	ITA	Slovakia	SVK
Colombia	COL	Japan	JPN	Slovenia	SVN
Czech Republic	CZE	South Korea	KOR	Spain	ESP
Denmark	DNK	Latvia	LVA	Sweden	SWE
Estonia	EST	Lithuania	LTU	Switzerland	CHE
Finland	FIN	Luxembourg	LUX	Turkey	TUR
France	FRA	Mexico	MEX	United Kingdom	GBR
Germany	DEU	Netherlands	NLD	USA	USA

Note: Iceland is excluded owing to missing data.

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