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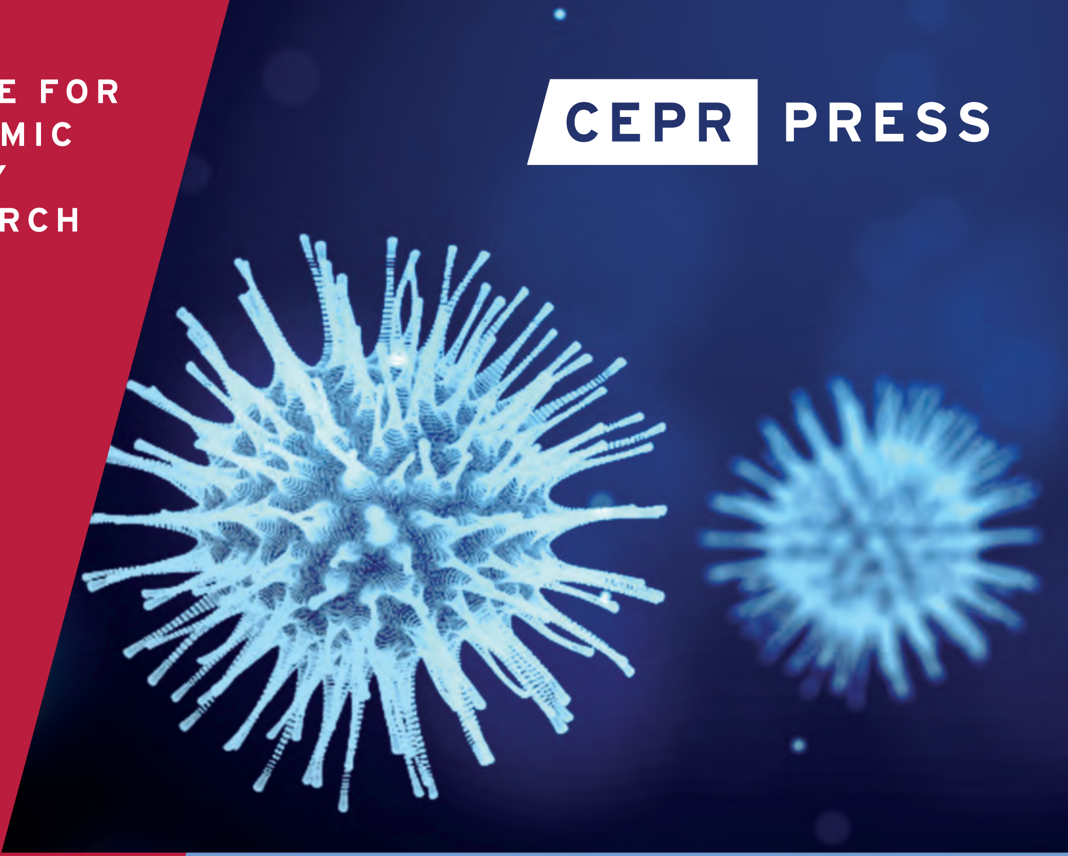

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

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Covid Economics
Vetted and Real-Time Papers

Covid Economics, Vetted and Real-Time Papers, from CEPR, brings together formal investigations on the economic issues emanating from the Covid outbreak, based on explicit theory and/or empirical evidence, to improve the knowledge base.

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Contact: Submissions should be made at https://portal.cepr.org/call-papers-covid-economics. Other queries should be sent to covidecon@cepr.org.

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Ethics

Covid Economics will feature high quality analyses of economic aspects of the health crisis. However, the pandemic also raises a number of complex ethical issues. Economists tend to think about trade-offs, in this case lives vs. costs, patient selection at a time of scarcity, and more. In the spirit of academic freedom, neither the Editors of *Covid Economics* nor CEPR take a stand on these issues and therefore do not bear any responsibility for views expressed in the articles.

Submission to professional journals

The following journals have indicated that they will accept submissions of papers featured in *Covid Economics* because they are working papers. Most expect revised versions. This list will be updated regularly.

American Economic Review

American Economic Review, Applied Economics

American Economic Review, Insights

American Economic Review, Economic Policy

American Economic Review, Macroeconomics

American Economic Review, Microeconomics

American Journal of Health Economics

Canadian Journal of Economics

Economic Journal

Economics of Disasters and Climate Change

International Economic Review

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*Journal of Econometrics**

Journal of Economic Growth

Journal of Economic Theory

*Journal of the European Economic Association**

Journal of Finance

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Journal of Monetary Economics

Journal of Public Economics

Journal of Political Economy

Journal of Population Economics

*Quarterly Journal of Economics**

Review of Economics and Statistics

*Review of Economic Studies**

Review of Financial Studies

(*) Must be a significantly revised and extended version of the paper featured in *Covid Economics*.

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Leading the fight against the pandemic: Does gender 'really' matter?[1]

Supriya Garikipati[2] and Uma Kambhampati[3]

Date submitted: 1 June 2020; **Date accepted:** 3 June 2020

Since the start of the ongoing coronavirus pandemic, the relationship between national female leaders and their effectiveness in handling the COVID-crisis has received a lot of media attention. In this paper we scrutinise this association more systematically. We ask if there is a significant and systematic difference by gender of the national leader in the number of COVID-cases and deaths in the first quarter of the pandemic. We also examine differences in policy responses by male vs. female leaders as plausible explanations for the differences in outcomes. Using a constructed dataset for 194 countries, a variety of socio-demographic variables are used to match nearest neighbours. Our findings show that COVID-outcomes are systematically better in countries led by women and, to some extent, this may be explained by the proactive and coordinated policy responses adopted by them. We use insights from behavioural studies and leadership literature to speculate on the sources of these differences, as well as on their implications. Our hope is that this article will serve as a starting point to illuminate the discussion on the influence of national leaders in explaining the differences in country COVID-outcomes.

1 We are grateful for research support provided by Antara Mandal. Any errors remain the responsibility of the authors.
2 Reader, University of Liverpool.
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Leading the Fight Against the Pandemic: Does Gender 'Really' Matter?

I. Introduction

National responses to the COVID-19 pandemic and their outcomes have been avidly compared across the world. Given the importance of leadership in times of crisis, national leaders have also been in the spotlight. Have leaders been slow in recognising the risks? Have they engaged with the science? Have they weighted the economic costs more heavily than the loss of lives? In this context, much has been written about the performance of women leaders (e.g., Taub, 2020; Friedman, 2020; Wittenberg-Cox, 2020). Much of the media analysis however, has been about two high-profile female leaders (Angela Merkel and Jacinda Ardern) who have steered their countries through the initial few weeks with less loss of life than their immediate comparators in Europe.

In this paper, we consider the question of national leader's gender and COVID-outcomes more systematically and discuss some of the plausible reasons for our findings. Using a 194-country dataset, specifically constructed for this purpose, we analyse two main questions. First, are there any significant and systematic differences in the COVID-outcomes of male and female led-countries in the first quarter of the pandemic? Second, can we point to any differences in policy measures adopted by male and female leaders that might explain the differences in outcomes? In particular, we consider the timing of lockdown in these countries.

The paper relates to various branches of literature that examine gender-differences in behaviour. Closely related is the literature on gender-differences in attitudes to risk and uncertainty. Studies in this area are largely focused on analysing decision-making in experimental settings. There is strong evidence within this literature that women, even those in leadership roles, appear to be more risk-averse than men (e.g., Croson and Gneezy, 2009; Charness and Gneezy, 2012). While this headline result is far from canonical (Nelson, 2015), especially given the role that cultural and contextual modulators play (see Finucane et al., 2000; Schubert, 1999), there is a high level of consistency in the frequency with which it surfaces. For example, Charness and Gneezy (2012) assemble 15 different studies that report findings from one underlying investment game, carried out in different countries, with different instructions, durations, payments and subject pools. They find a very consistent result that men invest more, and thus appear to be more risk taking than women. Indeed, in the current crisis, several incidents of risky behaviour by male leaders have been reported in the press. Particularly noteworthy among these are Brazil's Jair Bolsonaro's dismissal of COVID-19 as

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“a little flu or a bit of a cold”, while attending an anti-lockdown protest in April and Britain’s Boris Johnson’s statement, “I was at a hospital where there were a few coronavirus patients and I shook hands with everybody” (as reported in Lewis, 2020). Given the consistent result on women’s relative aversion to risk and anecdotal reports of risky behaviour by male leaders, it is tempting to draw simplistic conclusions. A reliable conclusion on the issue however requires more systematic investigation.

The second strand of literature that our paper relates to is that on the role of leaders in national outcomes. The question of national leadership has given rise to a voluminous literature that lends texture to two conceptually extreme opinions: the idea that powerful leaders are simply a social myth, created to satisfy our psychological needs (Gemmill and Oakley, 1992) vs. the view that, a handful of influential leaders could be seen as determining the course of history (Keegan, 2003). In their seminar work, Jones and Olken (2005) use death of a leader as an exogenous variation in leadership and find that individual leaders can play a crucial role in shaping the growth of nations. Building on this, Besley, Montalvo and Reynal-Querol (2011) find that more competent leaders (specifically in terms of education and skills) result in better national outcomes. The skill and attainment of the leader is also found to matter in other general settings, like that of organisational performance (Goodall, Kahn and Oswald, 2011).

The performance of female leaders in the COVID pandemic offers a unique global experiment in national crisis management where various issues, including that of effectiveness of leadership, can be examined across countries. There are very few studies about the impact of leader’s gender in a national crisis, partly at least, because there are so few female leaders. In our sample of 194 countries, we have just 19 (<10%) female leaders. This lack of female leadership has given way to ‘single-sex’ conjectures that support the ‘Great Men’ view of history, within which, events are determined by the instrumental and causal influence of a small number of men. For example, Keegan (2003) writes that the political history of the last century can be found in the biographies of six men: Lenin, Stalin, Hitler, Mao, Roosevelt, and Churchill. However, if a leader’s attributes have explanatory power, as much of the literature concludes, then it is a natural next step to ask whether the gender of the national leader, that may represent inherent proclivity for certain type of policy making, exerts an influence on outcomes, especially in the case of an emergency like the pandemic.

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A note of caution before we begin. The pandemic is still in its early stages and therefore our analysis relates only to the initial responses of national leaders and initial outcomes of the pandemic. Given the fast-evolving situation, much will change over the next few months. Despite this, the first quarter reactions and outcomes are revealing because they capture immediate policy responses during an emergency. They therefore highlight the significance of early and effective management in a crisis.

The rest of the paper is arranged as follows. The next section discusses construction of the dataset and methodology. Section 3 presents the results. Section 4 uses insights from risk and leadership literature to speculate on the sources of these differences. Section 5 concludes.

II. Data and Methodology

Data construction

This paper uses a dataset specially collected by the authors for the purpose of this enquiry. We gathered information on total deaths and total cases due to COVID up to May 19th from the Worldometer site. We merged this data with a range of socio-demographic and economic data obtained from the World Development Indicators and UNDP's Human Development Indicators for 194 countries. We collated data on current female leaders from various websites. If countries have more than one head of state, we made a distinction between the executive head (de facto head) and the titular head (de jure or nominal head) based on the characteristics of the political system. We followed the general rule that: in parliamentary regimes, the prime minister is the executive leader while in presidential systems, it is the president, and in communist states, the chairman of the party is the executive head of state. We use this dataset to analyse first, if there is a systematic difference by gender of the national leader in the total number of deaths and cases experienced due to COVID-19. We also use it to consider the national policy responses to the pandemic, particularly the timing of lockdown.

The first step of our analysis centres around two outcome variables – the total number of COVID cases and total deaths. There are several problems with the quality of data currently available. In particular, the number of cases depends on the amount of testing that a country has been able to undertake. With the shortage of test kits, most countries have undertaken less than optimal testing. Over time, the amount of testing being undertaken is increasing as more testing capacity is being made available. To the extent that tests are being reserved for those

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who are symptomatic, data on deaths is likely to be more reliable though there are concerns about its comparability across countries. In some countries, if a COVID-positive individual dies, the death is registered as a COVID-death, irrespective of any other previous illness (like tuberculosis, cancer). But this is not standard or mandatory, so practice varies across countries. Our analysis is based on the best and most comprehensive data available but it is subject to these limitations. As time progresses better COVID data will become available and this analysis can be updated.

One other issue that needs to be highlighted is the fact that we are still very much at the start of the pandemic. There is the expectation that the pandemic will last for another 12-18 months, until we find a vaccine or develop herd immunity (Gallagher, 2020). Our analysis therefore is only about the immediate reaction to the first wave. Outcomes by the end of the pandemic will depend on a range of other issues including the impact of other institutions, the cultural norms prevalent in countries and the impact of the lockdown on the economy, health and well-being of individuals.

Methodology

As mentioned above, any investigation involving female leaders suffers from the problem of small sample size, with only 19 out of 194 countries being led by women in our data. In addition, countries that select female leaders may have specific characteristics which enable them to respond to such crises better. They may be richer, less populous or have better gender relations. Countries that select female leaders may also be more ‘modern’ and ‘equitable’ and therefore perform better during crises. Thus, OLS estimation could suffer from two problems – that of a small number of female-led countries and the potential problem of selection. To correct for these two problems, we use the nearest neighbour matching method wherein we compare a unit in the treated group (female-led countries) with a unit in the control group that is as similar to it as possible along a range of covariates. Matching is a quasi-experimental technique that provides a more reliable way of comparing two groups when sample sizes are heavily imbalanced and where they may be selection issues (see Durrant, 2009; Stuart, 2010).

The nearest neighbour matching method pairs each female-led country in our sample with its closest comparator and estimates the effect of being female-led on the dependent variables (COVID-cases and deaths). The initial matching is done based on four socio-demographic and economic variables that have been seen as important in the transmission of COVID-19 – GDP

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per capita (current USD), Population, Population in Urban agglomerations and Population over 65 Years. We use these variables to match for a range of reasons. First, we include GDP per capita as both the impact of COVID-19 and the ability to respond to it are likely to be influenced by how rich or poor a country is (Barnett-Howell and Mobarak, 2020). Second, the population variable helps us to control for differences in population size and the statistical impact it may have on numbers and spread. Third, we include Population in urban agglomerations as a matching variable because it has been remarked that COVID-19 spreads faster in densely populated regions (Zhang, et.al., 2020). Finally, we include population over 65 because one of the few clear patterns of COVID-19 deaths across the world is that it is especially fatal amongst older individuals, with the death rates climbing steeply for the over 60s (Nikolich-Zugich, et.al., 2020; Zhang, et.al., 2020).

We follow this core analysis by testing for robustness across the sample as well as across matching variables. In our estimation, we consider not only the nearest neighbour but also two nearest, three nearest and five nearest neighbours to consider how robust the effect is. We also extend our matching variables to include three other characteristics – Annual Health Expenditure per capita, Number of Tourists entering the country and Gender Equality. Each of these variables allows us to control for a range of differences that could be significant in determining the outcome variables.

We may expect that countries that have a better equipped health system are likely to perform better in the ongoing crisis. We hence extend our matching model by including the annual expenditure on health in each country (current USD). We match by openness to tourism because the more open a country is to international travel, the harder it will be to control the initial importation of the pandemic. It has been mooted that countries that have more gender equitable institutions might well be those that elect women leaders and that, it is their gender equality more generally rather than their women leaders that have facilitated their differentially better outcomes (e.g., Champoux-Paillé and Croteau, 2020). This may not only mean that women find gaining power easier in these countries, but that women in power may also enjoy greater trust and support from a political and social context that perpetuates the acceptance of female leaders, and may find it easier to champion cautious policies, if they choose to do so. Indeed, the COVID-19 experience of a group of Scandinavian countries may well fall in this category. Matching by the Gender Inequality Index (GII) therefore allows us to control for

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these differences between the women-led countries and their comparators and to identify the impact of a country being female-led more precisely.

III. Results

COVID-cases and deaths by gender of leader

Table 1 below presents summary statistics for the matching covariates and dependent variables by gender of the country's leaders. Although these are raw statistics and not useful to draw inferences, it is clear that female-led countries have fared better in terms of absolute number of COVID-cases and deaths, with male-led countries having nearly double the number of deaths as female-led ones.

Table 1: Summary statistics for matching covariates and dependent variables by gender of leaders

	Female-led (N=19)				Male-led (N=172, unless stated otherwise)			
Study variable	Mean	SD	Min	Max	Mean	SD	Min	Max
First stage matching covariate								
GDP pc (current USD)	34,902	29,810	0	82,797	12,960	22,321	0	185,741
Population	2.017e+07	4.084e+07	38,717	1.647e+08	4.233e+07	1.564e+08	30,231	1.439e+09
Pop in urban agglomerations	24.56	29.16	0	100	15.04	16.89	0	72.25
Population 65 years and over	13.52	6.764	0	21.72	7.826	6.331	0	27.58
Extended matching covariate								
Avg annual pc health expenditure	2,150	2,469	0	7,375	659.9	1,207	0	7,456
Number of international tourists	7.554e+06	1.042e+07	0	3.888e+07	7.212e+06	1.473e+07	0	8.932e+07
Gender Inequality Index 2017	0.189	0.179	0.0390	0.542	0.365 (N=139)	0.185	0.0440	0.834
Dependent variable								
Total COVID-cases	19,064	41,040	12	177,289	26,468 (N=171)	127,125	8	1.550e+06
Total COVID-deaths	1,107	2,681	1	9,080	2,021 (N=148)	9,104	1	91,981

Source: Dataset constructed by authors from various sources.

Table 2: OLS results for COVID-cases and deaths

Covariates	Total cases	Total deaths
Female-led	-42,237.982	-3,553.061*
	(29,256.013)	(2,085.571)
GDP pc	0.780**	0.060**
	(0.388)	(0.029)
Population	0.000***	0.000**
	(0.000)	(0.000)
Population in urban agglomerations	870.373*	46.571
	(463.317)	(34.205)
Population 65 years and over	2,383.713*	252.498**
	(1,413.149)	(103.215)
	-23,216.544	-2,181.782*
Constant	(14,475.292)	(1,150.559)
Observations	190	167
R-squared	0.137	0.142

Note. Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

- *COVID-outcomes (first step matching)*

To get around the small sample size problem while also controlling for various characteristics, we use the nearest neighbour matching method. This method matches each of the 19 female-led countries in our sample with their nearest neighbour using four matching characteristics - GDP per capita, population, population in urban agglomerations and size of elderly dependants. To test the robustness of our results, we also match with two, three and five nearest neighbours. Table 3a presents the results for matched estimations for both total COVID-cases and deaths. Our matched estimations show a definite and consistent pattern, confirming that the number of deaths is lower in women-led countries than in countries led by men. This is also true of the number of cases, though here the significance of the treatment variable decreases as we increase the number of matches. This suggests that controlling for GDP per capita, population, size of urban population and of elderly, female-led countries perform significantly better than male-led countries.

Table 3a: Comparing COVID-outcomes in female-led countries with nearest neighbours (first step matching)

Dependent variable	Nearest neighbour	Two nearest neighbours	Three nearest neighbours
COVID-cases (*N*=190)	-20,578.153**	-18,976.005*	-15,836.658
	(9,546.513)	(9,748.711)	(9,769.106)
COVID-deaths (*N*=167)	-1,673.826**	-1,686.569**	-1,634.265**
	(739.533)	(705.023)	(713.384)

Note. Standard errors in parenthesis. Results for five nearest neighbours are similar.
** $p<0.05$, * $p<0.1$

- *COVID-outcomes (extended matching)*

As mentioned earlier, to test the robustness of our results, we extend the matching to include three other variables that are likely to have an impact on COVID-outcomes are: the condition of the country's health care systems which will impact on its ability to fight the pandemic; openness to tourism which has been professed to affect the rate and speed of transmission, especially in the first quarter before the lockdown; and finally, more liberal and equitable socio-cultural norms which may support policy making and compliance in times of crisis.

Table 3b presents the results for these extensions to the results. As before, we estimate the extension matching models for the nearest neighbours, for two, three and five nearest neighbours. Our results remain robust across these estimations, hence in the interest of space we present results only for the nearest neighbour. Overall, we find that both cases and deaths continue to be lower for female-led countries when we match using the three extension variables.

With respect to ***health expenditure***, conceptually speaking, we might expect this variable to both influence the number of deaths as well as the readiness with which a country is willing to shut down. In particular, countries with worse health infrastructure may choose to shut down quicker for fear of inability to cope with the impact of the virus. This has, in fact, been the case in many developing countries like India and South Africa. Empirically, however, we find that female-led countries with relatively good health care systems like Germany and Taiwan have led the decision to lockdown. After controlling for this, we find that female-led countries have significantly fewer deaths and also spread of COVID-19 than countries led by men.

There has been some concern that countries that are ***open to international travel*** are likely to be more badly affected by the virus, especially in the weeks before countries started closing borders. Our results show that, after controlling for such openness to travel, though female-led countries continue to have an advantage in COVID-19 deaths, they do not experience significantly lower cases. This is interesting as it confirms that women-led countries faced similar numbers of cases as other countries but they experienced fewer deaths. This seems to point to better policies and compliance in these countries.

When we match also by a ***gender equality*** measure (GII) (to consider the fact that countries that elect women are generally more equal and therefore likely to have better resilience), we find that, even after matching for gender-equitability indicators, female leadership provides an advantage.

We carry out one further test to check the robustness of our results. We ***drop the nations*** that have been in the COVID-spotlight - USA, Germany, and New Zealand - from our sample to see if they might be driving the results and we note that these changes in the sample only strengthen the results (Table 4). Finally, it is worth noting that Taiwan (a female-led country) has had a very good response to the crisis. However, we have been unable to include it because the World Bank no longer provides data for it separately from China. Given its exceptional performance during the COVID crisis, its inclusion in our data would reinforce our results rather than dampen them.

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Table 3b: Comparing COVID-outcomes in female-led countries with the nearest neighbour (extended matching)

Dependent variable	Health expenditure	Openness to tourism	Gender equality
COVID-cases	-22,001.621**	-16,164.047*	-24,639.020* (*N* =141)
(*N*=190, unless other stated)	(10,090.670)	(9,372.922)	(13,605.172)
COVID-deaths	-1,899.090**	-1,344.479**	-1,978.809** (*N*=153)
(*N*=167, unless other stated)	(793.446)	(654.175)	(920.060)

Note. Standard errors in parenthesis. Results for up to five nearest neighbours are similar.
** p<0.05, * p<0.1.

Table 4. Comparing COVID-outcomes in female-led countries without nations in the spotlight

Dependent variable	Without the USA	Without Germany	Without New Zealand
COVID-cases (*N*=190)	-20,578.153**	-20,578.153**	-20,578.153**
	(9,546.513)	(9,546.513)	(9,546.513)
COVID-deaths (*N*=167)	-1,673.826**	-1,673.826**	-1,673.826**
	(739.533)	(739.533)	(739.533)

Note. Standard errors in parenthesis.
** p<0.05.

Policy responses to COVID-19 by gender of leader

Our results so far confirm that women-led countries performed better in terms of the number of COVID-deaths experienced and also (though less significantly) in the number of cases. We now turn to consider whether these differences are caused by the immediate policy responses of the leaders. In particular, we are interested in whether female leaders locked down countries systematically more quickly than male leaders. The rate of transmission and deaths are likely to have been lower in countries which locked down early. Testing is another strategy that is likely to have helped with 'track and trace' type of strategies used to contain the pandemic. Given the global shortage of testing kit and associated equipment, we decided not to analyse the testing strategies of leaders. However, raw statistics indicate that the total number of tests is slightly higher in countries led by women and tests per million are significantly higher in countries led by women.

- *Policy responses (first step matching)*

We turn now to consider whether countries led by women locked down systematically more quickly than those led by men. The total deaths at lockdown in female-led countries are 22 fewer than male-led countries. Our matching estimates presented in Table 5a indicate that whether compared with the closest neighbours, two, three or five closest neighbours, women-

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led countries did close down significantly more quickly than countries led by men when considering number of deaths at lockdown.

Table 5a. Comparing timing of lockdown in female-led countries with nearest neighbours (first step matching)

Dependent variable (*N*=128)	Nearest neighbour	Two Nearest	Three Nearest
COVID-cases at lockdown	-339.320	-176.574	-219.622
	(340.825)	(464.340)	(526.868)
COVID-deaths at lockdown	-25.203***	-25.234***	-24.448***
	(8.446)	(8.424)	(8.128)

Note. Standard errors in parenthesis. Results for five nearest neighbours are similar.
*** p<0.01.

- *Policy response (extended matching)*

Extending our lockdown model to match for annual health expenditure, openness to tourists and GII, we find that the women-led countries locked down earlier (at lower number of deaths) than countries led by men (Table 5b). This means women leaders reacted more quickly and decisively to the crisis. Better initial outcomes in female led countries when compared to male led ones was because of this difference in responses. However, our results also make clear that the decisive factor was the number of deaths and not the number of cases at lockdown. There is no significant difference in the number of cases at lockdown for men and women led countries.

Table 5b. Comparing timing of lockdown in female-led countries with nearest neighbours (extended matching)

Dependent variable (*N*=128)	Nearest neighbour	Two Nearest	Three Nearest
COVID-cases at lockdown	-339.320	-176.574	-219.622
	(340.825)	(464.340)	(526.868)
COVID-deaths at lockdown	-25.203***	-25.234***	-24.448***
	(8.446)	(8.424)	(8.128)

Note. Standard errors in parenthesis. Results for five nearest neighbours are similar.
*** p<0.01.

Why did women leaders respond differently to the COVID-crisis from male leaders? What might explain the difference in the behaviour of women leaders as compared to their male counterparts? In the next section, we will consider some ideas from behavioural economics and leadership literature to speculate on the sources of these differences, as well as on their implications.

IV. Discussion

Our results above clearly indicate that women leaders reacted more quickly and decisively in the face of potential fatalities. In almost all cases, they locked down earlier than male leaders

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in similar circumstances. While this may have longer-term economic implications, which we cannot test here, it has certainly helped these countries to save lives, as evidenced by the significantly lower numbers of deaths in these countries. Why have women been quicker to lockdown? As discussed earlier, one idea that might have a bearing on our result is that there are gender-differences in attitudes to risk and uncertainty (e.g., Croson and Gneezy, 2009; Charness and Gneezy, 2012). However, this basic hypothesis has to be nuanced to highlight that women were less willing to take risks with lives but were more willing to accept risks in relation to the early lockdown of economies. We also consider learnings from the leadership literature to understand differences in leadership behaviours evidenced by men and women.

Gender differences in attitudes to risk

While risk aversion may explain why women leaders chose to close down their countries significantly early (in terms of the COVID-deaths at lockdown) when compared to their male counterparts, it does not explain the significant risk that women leaders were prepared to take with their economies by locking down early. Clearly, we need to look beyond the simplistic headline result. It could be that risks manifest differently in different domains – human life vs economic outcomes. If this were true, then women leaders could be seen as being significantly more risk averse than male leaders in the domain of human life, though, in the domain of the economy, these women leaders were clearly prepared to take more risk than male leaders.

We find some support for this idea in studies that examine risk taking behavior when lotteries are framed as losses. For example, Schubert et al. (1999) find that men are more risk averse than women when lotteries are framed as financial losses rather than gains. A similar result is also reported by Moore and Eckel (2006) who find that in the loss-domain gambles, men are more risk-averse and less ambiguity-seeking than women. It could well be that the relatively late lockdown decisions by male leaders may reflect male risk aversion to anticipated losses from locking down the economy.

Another strand of the risk literature that is of interest to us is one that considers risk-taking decisions by leaders on behalf of others in their group. Ertac and Gurdal (2012) observe that in terms of risk attitudes, the women who like to lead and decide for the group are no different from women who do not wish to lead. For men, however, they find that the ones who would like to lead tend to take more risk on behalf of the group. Similarly, studies examining

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confidence and associated behaviour among men and women find that while both men and women are often overconfident, men are more overconfident of success in uncertain situations than women (Barber and Odean, 2001; Niederle and Vesterlund, 2007).

Evidence in psychology also indicates that men and women react very differently to negative experiences. Women are seen to respond more strongly and intensely than men when anticipating negative outcomes (see Fujita et al., 1991; Kring and Gordon, 1998). This can affect their utility of a risky choice and hence their decision. For example, if a negative outcome is anticipated as being worse by women than by men, they will be more risk averse when facing a risky situation, like the current pandemic. Men are also found to respond with anger to negative experiences and anger is seen to make them less cautious about future gambles, but women respond with caution, making them more prudent in their beliefs and restrained in their actions (Lerner et al. 2003).

The neuroscience literature, in its turn, indicates that there could be sex differences in feelings of empathy which cannot be fully explained as cultural derivatives of socialisation alone but have deeper neurobiological drivers. Examining the neurobiological underpinnings of male and female feelings of empathy, Christov-Moore et. al., (2014) find that there are important quantitative gender differences in the basic networks involved in affective and cognitive forms of empathy, as well as a qualitative divergence between the sexes in how emotional information is integrated to support decision making processes (see also Eckel and Grossman, 2002). When combined with the findings from the risk literature and psychology, we begin to see how women leaders could have been risk-averse about anticipated losses to human life, while at the same time taking risk with negative financial outcomes associated with early lockdown.

Gender difference in leadership styles

It is likely that leadership characteristics other than risk attitudes may also systematically differ between men and women. The early literature on leadership associated leaders with attributes that are characteristic of the stereotypic male. For example, Rost (1991) examines 221 definitions of leadership from the last century and concludes that leadership has most frequently been described as "rational, management-oriented, male, technocratic, quantitative, cost-driven, hierarchical, short-term, pragmatic and materialistic". Of course, women can display these supposedly 'male' management traits and vice versa. For example, both Ardern and Trudeau present themselves as being socially and environmentally aware and as being able

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to communicate sensitively with minority groups (Lewis, 2020). Despite this, is it possible that male and female leaders are inherently different? Do male and female leadership styles differ?

Eagly and Johnson (1990) conduct a meta-analysis of research that compares male and female leadership styles and conclude that evidence can be found for both the presence and absence of differences between the sexes. While research in organisational studies found little difference between male and female leadership styles, laboratory experiments and assessment studies found evidence to suggest that leadership styles were somewhat gender stereotypic with men likely to lead in a 'task-oriented' style and women in an 'interpersonally-oriented' manner. Consistent with this finding, women tended to adopt a more democratic and participative style and a less autocratic or directive style than men. These attributes have been seen as key in a number of studies, especially in managing a crisis (Marcus, Dorn and Henderson 2006; Waugh and Streib 2006; Van Wart and Kapucu 2011). In line with this, Zheng, Kark and Meister (2018) propose that effective women leaders may adopt a paradoxical mindset that simultaneously embrace the dual demands of their role as leaders and their gender identify to build a more resilient leadership style.

Indeed, the decisive and clear communication styles adopted by several female leaders have received much praise in the ongoing crisis (e.g., Henley and Roy, 2020; McLean, 2020; Taub, 2020). Thus, Norway's Prime Minister, Solberg, spoke direct to children answering their questions, while the New Zealand Prime Minster, Ardern, was praised for the way in which she communicated and for checking in with her citizens through Facebook Live. Evidence also suggests that good communications skills are important for women to be chosen as leaders (Lemoine, Aggarwal, Steed, 2016).

There seems to be some evidence therefore that being risk averse with respect to loss of lives and having a clear, empathetic and decisive communication style made a significant difference to immediate outcomes of the COVID pandemic in women-led countries.

V. Conclusion

In this paper, we ask if there is a significant and systematic difference by gender of the national leader in the number of COVID-cases and deaths in the first quarter of the pandemic. We also examine differences in policy responses by male vs. female leaders as plausible explanations for the differences in outcomes. We use a specifically constructed dataset for 194 countries for our analysis. Our findings show that COVID-outcomes are systematically and significantly better in countries led by women and, to some extent, this may be explained by the proactive policy responses they adopted. Even accounting for institutional context and other controls, being female-led has provided countries with an advantage in the current crisis.

Examining what is already known about the gender differences in behaviour from a variety of disciplines gives us some insights into observed differential behaviour of female and male leaders in tackling the current pandemic. The factors affecting the pandemic outcomes in various countries are likely to be complex. However, the gender of leadership could well have been key in the current context where attitudes to risk and empathy mattered as did clear and decisive communications. It is clear that many of these factors will need to be considered in the months and years ahead as the outcomes of the pandemic mature and the impacts on the economy become apparent across countries. Our analysis relates to the immediate responses of world leaders, wherein women leaders seem to have emerged highly successful.

References

Barber, Brad and Terrance Odean. 2001. Boys will be boys: Gender, overconfidence, and common stock investment", *The Quarterly Journal of Economics*. 116(1): 261-92

Barnett-Howell, Zachary and Mobarak Ahmed Mush□q. 2020. The Benefits and Costs of Social Distancing in Rich and Poor Countries, *arXiv:2004.04867v1 [econ.GN]* https://arxiv.org/abs/2004.04867 (accessed on 20/05/2020)

Besley, Timothy, Jose G Montalvo and Marta Reynal-Querol. 2011. "Do Educated Leaders Matter?", *The Economic Journal,* 121 (554): 205-227.

Champoux-Paillé Louise and Anne-Marie Croteau. 2020. "Why women leaders are excelling during the coronavirus pandemic", Conversation. https://theconversation.com/why-women-leaders-are-excelling-during-the-coronavirus-pandemic-138098 (accessed 20/05/2020)

Charness, Gary, and Uri Gneezy, 2012. Strong Evidence for Gender Differences in Risk Taking, *Journal of Economic Behavior & Organization*,ISSN 0167-2681, http://dx.doi.org/10.1016/j.jebo.2011.06.007. Volume 83 (1): 50-58.

Christov-Moore, Leonardo, Elizabeth A. Simpson, Gino Coudéb, Kristina Grigaityte, Marco Iacobonia, Pier Francesco Ferrari.2014. Empathy: Gender effects in brain and behaviour, Neuroscience and Biobehavioral Reviews 46: 604–627.

Croson, Rachel, & Uri Gneezy. 2009. Gender differences in preferences. *Journal of Economic Literature*, 448-474.

Durrant, Gabriele B. 2009. Imputation methods for handling item-nonresponse in practice: methodological issues and recent debates, International Journal of Social Research Methodology, 12:4, 293-304.

Eagly, Alice H. and Blair T Johnson. "Gender and Leadership Style: A Meta-Analysis" 1990. *CHIP Documents*. 11. https://opencommons.uconn.edu/chip_docs/11 (accessed 02/05/2020)

Eckel, C., Grossman, P., 2002. "Sex differences and statistical stereotyping in attitudes toward financial risk", *Evolution and Human Behavior*, 23, 281–295.

Ertac Seda, Mehmet Y. Gurdal. 2012. "Deciding to decide: Gender, leadership and risk-taking in groups", *Journal of Economic Behavior & Organization*, 83:24-30.

Finucane, Melissa L., Paul Slovic, C. K. Mertz, James Flynn, and Theresa A. Satterfield. 2000. "Gender, Race, and Perceived Risk: The 'White Male' Effect." *Health, Risk and Society*, 2(2): 159–72.

Fujita, Frank, Ed Diener, and Ed Sandvik. 1991. "Gender Differences in Negative Affect and Well-Being: The Case for Emotional Intensity." *Journal of Personality and Social Psychology*, 61(3): 427–34.

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Gallagher, James.2020. https://www.bbc.co.uk/news/health-51963486(accessed 20/05/2020)

Gemmill, Gary and Judith Oakley. 1992. "Leadership: An Alienating Social Myth?" *Human Relations,* XLV, 113–129.

Goodall, Amanda H, Lawrence M. Kahn and Andrew J. Oswald. 2011. "Why do leaders matter? A study of expert knowledge in a superstar setting." *Journal of Economic Behavior & Organization,* 77(3): 265-284.

Henley, Jon and Eleanor Ainge Roy. 2020. Are female leaders more successful at managing the coronavirus crisis?, Guardian, 25th April https://www.theguardian.com/world/2020/apr/25/why-do-female-leaders-seem-to-be-more-successful-at-managing-the-coronavirus-crisis (accessed 25/05/2020)

Jones, Benjamin and Benjamin A. Olken. 2005. "Do Leaders Matter? National Leadership and Growth Since World War II" *The Quarterly Journal of Economics*, 120(3): 835-864.

Keegan, John. 2003. "Winston Churchill," *Time Magazine*, World Wide Web: http://www.time.com/time/time100/leaders/prole/churchill.html. (accessed 10/05/2020)

Kring, Ann M and Albert H. Gordon.1998. "Sex Differences in Emotion: Expression, Experience, and Physiology," *Journal of Personality and Social Psychology*, 74(3): 686-703

Lerner, Jennifer S., Roxana M. Gonzalez, Deborah A. Small, and Baruch Fischhoff. 2003. "Effects of Fear and Anger on Perceived Risks of Terrorism: A National Field Experiment." *Psychological Science*, 14(2): 144–50.

Lemoine G. James, Aggarwal Ishani, Laurens Bujold Steed. 2016. "When women emerge as leaders: Effects of extraversion and gender composition in groups", *The Leadership Quarterly*, 27(3): 470-486.

Lewis Helen. 2020. The Pandemic has Revealed the Weakness of Strongmen, The Atlantic, 6th May. https://www.theatlantic.com/international/archive/2020/05/new-zealand-germany-women-leadership-strongmen-coronavirus/611161/ (accessed 20/05/2020)

Marcus, Leonard J., Barry C Dorn and Joseph M. Henderson. 2006. Meta-Leadership and National Emergency Preparedness: A Model to Build Government, Biosecurity and Bioterrorism, 4(2): 128-134.

McLean, V. 2020. Coronavirus is showing yet again why the world needs more strong female decision-makers, 12th April, https://www.euronews.com/2020/05/12/coronavirus-showing-yet-again-why-the-world-needs-more-strong-female-decision-makers-view (accessed 20/05/2020)

Moore Evan and Catherine Eckel. 2006. "Measuring ambiguity aversion", Research Gate. https://www.researchgate.net/publication/228790553_Measuring_ambiguity_aversion (accessed 05/05/2020)

Nelson A Julie. 2015. "Are women really more risk-averse than men? A re-analysis of the literature using expanded methods", *Journal of Economic Surveys*, 29(3): 566-85.

Niederle, Muriele and Lise Vesterlund.2007. Do women shy away from competition? Do men compete too much? *The Quarterly Journal of Economics*, 122(3):1067-1101

Nikolich-Zugich, Janko., Kenneth S Knox, Carlos Tafich Rios, Natt Bhupinder, Deepta Bhattacharya and Mindy J. Fain. 2020. "SARS-CoV-2 and COVID-19 in older adults: what we may expect regarding pathogenesis, immune responses, and outcomes", *GeroScience*, 42:505–514.

Rost, Joseph C.1991. *Leadership in the 21st Century.* New York: Praeger

Schubert, Renate, Martin Brown, Matthias Gysler, and Hans Wolfgang Brachinger. 1999. "Financial Decision-Making: Are Women Really More Risk-Averse?" *American Economic Review*, 89(2): 381–85.

Stuart Elizabeth A. , 2010. Matching Methods for Causal Inference: A Review and a Look Forward, *Statistical Science*, 25, (1):1-21.

Taub Amanda. 2020. "Why Are Women-Led Nations Doing Better With Covid-19?"*, New York Times,* 15 May. https://www.nytimes.com/2020/05/15/world/coronavirus-women-leaders.html (accessed 25/05/2020)

Van Wart, Montgomery and Naim Kapucu. 2011. "Crisis Management Competencies: The case of emergency managers in the USA", *Public Management Review*, 13 (4): 489-511.

Waugh, William L. and Gregory Streib. 2006. Collaboration and Leadership for Effective Emergency Management, Public Administration Review, 66(1): 131-140.

Wittenberg-Cox, Avivah. 2020. "What do countries with best coronavirus responses have in common?", Forbes. 13/04/2020. https://www.forbes.com/sites/avivahwittenbergcox/2020/04/13/what-do-countries-with-the-best-coronavirus-reponses-have-in-common-women-leaders/#3ce529813dec (accessed on 10/05/2020)

Zhang, Juanjuan, Maria Litvinova, Yuxia Liang, , Yan Wang, Wei Wang, Shanlu Zhao, Qianhui Wu, Stefano Merler, Cécile Viboud, Alessandro Vespignani, Marco Ajelli, Hongjie, Yu. 2020. "Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China", *Science*, 29 April.

Zheng Wei., RonitKark, Alyson L.Meister. 2018. "Paradox versus dilemma mindset: A theory of how women leaders navigate the tensions between agency and communion", *The Leadership Quarterly*, 29(5): 584-596

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Lockdowns and COVID-19 deaths in Scandinavia[1]

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We estimate the impact of non-pharmacological interventions (NPIs) on COVID-19 deaths in Scandinavia. We exploit policy variation between Denmark and Norway on the one hand and Sweden on the other. The former deployed relatively more stringent lockdowns, the latter did not. Our difference-in-differences models show that stricter lockdown policies are associated with fewer COVID-19 deaths.

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1. Introduction

Do lockdowns lead to fewer deaths from COVID-19? We contrast two types of non-pharmacological interventions (NPIs). Denmark and Norway have pursued a strict lockdown policy in response to the COVID-19 pandemic. This includes widespread business and school closure, as well as travel restrictions. In contrast, Sweden implemented a less strict NPI, based more on community trust and far fewer business and school interruptions. In our statistical model we assign Denmark and Norway to the treatment group and Sweden to a control group based on their use of different NPIs. We then estimate a difference-in-differences model to identify the (potentially causal) effect of lockdown NPIs on COVID-19 deaths. We use daily data from March 2020 to the end of May 2020.[1]

Why is the research question important? Many major countries have employed strict lockdown policies. These NPIs include closing businesses, closing schools and imposing stay-at-home or shelter-in-place orders. Government imposed shutdowns have led to sharp declines in growth, massive dislocations in capital and product markets, and surging levels of unemployment. So, how do NPI policies save lives?[2] To satisfactorily answer that question, one needs an appropriate comparison group. Namely, do lockdowns reduce COVID-19 deaths comparatively and if so, compared to what? We exploit the fact that *ex ante* Denmark, Norway and Sweden are very similar societies (i.e. a deep enduring Scandinavian tradition and culture) but *ex post* Sweden diverged

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[1] Ultimately, we only have observational data. The 'gold standard' of random assignment to treatment/control groups is not possible. But the three sample countries are sufficiently similar, *ex ante*, to make the allocation reasonable and then evaluate *ex post* the policy response to an exogenous supply/demand shock caused by the novel coronavirus.

[2] See Haushofer& Metcalf (2020) on which interventions work best during a pandemic. See Kraemer et. al. (2020) for social distancing policies in China. See Born et al (2020) for the case of Sweden.

from Denmark and Norway by not engaging in strict lockdowns. Accordingly, Sweden emerges as a potentially reasonable control group to evaluate the efficacy of 'lockdown policy' in the treatment countries.

2. Institutional Context

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is the novel coronavirus that causes the coronavirus disease 2019 (COVID-19).[3] The disease primarily impacts the lower respiratory system. However, SARS-CoV-2 also affects the heart, kidneys and brain.[4] The case fatality rate is highest among older people (>60 years of age) and those with comorbidities (pre-existing medical conditions such as diabetes and cardiovascular disease).[5] SARS-CoV-2 is highly infectious (more so than influenza).

COVID-19 originated in China and Asia in December 2019, and then spread to Europe and the United States in early 2020. The World Health Organization (WHO) declared the disease a global pandemic on Wednesday 13 March 2020. There is currently no vaccine for SARS-CoV-2. There is no herd immunity in the community because SARS-CoV-2 is novel. The world is, at the time of writing, in a race to develop an efficient and safe pharmacological vaccine to treat SARS-2.

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[3] See Gorbalenya et. al. (2020).

[4] See Puelles, et. al. 2020 on how COVID-19 can be thought of as a whole-body disease, even though the SARS-CoV-2 primary effect is on the lower respiratory system.

[5] According to the Worldometer (2020) data, the crude mortality rate of COVID-19 is less than 0.5% for 50 years or younger, 1.3% for 50-59 years old, 3.6% for 60-69 years old, 8.0% for 70-79 years old, and 14.8% for 80+ years old. The mortality rate is 10.5% for those with cardiovascular disease, 7.3% for those with diabetes, in comparison to 0.9% for patients without pre-existing conditions.

Recorded global cases from COVID-19 at the end of May 2020 exceed six million people, including more than 350,000 deaths.

In the absence of pharmacological solutions, the primary global response has been non-pharmacological interventions (NPIs). These strategies include closing businesses, closing schools and educational establishments, and restrictions on the number of people who can gather at any one time. A new phrase entered the English language overnight: Social Distancing. And, in a stroke, many previously enjoyed civil liberties were suspended. Importantly, do NPIs targeted at modifying human behavior lead to fewer deaths? [6]

Why Scandinavia? In the absence of randomized controlled trials, we are compelled to use observational data to test the efficacy of NPIs on COVID-19 deaths. Denmark, Norway and Sweden share sufficient similarities so that when faced with an exogenous policy intervention in one country, we can split these countries into a 'treatment' and a 'control' group. This allows a direct test of strict lockdowns, compared to an otherwise similar control group without it.

Table 1 shows that the three economies are small. Denmark and Norway have populations of approximately five million people, and Sweden is about twice as large. Our econometric models below normalize on country size. Denmark and Sweden have approximately the same GDP per capita (about $48,000) and Norway is higher (about $65,000) — all measured at constant PPP US dollar.

[6] Van Bavel et. al. (2002) discuss how behavioral science can help align human behavior with best practice recommendations from epidemiologists and public health professionals.

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Table 1: Summary Data on Country Characteristics

	Denmark	Norway	Sweden
Population[1]	5,790,172	5,416,936	10,093,210
GDP per capita PPP[2]	$47,673	$65,441	$ 47,194
Trust most other people – "Yes"?[3]	83.0%	73.8%	63.8%
Hospital beds per 1000 people[4]	2.5	3.6	2.2
Medical doctors per 1000 people[4]	4.27	5.53	4.32
Nurses per 1000 people[4]	11.24	20.83	11.49
ICU beds per 1000 people[4]	246	343	234
Number of cases on 03/13/20[5]	676	621	620
Confirmed cases per million people on 03/13/20[5]	116.7	114.6	61.4
Number of recorded deaths on 03/13/20[5]	0	1	1
Number of recorded deaths per million on 03/13/20[5]	0	0.18	0.09
Number of tests per million[6]	33.7	25.1	9.1

Notes:
[1] *Population data: https://worldpopulationreview.com/*
[2] *GDP data: https://tradingeconomics.com/ GDP data for each country.*
[3] *Trust data: https://ourworldindata.org/trust and originally the World Value Survey. The Danish trust data are estimated from the Eurostat data reported by Esteban Ortiz-Ospina and Max Roser on https://ourworldindata.org/trust.*
[4] *Hospital & healthcare capacity data: https://tradingeconomics.com/ health indicators for each country.*
[5] *COVID-19 data: https://ourworldindata.org/.*
[6] *COVID-19 data: https://ourworldindata.org/. Average number between 1 March 2020 and 31 May 2020*

The World Values Survey data show that Scandinavian countries are characterized by very high and persistent levels of trust. The percentage of people agreeing with the statement 'most people can be trusted' is about 64% in Sweden and 74% in Norway and appears to be slightly higher (around 83%) in Denmark.[7] There is little evidence, however, that Sweden is more trusting vis-a-vis its Nordic neighbors.

Table 1 shows that health service capabilities are broadly similar across the three countries. This is measured by the number of doctors, nurses, hospital beds and intensive care unit facilities. At a top level, there is little evidence to suggest that the health care systems cannot respond in similar ways to the COVID-19 pandemic. However, Juranek and Zoutman (2020) show that if Denmark and Norway had followed Sweden's more lenient policy, hospitalizations and ICU cases would have been significantly higher.

The data show, too, that each country has shared experience of the COVID-19 disease when the World Health Organization (WHO) announced a pandemic on 13 March, 2020. There were about the same number of cases reported in each country (about 650); the population-adjusted number being lower in Sweden compared to Denmark and Norway. The number of recorded case fatalities from COVID-19 was zero or one.

2.1 Scandinavian NPI Policy Response to COVID-19.

We study the Scandinavian countries, Denmark, Norway and Sweden. Broadly, Denmark and Norway introduced 'strict' non-pharmacological interventions (e.g. closing schools, travel restrictions and businesses). Sweden introduced 'less-strict' NPIs, based on trust and individual responsibility.[8] Interestingly, the Danish Health Authority (2020) essentially recommended a

[7] In comparison, the United States has lower trust levels. Less than 40% of people surveyed say that most people can be trusted.

[8] Sweden's senior epidemiologist, Anders Tegnell, discusses the benefits of the strategy (Nature, 2020)

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Swedish strategy in early March, but was overridden by the Danish government, which instructed its Head Søren Brostrøm to apply "a principle of extreme caution" in communicating about the epidemic (Politiken, 2020). *Ex ante*, it was unclear that Denmark, Norway or Sweden would choose the intervention they did. This gives credence to the idea that the NPI strategies pursued by each country were, prior to the pandemic shock, largely exogenous. The implicit reasoning is that both types of intervention (stringent/less stringent) modify human behavior and interaction. The binary classification of NPIs is, of course, somewhat crude as each country displays nuanced features. The mapping into strict and non-strict NPIs suffices for our purposes.

Table 2 shows Scandinavian interventions, using the classification schema developed by the Institute for Health Metrics and Evaluation at the University of Washington. Among the six categories, Denmark and Norway implement three: closing educational facilities, restrictions on gatherings, and various forms of business closure. Sweden implements only one: restrictions on gatherings. Note that stay-at-home orders, closure of all non-essential businesses and complete travel restrictions are not imposed in any of the three countries, although Denmark and Norway did close their borders to non-essential travel while keeping them open for returning citizens.[9] The final row shows the mean value of the Government Response Stringency Index. This is a composite measure (based on 9 response indicators including school closures, workplace closures, and travel bans, etc.) ranging from 0 to 100 (100 = strictest response). As shown, Denmark and Norway have relatively high intervention stringency (63/69), whereas Sweden is the least strict (33).

[9] Other European economies did completely lock down, deploying stay-at-home orders, closing all non-essential businesses, and restricting movement of people. For example, the United Kingdom and France.

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Table 2: Scandinavian COVID-19 Government Interventions

Type of Social Distancing Intervention	Denmark	Norway	Sweden
Educational facilities closed[1,2]	Start 16 March 2020	Start 12 March 2020. Schools, kindergartens closed, but gradually reopened starting from April 20	Never fully implemented. Preschools or elementary schools not closed
Any gathering restrictions[1, 2]	Start 13 March 2020. 18 March 2020 ban on > 10 people. Fines for violations.	Start 12 March 2020. Sports and cultural events and gatherings on >50 people are banned.	Start 11 March 2020 ban on > 500 people. On 27 March ban on > 50 people.
Stay-at-home order[1]	Never fully implemented	Never fully implemented	Never fully implemented
Any business closure[1]	Start 18 March 2020	Start 12 March 2020	Never fully implemented
All non-essential business closed[1]	Never fully implemented	Never fully implemented	Never fully implemented
Travel severely limited[1]	Never fully implemented	Never fully implemented	Never fully implemented
Stringency Index[3] – range 0 to 100 (low to high)	69.4	63.0	32.8

[1] *Sources: Institute for Health Metrics and Evaluation, University of Washington. https://covid19.healthdata.org/denmark, https://covid19.healthdata.org/norway, https://covid19.healthdata.org/sweden*

[2] Sources: Wikipedia pandemic pages. https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Sweden. https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Denmark. https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Norway.

[3] Government Response Stringency Index: Composite measure based on 9 response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response). Mean response reported for the sample period. Source is the Oxford COVID-19 Government Response Tracker, Blavatnik School of Government

We do want to stress, though, that there are important nuances in the responses of the respective Scandinavian countries. For example, we use the shorthand phrase, 'lockdown' for Denmark and

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Norway, yet neither country went as far as for example Italy or the United Kingdom. So, the term 'lockdown' in this paper refers to Sweden relative to Denmark and Norway. At the same time, the 'softer' or 'less strict' measures implemented in Sweden (including encouraging work-from-home, avoiding social contact for high-risk groups etc.) also appeared to influence human behavior and social distancing. This could imply that there was more public fear of contacting or spreading the SARs-2-CoV virus. We note that Google (2020) community mobility data (reported on May 25, 2020) show a clear decline in transit station and workplace mobility in Sweden. The same magnitude of relative decline is observed in Denmark and Norway.[10]

Moreover, Sweden stands out in other nuanced ways compared to Denmark and Norway. Sweden was not only less strict in its policy implication but also later in implementing them. For example, gatherings of more than 50 people were allowed until March 29th (gatherings with 500 or more were allowed until March 11th) and visits to relatives in elderly homes were allowed until April 1st. (see Table 2). Lastly, we note that Sweden has done less testing compared to Norway and Denmark (See Table 1). The number of tests per million people has been increasing over time, but the average in Sweden remains below that of the other two countries.

3. Econometric model and data

We estimate a simple difference-in-differences (DiD) model to identify the lockdown effect on death rates:

[10] For example, workplace mobility was down 25% relative to the baseline estimate in Sweden. It declined 26% in Norway and was down 24% in Denmark. Mobility trends for places of public transport hubs including subway, bus, and train stations were down 27% in Denmark, 26% in Norway and 25% in Sweden. The percentage changes are based on the 6 weeks before the report date. In the future, we think such data could be used to provide a more detailed picture of what has happened in the Nordic countries.

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$$y = \beta_0 + \delta_0 dP + \beta_1 dT + \delta_1 dP \times dT + \epsilon$$

Where y is the outcome variable. dP is a dummy equal to one for the post-policy time period, and zero indicating the pre-policy era. dT is a dummy equal to one for countries in the treatment group (Denmark/Norway) and zero referring to the control group (Sweden). δ_1 measures the effect of the NPI policy, which is simply:

$$\widehat{\delta_1} = \left(\bar{y}_{2,T} - \bar{y}_{1,T}\right) - (\bar{y}_{2,C} - \bar{y}_{1,C})$$

Namely, it is the difference in means for the treatment group [T] over time from period 1 to period 2 compared to the difference in mean outcomes for the control group [C] over the same time period. The dependent variable, y, is measured as recorded deaths from COVID-19 per million of the population. The data are sourced from "Our World in Data". The github repository is https://github.com/owid/COVID-19-data. The original data are published by the European Centre for Disease Prevention and Control (ECDC). Our model uses daily data from 6 March 2020 to the 25 May 2020.[11]

There is a reasonable debate as to whether the dependent variable is measured with error or not. For instance, deaths might be over-stated if a person dies *with* the disease but not directly *from* the disease because of some other comorbidity. Conversely, people might die at home rather than in hospital and there is a failure to count a COVID-19 death. Measurement error can go both ways. We acknowledge but sidestep these issues in the current paper. To make progress, we work with the data currently available to the scientific community.

[11] Our approach differs from Born et. al. (2020) who compare Sweden to a synthetic control group. They find that "… infection dynamics in the doppelganger since the lockdown do not systematically differ from the actual dynamics in Sweden".

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The treatment group [T] is Denmark and Norway (i.e. the 'lockdown' NPI). The control group [C] is Sweden, who favored trust-based social distancing measures (i.e. 'non-lockdown' NPI). The interaction term in the model identifies the policy effect of the lockdown in the treated group. Within the potential outcomes framework (Angrist and Pischke, 2008), this is simply the average treatment effect of the treated (ATT). In expectation, the sign is negative and significant. Lockdowns lead to fewer deaths from COVID-19 post intervention.

There is a question as to the exact date on which to split the data into a 'before' and 'after' period. Scandinavian countries implemented varying degrees of NPIs around the 13 March 2020. However, there is a time lag between infection and recovery (including death) which could well exceed many weeks. This means we might not observe an immediate policy effect since there is an infection event, followed by an incubation period (e.g. about ten days on average), and then a further illness period (e.g. another ten days on average) when the person either recovers or dies.

How do we deal with this? We follow a simple strategy. We first estimate the difference-in-differences (DiD) model setting the time period *t* equal to the 18 March 2020. We then move the splitting date forward in increments of two week (fourteen days) to account for possible lag effects. So, model 1 defines the break at time (*t*) equal to 03/18/20. At this date we estimate the difference-in-differences model using a 15-day window from (t-7) to (t+7) surrounding the break time. Next, model 2 defines the new break at time (*t*) equal to 04/1/20. At this new date, we again estimate the difference-in-differences model using a 15-day window from (t-7) to (t+7). And so on, in equal two-weekly increments. This might seem arbitrary but specifying a full model with daily lags and

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country effects is not statistically identifiable due to lack of cross-sectional data.[12] It also has the advantage of not using overlapping data. As the results below show, the empirical findings are very robust and in non-tabulated regressions the findings did not appear to be sensitive to these bloc classifications.

4. Results

Figure 1 shows Scandinavian deaths per million people from the 6 March 2020 through the end of May 2020. The vertical line is set at 18 March 2002, the date when Scandinavian countries started non-pharmacological interventions to combat COVID-19. The next vertical lines are spaced at 14-day intervals. At each of these dates (i.e. dashed line) we estimate the difference-in-differences model using data 7 days before and 7 days after. The data illustrate our main point, formally shown in the DiD estimates below. Prior to the NPI all countries were broadly similar. Post NPI COVID-19 case fatalities in Denmark and Norway move broadly together, whereas deaths per million in Sweden rise sharply.

[12] Country N=3, Daily T= # of days in the event window. Therefore, degrees of freedom are used up rapidly if a pooled DiD model is specified with many daily lags.

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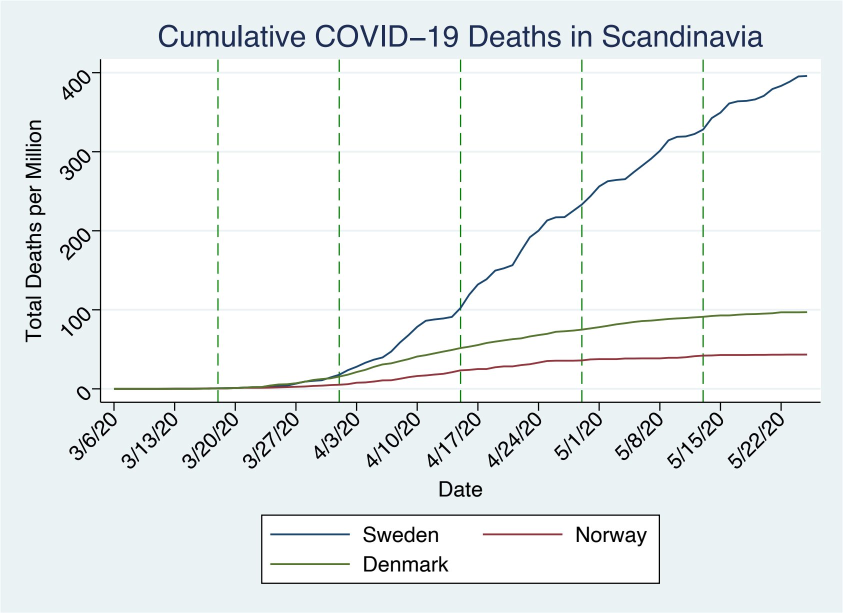
Figure 1: Scandinavian COVID-19 Cumulative Deaths per Million People



Data source: https://raw.githubusercontent.com/owid/COVID-19-data/master/public/data/owid-covid-data.csv. Original data published by the European Centre for Disease Prevention and Control (ECDC). The first dashed vertical line is the date when countries are assumed to begin interventions. The next lines are spaced at 14-day intervals. At each of these dates (i.e. dashed line) we estimate the difference-in-differences model using data 7 days before and 7 days after. See Table 3 below for results.

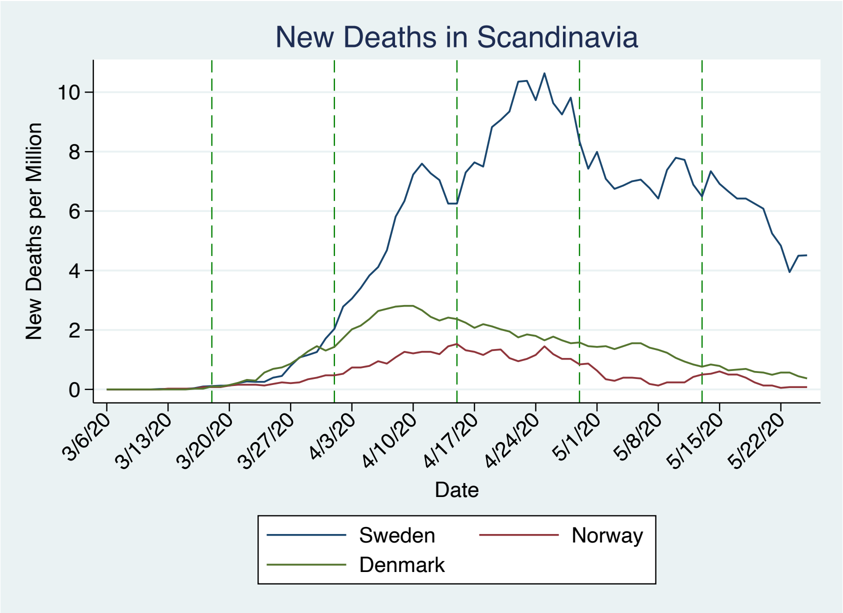
Implicit in Figure 1 is that the change in the COVID-19 growth rate is lower in Denmark and Norway compared to that in Sweden. This means that the number of additional daily deaths is fewer in the lockdown treatment group.[13] This result is confirmed in Figure 2 where a seven-day moving average of death toll is plotted.[14] Following government NPIs, the daily death rate rose in

[13] Namely, $\left(\frac{\Delta^2 y}{\Delta t^2}\right)^T < \left(\frac{\Delta^2 y}{\Delta t^2}\right)^C$ so cumulative deaths are rising more slowly in the treatment group [T] relative to the control group [C].

[14] A seven-day moving average is calculated to smooth the data. Deaths at time d(t)= $\frac{1}{7}\sum_{i=0}^{7} d(t-i)$.

all three countries. The daily new deaths per million are consistently higher in Sweden relative to figures in Denmark and Norway. Also, the rate of increase is higher for Sweden, with the peak in new deaths happening later in the nation than in Denmark and Norway.

Figure 2: Scandinavian COVID-19 New Deaths per Million People



Notes and data sources: A seven-day moving average is calculated to smooth the data. Deaths at time $d(t) = \frac{1}{7}\sum_{i=0}^{7} d(t-i)$

Data source: *https://raw.githubusercontent.com/owid/COVID-19-data/master/public/data/owid-covid-data.csv. Original data published by the European Centre for Disease Prevention and Control (ECDC). The first dashed vertical line is the date when countries are assumed to begin interventions. The next lines are spaced at 14-day intervals. At each of these dates (i.e. dashed line) we estimate the difference-in-differences model using data 7 days before and 7 days after. See Table 3 below for results.*

We also note that there can be a lag in Sweden's reporting of deaths (Altmejd, 2020). The lag seems to be substantial for two weeks and nontrivial for three weeks. The reported and actual dates of a person's death are thus not the same, and the ECDC aggregate statistics data that we use in

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this study reflected reported but not actual death dates. Part of the drop toward the end in Sweden's death stats (Figure 2) may be due to such reporting effects. Overall, though, we contend that this does not change the main pattern of results.

Table 3 shows the main results from estimating the difference-in-differences models. Bootstrap standard errors (50 reps) are reported. The coefficient of interest is the Diff-in-diff in the first row. Column 1 shows the change in deaths per million people in Denmark and Norway relative to the change in deaths per million people in Sweden around the 15-day event window surrounding the 18 March 2020. The coefficient is not statistically significant, meaning that the policy introduction in Denmark and Norway had no immediate effect on deaths relative to Sweden. This is likely due to lag effects.

Columns (2) to (5) use different dates to mark the pre/post period. These are set at 14-day intervals after the initial cutoff date of 3/18/20. At each date we estimate the difference-in-differences model using a 15-day window from (t-7) to (t+7). The results show that the change in case fatality rates in Denmark and Norway is significantly lower compared to the change in case fatality rate in Sweden. Estimates indicate that Denmark and Norway have 16 to 48 people per million fewer deaths in a 15-day window, relative to the control group of Sweden. Multiplying this number to the Swedish population of 10 million, non-strict lockdowns may result in 160 to 480 more deaths in Sweden every 15 days after the COVID-19 outbreak compared to its Scandinavian neighbors. The constant shows the mean in the control group of Sweden in the (7-day) pre-estimation period. We note that it is increasing at each estimation stage.

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Table 3: Scandinavian COVID-19 Deaths per Million People: Difference-in-differences Estimates

Variables	Deaths per mil.	Deaths per mil.	Deaths per mil.	Deaths per mil.	Deaths per mil.
	t = 18 March 2020	t = 1 April 2020	t = 15 April 2020	t = 29 April 2020	t = 13 May 2020
Diff-in-diff	-0.00	-16.17***	-48.17***	-47.19***	-44.36***
	(0.498)	(5.660)	(11.504)	(11.211)	(13.355)
Constant	0.20**	8.40***	79.86***	205.60***	307.11***
	(0.087)	(1.520)	(4.389)	(7.264)	(6.279)
Observations	45	45	45	45	45
R-squared	0.460	0.617	0.866	0.955	0.971
Mean control t(0)	0.198	8.402	79.864	205.602	307.109
Mean treated t(0)	0.117	6.181	29.733	51.643	63.758
Difference at t(0)	-0.081	-2.222	-50.132	-153.959	-243.350
Mean control t(1)	1.807	35.597	140.666	260.254	355.744
Mean treated t(1)	1.721	17.201	42.369	59.108	68.030

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Notes: Difference-in-differences estimates. Dependent variable is deaths per million people. Treatment group = Denmark/Norway. Control group = Sweden. Each column defines the break line for pre and post policy (i.e. accounting for lags). Terms t(0) and t(1) refer to pre and post treatment respectively. Models estimated using diff package in Stata 16. Bootstrap standard errors (50 reps) reported. At each date t, the difference-in-differences model is estimated using data in the event window (t-7, t+7).

4.1 Discussion

The speed that COVID-19 has ravaged the global economy is unprecedented in modern times. It is important to stress that our analysis is based on the limited data and time that we have had to probe one focused research hypothesis. However, the results must be seen in the light of a very fluid and fast changing set of events, that will likely throw more light on the claims raised in this paper. We consider a few of these.

First, the (inverse) welfare measure used in this paper is the cumulative deaths from COVID-19. Other health outcomes can and should be investigated. The Swedish strategy opens up the

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possibility of more infections in the community but also more antibody protection. In the longer-term, is the change in antibody protection in Sweden greater than the change in immunity in Denmark and Norway? And, if so, is it sufficient to create overall herd immunity?

Second, our analysis is based on the currently available data (from March to May 2020). What are the possible long-term effects when Denmark and Norway open up to Swedish levels? Will death rates in Denmark and Norway converge to Swedish levels? If so, lockdowns might still be justified to prevent bottle necks in the hospital system. However, our estimates provide an assessment of the short-term impact of lockdowns. The long-term impact might differ because the COVID-19 virus could spread again once an economy is opened up (i.e. a 'second wave'). In fact, the Swedish strategy is deliberately directed at the long term.

The Economist (2020) addresses these points: *"Sweden chose this path because it looked at the longer term, says Johan Giesecke, an epidemiologist advising the authorities. Full lockdowns are stop-gap measures, he says, and European governments rushed to put them in place without plans for what would replace them….Mr Giesecke reckons that Stockholm will reach "herd immunity", the 40-60% rate of infection needed to halt the spread of the coronavirus, by June. He thinks that when European countries count deaths a year from now their figures will be similar, regardless of the measures taken and the numbers now. The economic damage in Sweden, however, may be smaller."* However, we note that the current situation is fluid and predictions of herd immunity have yet to be substantiated. A recent study by the Swedish Public Health Authority (2020) showed that only 7.3% of people in Stockholm had antibodies around the start of May 2020. This

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implies that herd immunity has yet to be achieved. As the number of new cases decline over time, the challenges to reach herd immunity increase even more.

Table 4: Projected GDP Growth in Scandinavia

	GDP billion $ 2018	Growth estimate % 2019	Growth forecast % 2020	Growth forecast % 2021
Denmark	355	2.4	-5.9	5.1
Norway	434	1.2	-6.1	5.0
Total for Denmark and Norway	789	1.7	-6.0	5.0
Sweden	554	1.2	-6.1	4.3

Sources: European Commission (2020). SEB Group (2020).

Third, there is a sharp trade-off between economic activity and positive health outcomes during the sample period. Are there potential economic benefits from leaving the Swedish economy partially open? Future research might want to model GDP growth to evaluate the GDP economic benefits (or costs) of the Scandinavian NPI strategy. As Anderson et. al. (2020) remark: "Governments will not be able to minimize both deaths from coronavirus disease 2019 (COVID-19) and the economic impact of viral spread." Table 4 shows that projected GDP growth rates in Denmark, Norway and Sweden are very similar. In fact, GDP in Denmark and Norway is forecasted to fall slightly less than in Sweden in 2019 and to increase slightly more in 2021. This does not indicate that lockdowns are associated with worse economic outcomes. However, the Swedish economy grew slower already in 2019 and economic growth was forecasted to decline before the COVID-19 outbreak at the beginning of 2020 (Danske Bank 2020) so it is possible that

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the decline in economic activity would have been even worse if Sweden had instituted a strict lockdown.

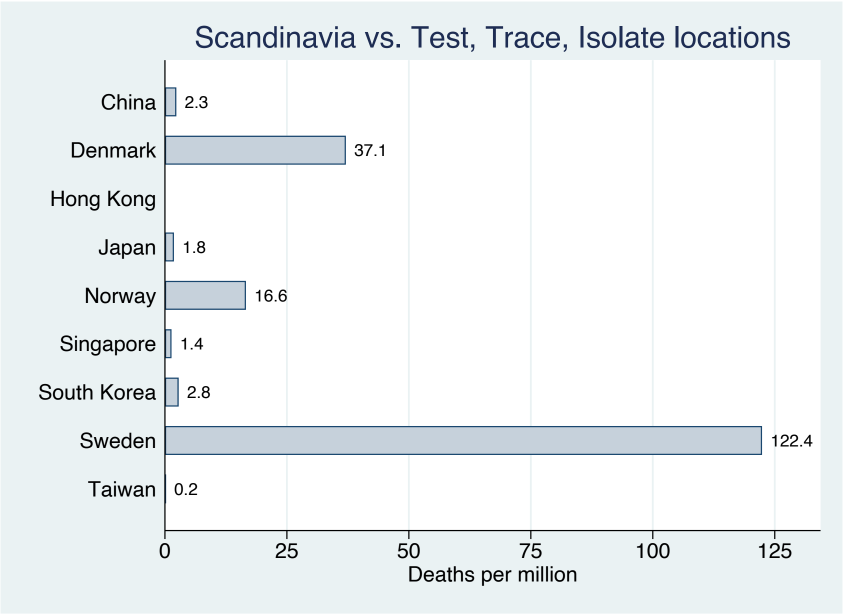
Fourth, deaths in several Asian economies including South Korea, Taiwan, Japan, Singapore and China have been low. The fewer deaths seem correlated to robust strategies for testing, tracing and isolation. Similar investments in Scandinavia might, therefore, mitigate the need for universal 'one-size-fits all' lockdowns. Relatedly, comparisons with normal influenza show similar or lower COVID 19 death rates in people below 70 compared to a normal influenza (Statens Seruminstitut SSI, 2020), but much higher death rates in people above 70, which indicates that governments might want to focus on protecting the sick and elderly rather than locking down the whole population.

The importance of lockdowns versus testing, tracing, and isolation is highlighted in Figure 3. In contrast to the approach adopted in Scandinavian nations, South Korea, Taiwan, Singapore, and other Asian economies used test, trace, isolate strategies more aggressively (perhaps due to historical experience with SARS).[15] This has been far more successful in terms of lower average deaths during the pandemic. Also, test, trace, and isolate have the capability of both keeping the number of total deaths low and keeping economies open. The strategy is seen as central to slow the spread of COVID-19 (World Economic Forum, 2020). Finally, looking at a snapshot of

[15] Japan did relatively little testing but focused on contact tracking (New York Times 2020). Taiwan used aggressive contact tracing (The Guardian 2020). South Korea publicly disclosed detailed location information of individuals that tested positive for COVID-19 (Argente, Hsieh and Lee 2020). Singapore actually implemented a kind of lockdown through the so-called circuit breaker (stay-at-home) order (Singapore Government 2020).

Worldometer data on 29 May 2020, we note that the death rates per million in Sweden (431), Denmark (98) and Norway (44) are still much higher than in Japan (7) and Singapore (4).

Figure 3: Scandinavian Deaths per Million versus Selected Test, Trace, Isolate Countries



Notes: Height of the bar is the average deaths per million in each location. The date range is the 1 February 2020 to 1 June 2020. All available data for each location are used.

Data source: *https://raw.githubusercontent.com/owid/COVID-19-data/master/public/data/owid-covid-data.csv*

Lastly, we remark on the interconnection between economics, politics and ethics. Strict non-pharmacological interventions involve reduced travel, mobile phone tracking, shelter-in-place orders, or limitations on the number of people who can meet in person. Such measures reduce individual choice, the right to freedom of assembly, and challenge rights to individual privacy. At

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the same time strict NPIs buy time and potentially protect against the COVID-19 disease, especially for older and vulnerable people.[16] Striking the optimal balance between competing societal welfare objectives is key. Our paper has not accounted for the potentially very important costs associated with (temporarily) reduced freedoms (Mello and Wang, 2020, Thorp, 2020).

5. Conclusions

This paper investigated the effect of lockdowns on COVID-19 deaths in Scandinavian countries. Denmark and Norway are assigned to a treatment group (lockdowns) and Sweden to the control (non-lockdowns). Ex-ante the three economies are similar in terms of economics, healthcare capacity, trust and culture. This allows us to identify a causal lockdown effect on COVID-19 deaths using difference-in-differences estimators. We appreciate, though, that there are nuances across countries in their different responses to the coronavirus.

The paper's findings are as follows. First, around the announcement date of the pandemic (March 13, 2020), the recorded number of COVID-19 cases and deaths were approximately the same in all three countries. So, too, was the upward trend in total cases. Second, the lockdown policy in the treatment group is associated with fewer total COVID-19 deaths in the estimation period relative to the control. The number of deaths per million people is significantly lower in Denmark and Norway compared to Sweden. Denmark and Norway pursued a relatively hard lockdown policy compared to a softer NPI strategy in Sweden, which was based on community trust and individual decision-making.

[16] In addition to this paper, see also Rocklov (2020) and Juranek and Zoutman (2020) in the context of Scandinavia.

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We would remark that research on the optimal response to the COVID-19 pandemic is ongoing. On 3 June 2020 Sweden's chief epidemiologist Dr. Anders Tegnell underscored the complexity involved in maintaining an open society and economy as well as saving lives. He conceded that Sweden's response to the coronavirus had resulted in too many deaths and the policy could be improved given what has been learned (Sverigesradio, 2020).

This paper has provided one piece of empirical evidence on how heterogeneity in interventions affects deaths in Scandinavia. But it is only one piece of a very large jigsaw. Before anyone can conclude that strict non-pharmacological interventions are a 'success', the other effects of NPIs need to be evaluated (e.g. on economic growth, civil liberties) as we noted.

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References

Altmejd (2020). Confirmed Covid-19 deaths in Sweden. https://adamaltmejd.se/covid/ (accessed date 2020/06/03)

Anderson, R. M., Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. D. (2020). How will country-based mitigation measures influence the course of the COVID-19 epidemic?. The Lancet, 395(10228), 931-934.

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Argente, David and Hsieh, Chang-Tai and Lee, Munseob (2020). The Cost of Privacy: Welfare Effects of the Disclosure of Covid-19 Cases (May 14, 2020). University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-64. Available at SSRN: https://ssrn.com/abstract=3601143

Boier, Peter; Ingvorsen, Emil Søndergård; Hagemann-Nielsen, Frederik (14 March 2020). "To coronarelaterede dødsfald i Danmark". DR (in Danish). Retrieved 14 March 2020.

Born, Benjamin, Alexander M. Dietrich and Gernot J. Müller (2020) 'Do lockdowns work? A counterfactual for Sweden,' Covid Economics, May 2020.

Danish Health Authority (2020). Risk assessment, strategy and measures concerning epidemic in Denmark. (Sundhedsstyrelsen. COVID-19 Risikovurdering, strategi og tiltag ved epidemi i Danmark Sundhedsstyrelsen 10. marts 2020. Document version 5 March 2020) https://www.sst.dk/-/media/Udgivelser/2020/Corona/Strategi-for-COVID-19.ashx?la=da&hash=067BF6AF0A95D88B3E0A329ABB3C8935E12DDDFF

Danske Bank (2020). Nordic Outlook. https://danskebank.com/news-and-insights/news-archive/insights/2020/06012020. January 2020.

European Commission. (2020). European Economic Forecast. https://ec.europa.eu/info/sites/info/files/economy-finance/ip125_en.pdf

Google LLC (2020) "Google COVID-19 Community Mobility Reports". https://www.google.com/covid19/mobility/ Accessed: 06-03-2020

Gorbalenya AE, Baker SC, Baric RS, de Groot RJ, Drosten C, Gulyaeva AA, et al. (March 2020). "The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-

nCoV and naming it SARS-CoV-2”. Nature Microbiology. 5 (4): 536–544. doi:10.1038/s41564-020-0695-z. PMC 7095448. PMID 32123347

Haushofer, J., & Metcalf, C. J. E. (2020). Which interventions work best in a pandemic?. Science (New York, NY). Science 21 May 2020:eabb6144 DOI: 10.1126/science.abb6144

Juranek, Steffen and Zoutman, Floris, The Effect of Social Distancing Measures on the Demand for Intensive Care: Evidence on COVID-19 in Scandinavia (2020). CESifo Working Paper No. 8262. Available at SSRN: https://ssrn.com/abstract=3594014

Kraemer, M. U., Yang, C. H., Gutierrez, B., Wu, C. H., Klein, B., Pigott, D. M., ... & Brownstein, J. S. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. Science, 368(6490), 493-497.

Mello, M. M., & Wang, C. J. (2020). Ethics and governance for digital disease surveillance. Science. (11-May-2020 DOI: 10.1126/science.abb9045)

Nature (2020) ‘Closing borders is ridiculous’: the epidemiologist behind Sweden’s controversial coronavirus strategy -- Anders Tegnell talks to Nature about the nation’s ‘trust-based’ approach to tackling the pandemic. Nature 580, 574 (2020) doi: 10.1038/d41586-020-01098-x.

New York Times (2020). Testing Is Key to Beating Coronavirus, Right? Japan Has Other Ideas. By Ben Dooley and Makiko Inoue. .Published May 29, 2020. https://www.nytimes.com/2020/05/29/world/asia/japan-coronavirus.html.

Pech de Laclause, Gilles and Delenda, Arnaud (2020). Non Pharmaceutical Interventions, Hospital Overload and Excess Mortality: Statistical Analysis and Mathematical Study of the NPIs Results in ‘COVID 19’ Outbreak (May 10, 2020). Available at SSRN: https://ssrn.com/abstract=3598484 or http://dx.doi.org/10.2139/ssrn.3598484

Politiken (Danish newspaper) (2020). Internal mail reveals: Permanent Secretary asked Brostrøm to drop his professionalism. (Politiken. Intern mail afslører: Departementschef bad Brostrøm om at skrotte sin faglighed. 29 Maj 2020.) https://politiken.dk/indland/art7804674/Departementschef-bad-Brostr%C3%B8m-om-at-skrotte-sin-faglighed

Puelles, V. G., Lütgehetmann, M., Lindenmeyer, M. T., Sperhake, J. P., Wong, M. N., Allweiss, L., ... & Braun, F. (2020). Multiorgan and renal tropism of SARS-CoV-2. New England Journal of Medicine.

Covid Economics 26, 5 June 2020: 17-42

Rocklov, Joachim (2020) COVID-19 healthcare demand and mortality in Sweden in response to non-pharmaceutical (NPIs) mitigation and suppression scenarios, medRxiv 2020.03.20.20039594; doi: https://doi.org/10.1101/2020.03.20.20039594

Roser, Max, Hannah Ritchie, Esteban Ortiz-Ospina and Joe Hasell (2020) - "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/coronavirus' [Online Resource]

SEB Group. 2020. Nordic Outlook. May 2020. https://sebgroup.com/siteassets/large_corporates_and_institutions/prospectuses_and_downloads/research_reports/nordic_outlook/2020/nordic_outlook_may_2020_eng.pdf

Singapore Government (2020). PM Lee's address on the COVID-19 Situation in Singapore (21 April 2020). https://www.gov.sg/article/pm-lees-address-on-the-covid-19-situation-in-singapore-21-april-2020.

Statens Seruminstitut SSI (2020). COVID-19 in Danmark. Epidemiological trend and Focus: Mortality (COVID-19 i Danmark. Epidemiologisk trend og focus: Dødelighed). https://files.ssi.dk/COVID19-epi-trendogfokus-30042020-61ls.

Sverigesradio (2020) https://sverigesradio.se/sida/artikel.aspx?programid=83&artikel=7487188 (Tegnell: More action was needed) Accessed 3 June 2020.

Swedish Public Health Authority (2020) Första resultaten från pågående undersökning av antikroppar för covid-19-virus (https://www.folkhalsomyndigheten.se/nyheter-och-press/nyhetsarkiv/2020/maj/forsta-resultaten-fran-pagaende-undersokning-av-antikroppar-for-covid-19-virus/) (accessed, 3 June 2020).

The Economist (2020). Herd on the street. Is Sweden's approach to covid-19 wise or reckless? May 16th 2020 edition. https://www.economist.com/europe/2020/05/16/is-swedens-approach-to-covid-19-wise-or-reckless.

The Guardian (2020). Could the 'liberal' Dutch have learned from Taiwan's approach to coronavirus? Cha-Hsuan Liu and Jaap Bos. 19 May 2020. https://www.theguardian.com/commentisfree/2020/may/19/liberal-dutch-taiwan-coronavirus-covid-19-netherlands

Thorp, H. H. (2020). The costs of secrecy. Science 28 Feb 2020: Vol. 367, Issue 6481, pp. 959 DOI: 10.1126/science.abb4420

Van Bavel, J. J., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., ... & Drury, J. (2020). Using social and behavioural science to support COVID-19 pandemic response. Nature Human Behaviour, 1-12.

Worldometer (2020). https://www.worldometers.info/coronavirus/. 29 May, 2020

World Economic Forum (2020) https://www.weforum.org/agenda/2020/03/testing-tracing-backbone-who-coronavirus-wednesdays-briefing/ (accessed 29 May, 2020)

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Covid Economics **Issue 26, 5 June 2020**

Latent social distancing: Identification, causes and consequences[1]

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This paper derives a Model-Inferred DIStancing (MIDIS) measure using an extended version of the Susceptible-Exposed-Infected-Recovered-Deceased (SEIRD) framework. The paper argues that, when a disease has an incubation period, explicitly accounting for the exposed compartment is necessary in this class of epidemiological models. An important advantage of the proposed identification strategy lies in its ease to put into practice by other researchers because it employs a relatively simple model and readily available data. When MIDIS is taken to data, results exhibit cross-country and over-time heterogeneity in social distancing during the COVID-19 pandemic. Furthermore, MIDIS is highly correlated with the mobility data, and it embeds both governmental and behavioral responses to the COVID-19 pandemic. Finally, as an application, the paper uses MIDIS to explain output losses experienced during the pandemic, and there exists a robust positive correlation between the two|with sizable economic effects.

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1. Introduction

The COVID-19 pandemic has already enveloped the planet in its entirety and triggered a wide range of containment or distancing measures in almost all parts of the world. These measures have resulted in a serious economic downturn with the potential to dwarf the Great Depression. As of June 1, 2020, the disease claimed nearly 375,000 lives, and the case numbers reached more than 6 million worldwide with no vaccine or antiviral therapy in close sight.

The only available instrument to slow down the rate of infection was and continues to be social distancing, which can be loosely defined as a set of non-pharmaceutical interventions (NPIs) to reduce person-to-person contact. These interventions can be taken by governments or individuals and serve the objective of "flattening the epidemiological curve," a plot of the number of new cases per day. Theoretical reasoning suggests that the social return to distancing exceeds its private return, thereby necessitating policy interventions (e.g., Bethune and Korinek, 2020; Farboodi et al., 2020).

Social distancing to "flatten the curve" unequivocally creates a plethora of economic shocks. But which countries have experienced the highest rates of increase in social distancing, and what is the extent of social distancing? These questions are imperative for understanding what triggers economic tremors felt all over the world, yet we know remarkably little about social distancing that has the power of creating major economic downturns. Why? Because, it belongs to a set of *intrinsically latent variables* which are typically well understood but rarely rigorously defined (Kmenta, 1991). Unlike a proxy variable, an *intrinsically latent variable* is unobserved and never characterized by just one measurable factor. Hence, it can only be inferred from other observable variables using formal (mathematical) theory that provides identification restrictions.

This paper sheds light on these issues by developing a way of identifying unobserved social distancing and aims to contribute to the vivid debate on "flattening the curve," cross-country heterogeneity in the effectiveness of governmental and behavioral responses, and economic costs of the pandemic.

In the first part of the paper, we derive a **M**odel-**I**nferred **DIS**tancing (MIDIS) measure using an extended version of the workhorse **S**usceptible-**E**xposed-**I**nfected-**R**ecovered-**D**eceased (SEIRD) framework.[1] In the typical SEIRD model, there is a nonlinear dynamical system that explains the spread and eventual containment of an infection over time. In this paper, we extend the simple SEIRD model with a time-varying and country-dependent social distancing term. The core idea of our paper is to identify this distancing term, MIDIS, for each country and each day by exploiting the fact that the pure probability of transmission and the average incubation period are constant and common across countries. The resulting solution expresses MIDIS as a function of observable epidemiological data and thus provides a model-inferred measure of a latent variable that can be tracked over time. An important

1 The model was originally proposed as a SIR model by Kermack and McKendrick (1927) and, later, various extensions with stochastic specifications and more compartments were produced. We briefly review that literature below.

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advantage of our identification strategy lies in its ease to put into practice by other researchers because it employs a relatively simple epidemiological model and readily available data.

To the best of our knowledge, Fernández-Villaverde and Jones's (2020) paper is the closest one to ours with respect to identification. These authors also use a compartmental model (the SIRD version) and daily epidemiological data, and their identification strategy of recovering time-varying transmission rate using observables is similar to our identification of distancing. However, there are four substantial differences. First and the foremost, our model has the exposed compartment between the Susceptible and Infected compartments whereas Fernández-Villaverde and Jones (2020) implicitly assume that the exposed individuals are in the Susceptible compartment. Second, while both papers use the daily epidemiological data on the numbers of deceased and recovered individuals, we use observed data of country-dependent and time-varying recovery and fatality rates in identification. In contrast, Fernández-Villaverde and Jones (2020) assign fixed and country-independent values to several model parameters (but of course do so rigorously). Third, our approach exploits the fact that the pure probability of transmission is fixed and common across countries and thus identifies the unobserved distancing term directly for each country and day. Fernández-Villaverde and Jones (2020), however, identify the effective transmission rate directly, and they do not put an effort to differentiate the distancing term from pure probability of transmission. Finally, our paper focuses on the identification, causes, and economic consequences of distancing, but Fernández-Villaverde and Jones (2020) use their model and the recovered sequences of time-varying transmission rates to understand the evolution of death rates and the progression of the pandemic in the near future. We believe that explicitly accounting for the exposed compartment is necessary since COVID-19 has a strictly positive average incubation period. Besides, our approach of utilizing observed changes in recovery and fatality rates allows us in understanding the evolution of distancing during the pandemic.

One advantage of our identification strategy is that MIDIS captures a wide range of social distancing components. These include not only policy interventions (school/work closures, bans on traveling and mass gatherings or stay-home orders) but also behavioral responses such as fear, trust, or reciprocity which cannot be measured in a straightforward way. As underlined by Toxvaerd (2020), modeling how people behave during a pandemic (under the presence of distancing interventions) by exogenously given diffusion parameters is not sufficient for the analysis of disease control. There exists an endogenous response of human behavior to a highly contagious disease—embodied in every day social interactions—that needs to be accounted for in epidemiological models.

While it would be the first-best to collect direct data on different components of social distancing, this is hardly likely in practice due to severe data limitations. The data on policy measures taken to curb the spread of the disease may not always be readily available for a number of countries on a daily basis, let alone the daily data for behavioral responses. MIDIS derived in this paper eschews this problem by providing researchers a measure that is easy to construct. It can be useful not only for studying economic costs but also for other applications that require a time-varying measure of social distancing.

Naturally, our analysis encompasses some of the caveats of SEIRD modeling as well as

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measurement errors in the observed data. For the latter problem, it is known that countries are not equally successful in testing and tracking, and data manipulation by official bodies in some countries could cause quantitative results to be misleading to some extent. For the former issue, one of the most serious problems of SEIRD models is the weak identification of model parameters (Avery et al., 2020). As Fernández-Villaverde and Jones (2020) have underlined as well, different constellations of model parameters that have similar fits in the short run—days to weeks—may imply significantly diverse outcomes in the long run—months to years. Our imperfect remedy for this problem is to check the sensitivity of our results, and we show that the evolution of MIDIS is considerably robust under alternative parameter values. Another issue is parameter stability under the presence of policy changes as underlined by Chang and Velasco (2020) with reference to the Lucas critique. Since we do not pursue counterfactual policy analyses, parameter stability is not a central concern for us. The last but not least, the simple models with homogeneous individuals inhabiting a single society may be misleading because of (i) population heterogeneity in age structure, exposure risk, and health status, (ii) the regional differences within a country, and (iii) spatial linkages among the localities. However, currently available data do not allow us to pursue such intriguing dimensions for the moment.

In the second part of the paper, we take MIDIS to the data compiled by Johns Hopkins University (JHU, 2020) and compute it for 44 countries with a total number of confirmed COVID-19 cases that exceeds 10,000 as of May 11, 2020. For the immediate 30-days in the aftermath of the 500th case, our results show that countries exhibit considerable variation with respect to initial social distancing levels. With the exceptions of the US and Spain, countries start with an initial social distancing level that is larger than the Chinese benchmark. Furthermore, in a large number of countries, there is a minor decline of MIDIS within the first week that is followed by a slow yet persistent increase later on. South Korea is the country that sustains the highest average level of distancing, and the US is the least effective country. That there is considerable cross-country variation in social distancing levels and the South Korean success relative to the European countries are consistent with the SIR-based empirical evidence presented by Chudik et al. (2020).

We, then, compare MIDIS values to the mobility data supplied by Apple and Google that have now been used in the burgeoning COVID-19 literature—sometimes as a proxy for social distancing.[2] Our results indicate a highly significant negative correlation between MIDIS values and different components of mobility. The advantage of MIDIS over the mobility data is its wide coverage at country-day detail as long as the epidemiological basic data are available.

In the third part of the paper, we try to identify the cross-country heterogeneity in MIDIS that might be a result of differences in governmental response, behavioral response and a plethora of country-specific factors. We argue that behavioral response to a pandemic is at least as important—if not more—as governmental response in explaining the variation in MIDIS across countries and time. As expected, our results show that our social distancing

2 See Alfaro et al. (2020), Coven and Gupta (2020), Durante et al. (2020), and Doganoglu and Ozdenoren (2020) and the references therein.

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measure varies positively with containment measures taken by governments and people's reaction to the pandemic in a robust manner. Indeed, the impact of behavioral response measured by the numbers of deceased on the previous day is stronger than the impact of containment measures. Almost all country-specific variables we use are unsuccessful in explaining the variation in MIDIS. This last result may indicate that the virus—hence social distancing—does not differentiate between developed or otherwise and can manifest itself in unexpected ways compared to our conventional wisdom.

In the final part of the paper, we use our model-inferred social distancing measure to study the economic costs of social distancing during a pandemic. While doing so, we stay oblivious to supply or demand side dynamics of these economic costs and focus on their outcome in terms of output loss only. Our daily measure of output loss is derived from the peak-hour electricity consumption data, generously provided by McWilliams and Zachmann (2020). Our results indicate a significant negative output response to social distancing during the COVID-19 pandemic. In other words, in countries with higher levels of MIDIS, there is a higher level of output loss in the 30-days following the 500th case. Indeed, a 10 percent increase in social distancing causes up to a 3.7 percent increase in output loss.

The paper is structured as follows: Section 2 reviews the related literature. Section 3 introduces the model and our identification strategy. Section 4 summarizes the main patterns of distancing using the identified MIDIS values and validates MIDIS through mobility data. Section 5 investigates the cross-country differences in MIDIS using various explanatory variables. Section 6 then investigates whether and to what extent distancing during the pandemic is related with output losses. Section 7 concludes the paper with some final remarks. We present the results of sensitivity analyses in Appendix A, and variable definitions, data sources, and statistical summaries in Appendix B. Computer codes and MIDIS data can be accessed at the MIDIS website.

2. Related Literature

There is now a large and growing literature studying various economic aspects of the COVID-19 pandemic. As of May 31, 2020, there exist over 70 COVID-19-related research papers documented by the NBER, all written in the last few months.[3] There also exist other outlets where researchers share their recent works on the COVID-19 pandemic. *Covid Economics: Vetted and Real-Time Papers*, published by the Centre for Economic Policy Research since March 2020, has now 24 completed issues containing dozens of papers on the COVID-19 pandemic.

Our purpose in this section is to present a discussion of the related literature by focusing on the papers that are most directly related to ours. Compartmental models such as SIR, SEIR, or SEIRD are useful tools in the mathematical study of infectious diseases. Originally developed by Kermack and McKendrick (1927) in the form of SIR, the (stochastic versions of) models with more compartments (e.g., with the Quarantined or the Hospitalized ones) have been proposed to make the analysis more realistic (e.g., Chowell et al., 2003; Zhou

3 These papers can be accessed at `https://www.nber.org/wp_covid19.html`

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et al., 2004; Lekone and Finkenstädt, 2006; Feng, 2007). Most recently, researchers estimated such realistic versions with the Chinese COVID-19 data (Tang et al., 2020; He et al., 2020). In this paper, we focus on the simplest version of a compartmental model that fits our purposes. Hence, we build on a deterministic version that explicitly accounts for the exposed compartment and extend it with time-varying and country-dependent (unobservable) distancing.

Recent work by economists is related to our paper in two respects. First, several papers embed a compartmental epidemiological model (within a dynamic equilibrium framework) to tackle a diversity of research questions. Second, another set of papers empirically investigate the causes and consequences of social distancing, identified or measured/proxied in one way or another.

In the first strand where researchers use a version of a compartmental model, they generally focus on how governmental and behavioral responses affect the progression of the pandemic through distancing. Other than Fernández-Villaverde and Jones (2020) that we have discussed above, there is a large number of papers in this category, and we choose to discuss only some of them for space considerations.

Building on the SIR model, Toxvaerd (2020) designs an optimal control problem at the individual level to solve for daily equilibrium dynamics of social distancing. The model implies that there exists an episode during which the number of infections does not increase as a result of optimal behavioral responses. In a similar fashion, Cochrane (2020) shows simulations of a SIR model where distancing behavior depends on the infection rate or the increase in the death toll as people decrease their exposure under the presence of increasing infection rates or deaths. Acemoglu et al. (2020) extend the SIR model with three age groups that face different levels of mortality risks and show that targeted policies are more effective than uniform policies in terms of both economic costs and health outcomes. Authors also emphasize the sizable positive effects of group distancing that isolates the most vulnerable from the rest of the society. Alvarez et al. (2020) also use the SIR model and study the optimal control problem of lockdown policies. The optimal policy they find depends on the fractions of susceptible and infected individuals, and it prescribes a severe initial lockdown and a gradual withdrawal of it in months. Berger et al. (2020) extend a SEIR model with incomplete information, testing, and quarantine policies. They find that targeted quarantine policies with higher testing rates are effective in mitigating the adverse economic and epidemiological effects. Eichenbaum et al. (2020) embeds the SIR model within a typical dynamic macroeconomic model to study the effects of various policy responses. In their SIR-macro model, individuals' distancing decisions that decrease their consumption and labor supply have positive health impacts but increase the size of economic downturn. Another modeling exercise pursued by Kaplan et al. (2020) incorporates the SIR model within a New Keynesian model with heterogeneous agents (HANK). Authors underline the differential impact of the pandemic across different types of consumer goods and occupations, and they also show that the ownership structure of liquid versus illiquid assets matters because the group of individuals that are most exposed to economic risks have lowest liquidity.

Our paper benefits from this literature in motivating the roles of governmental and behavioral responses to the pandemic; our empirical results—confirming that governmental

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and behavioral responses drive effective distancing—have a strong theoretical basis. However, our approach differs from all these papers in two respects: First, a vast majority of the papers ignore the role of the exposed compartment but realistic epidemiological studies of the COVID-19 pandemic necessitates a S"E"IRD framework (He et al., 2020; Tang et al., 2020). Second, instead of investigating whether a particular policy or behavior is optimal, we remain agnostic about such a counterfactual question and assume that the observed epidemiological data reflect the decentralized equilibrium of distancing. The presumption that the observed data must be consistent with a SEIRD model then allows for the identification of distancing during the pandemic.

The second strand of literature we discuss here focuses more on the empirics of distancing and disease progression, and more specifically on whether governmental and/or behavioral responses are statistically associated with increased distancing and decreased mobility.

Chen and Qiu (2020) and Castex et al. (2020) investigate the role of governmental responses on the infection rates by recovering the daily infection rates from a SIR model. The former paper designs different scenarios using NPIs for nine countries and shows that school closures, mask wearing, and centralized quarantine measures are effective in reducing the transmission rates. Authors also show that these three measures have quantitatively similar effects when compared with a strict lockdown. The latter paper implements the analysis for a large number of countries and finds that GDP per capita, population density, and surface area decrease policy effectiveness.

Doganoglu and Ozdenoren (2020) investigate the role of trust and social norms on behavioral responses to the pandemic. They first isolate the effects of (i) policy measures using the Stringency Index of Hale et al. (2020), (ii) the number of infections, and (iii) the temperature on people's mobility using the Google (2020) data. They then estimate the role of trust on the country fixed effects that cannot be explained by policies, infections, and temperature. Their results indicate that, while policies and infections decrease mobility levels, trust has a positive impact on mobility. Alfaro et al. (2020) also focus on behavioral responses motivated by fear, altruism, and reciprocity, and they investigate the effects of both policy measures and these traits. Their empirical results that utilize Apple (2020) mobility data show that the effects of policy measures is less pronounced if people are more patient and more altruistic and if they exhibit a lesser degree of negative reciprocity.

The empirical literature also shows that partisanship may be an important dimension in guiding people's distancing behavior. Painter and Qiu (2020) use geolocation data for the US counties to show that people in Democratic counties are more responsive to policy interventions, and Engle et al. (2020) estimate that an official stay-at-home restriction decreases mobility by more than 7 percent in the US. In a separate study (on the US counties), Brzezinski et al. (2020) confirm that the effect is indeed close to 8 percent. In another interesting paper related with partisanship effects, Argentieri Mariani et al. (2020) demonstrate—using an event-study approach and regional variation of vote shares in Brazil—that the president's public disrespect for the recommendations of health authorities has increased the infection rates.

Empirical studies demonstrate that policies are effective in reducing the infection rates and the number of deaths through distancing (Deb et al., 2020; Askitas et al., 2020). How-

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ever, estimates also show that people respond to the pandemic by decreasing their mobility to some extent even in the absence of policy interventions (Brzezinski et al., 2020). This result (for the US) has also been supported by the mobility data of Google (2020) in a paper by Maloney and Taskin (2020). These authors also estimate that the effect of voluntary distancing is larger than that of policy interventions for a large number of countries.

Our empirical results are consistent with the main lessons of this literature, namely that both governmental and behavioral responses are significantly associated with distancing and mobility. We should also note that our approach is closer to those of Chen and Qiu (2020), Castex et al. (2020), and Alfaro et al. (2020). Differently from the latter paper, we use a distancing measure originating from an epidemiological model, and, contrary to the first two of these papers, we explicitly account for the exposed individuals in identifying our distancing measure, MIDIS.

3. A SEIRD Model with Distancing

We consider J countries indexed by $j \in \{1, 2, ..., J\}$. The model time, denoted by t, is discrete, and the length of a period is a day. For all countries, the model horizon is the first 30 days after the 500th COVID-19 case is confirmed. Hence, time periods are not synchronized across countries with respect to the calendar time.

The need to restrict our analysis to the period after the 500th case for each country originates from the fact that the official COVID-19 statistics for China starts with 548 cases on January 22, 2020. Furthermore, we choose to restrict the analysis to the first 30 days after 500th case to disregard the effects of partial removal of NPIs.

3.1. Compartments and the Laws of Motion

Following Degue and Le Ny (2018), we study a deterministic version of the SEIRD model where the size of each compartment is expressed as a fraction of population in each country. In this model, susceptible (S) individuals transit to the exposed (E) compartment after being infected, but they stay in the exposed compartment until they become infectious. Individuals in the infected (I) compartment transmit the virus to susceptible individuals, and they either recover (R) or die (D).

Importantly, we extend the basic model with a time-varying transmission rate that is determined by distancing behavior of susceptible and infected populations. Formally, we have

$$S_{t+1}^j = S_t^j - \beta \left[\left(\frac{1 - d_t^j}{\mu} \right) S_t^j \right] \left[\left(\frac{1 - d_t^j}{\mu} \right) I_t^j \right] \tag{1}$$

$$E_{t+1}^j = E_t^j + \beta \left[\left(\frac{1 - d_t^j}{\mu} \right) S_t^j \right] \left[\left(\frac{1 - d_t^j}{\mu} \right) I_t^j \right] - \alpha E_t^j \tag{2}$$

$$I_{t+1}^j = I_t^j + \alpha E_t^j - \gamma_{R,t}^j I_t - \gamma_{D,t}^j I_t^j \tag{3}$$

$$R_{t+1}^j = R_t^j + \gamma_{R,t}^j I_t^j \tag{4}$$

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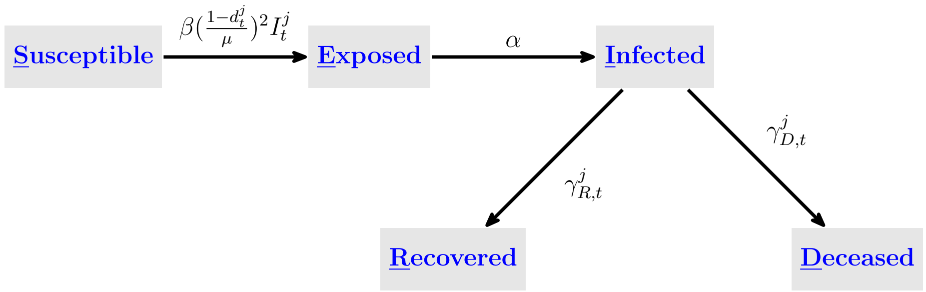

Figure 1: Compartments and Transition Rates in the SEIRD Model

$$D_{t+1}^j = D_t^j + \gamma_{D,t}^j I_t^j \tag{5}$$

where S_t^j, E_t^j, I_t^j, R_t^j, and D_t^j denote the fractions of susceptible, exposed (but not infectious), infected (and infectious), recovered, and deceased individuals in country j on day t. By the Law of Large Numbers, each denotes the probability that any given individual is in the associated compartment. Hence, we have

$$S_t^j + E_t^j + I_t^j + R_t^j + D_t^j = 1 \tag{6}$$

for all j and t.

The fixed parameter $\beta \in (0, 1)$ denotes the pure probability of transmission; it is the probability that an infected individual transmits the virus to a susceptible individual if the two get into contact. However, the probability of contact depends on *effective* (or *de facto*) distancing, or MIDIS, denoted by $d_t^j \in [0, 1]$. If both susceptible and infected individuals utilize social distancing instructions, then the probability that a susceptible individual and an infected individual get into contact is equal to

$$\left(\frac{1-d_t^j}{\mu}\right)^2 S_t^j I_t^j \tag{7}$$

If a country can completely isolate susceptible and infected individuals with $d_t^j = 1$, then no individuals migrate from the susceptible to the exposed compartment. This is the quadratic, one-parameter (μ), one-variable (d_t) formulation that is now familiar in the related literature (Acemoglu et al., 2020; Alvarez et al., 2020). However, the present formulation is slightly different from those of Acemoglu et al. (2020) and Alvarez et al. (2020) since our model features the exposed compartment as well. Here, $\mu > 0$ allows us to identify d_t^j for all countries and all days within the unit interval.[4]

4 In both Acemoglu et al. (2020) and Alvarez et al. (2020), the effect of distancing is introduced via $(1 - \theta L_t)^2$ where $L_t \in [0, 1]$ is the lockdown variable, and $\theta \in [0, 1]$ governs the effectiveness of the lockdown.

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Another fixed parameter that is also common across countries is $\alpha \in (0,1)$ that denotes the inverse of the average incubation period of the virus in days. This parameter determines the fraction of exposed individuals that migrate to the infected compartment on any day.

Finally, time-varying fractions of individuals in the infected compartment move to the recovered and deceased compartments on any day. These fractions are denoted by $\gamma^j_{R,t} \in (0,1)$ and $\gamma^j_{D,t} \in (0,1)$, respectively. Figure 1 pictures the compartments and transitions rates in the SEIRD model.

3.2. Identification

Our purpose is to use the above model and observed epidemiological data to achieve a numerical identification of d^j_t for all (j,t). The strategy builds on the notion that, while the pure probability of transmission (β) and the inverse of the average incubation period (α) are fixed and common across countries, there is daily variation in (I^j_t, R^j_t, D^j_t). Hence, the observed data and the model must be consistent with each other for some realization of d^j_t. In other words, we use the model and data to recover d^j_t for any (j,t).[5]

Since whether an infected individual recovers or dies does not matter for d^j_t, we define the compartment X^j_t as the sum of R^j_t and D^j_t as in

$$X^j_t = R^j_t + D^j_t, \tag{8}$$

and we also define $\gamma^j_{X,t} = \gamma^j_{R,t} + \gamma^j_{D,t}$. The SEIX model is then characterized by

$$S^j_{t+1} = S^j_t - (\beta/\mu^2)\left(1-d^j_t\right)^2 S^j_t I^j_t \tag{9}$$

$$E^j_{t+1} = E^j_t + (\beta/\mu^2)\left(1-d^j_t\right)^2 S^j_t I^j_t - \alpha E^j_t \tag{10}$$

$$I^j_{t+1} = I^j_t + \alpha E^j_t - \gamma^j_{X,t} I^j_t \tag{11}$$

$$X^j_{t+1} = X^j_t + \gamma^j_{X,t} I^j_t \tag{12}$$

The unobserved state variable that is central to our identification strategy is the ratio of exposed to infected individuals, defined as in $e^j_t = E^j_t / I^j_t$. Notice that (10) and (11) allow us to write the law of motion of e^j_t as in

$$\frac{e^j_{t+1}}{e^j_t} = \frac{(\beta/\mu^2)\left(1-d^j_t\right)^2 S^j_t (e^j_t)^{-1} + (1-\alpha)}{\alpha e^j_t + (1-\gamma^j_{X,t})}. \tag{13}$$

The MIDIS term d^j_t for country j on day t can then be written as a function of $(e^j_{t+1}, e^j_t, S^j_t, \gamma^j_{X,t}, \alpha, \beta, \mu)$:

$$d^j_t = 1 - \left[\frac{e^j_{t+1}\alpha e^j_t + e^j_{t+1}(1-\gamma^j_{X,t}) - (1-\alpha)e^j_t}{(\beta/\mu^2)S^j_t}\right]^{1/2}. \tag{14}$$

5 JHU (2020) shares daily data of cumulative confirmed cases (C^j_t) and the cumulative numbers of recovered (R^j_t) and deceased (D^j_t) individuals. We calculate the daily number of actively infected individuals as $I^j_t = C^j_t - R^j_t - D^j_t$.

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Table 1: Confirmed Cases of COVID-19 as of May 11, 2020

Country	Cases	Country	Cases	Country	Cases
USA	1,347,881	Netherlands	42,788	Poland	16,326
Spain	227,436	Saudi Arabia	41,014	Austria	15,882
United Kingdom	223,060	Mexico	36,327	Japan	15,847
Russia	221,344	Pakistan	32,081	Bangladesh	15,691
Italy	219,814	Switzerland	30,344	Ukraine	15,648
France	175,479	Chile	30,063	Romania	15,588
Germany	172,576	Ecuador	29,509	Indonesia	14,265
Brazil	169,594	Portugal	27,679	Colombia	11,613
Turkey	139,771	Sweden	26,670	Philippines	11,086
Iran	109,286	Belarus	23,906	South Korea	10,936
China	84,011	Singapore	23,822	South Africa	10,652
Canada	71,247	Qatar	23,623	Dominican Rep.	10,634
India	70,768	Ireland	23,135	Denmark	10,513
Peru	68,822	UAE	18,878	Serbia	10,176
Belgium	53,449	Israel	16,506		

Source: JHU (2020)

Under the assumptions that fixed parameters are known and that d_t^j takes values between 0 and 1 (inclusive), calculating d_t^j requires the values of $(e_{t+1}^j, e_t^j, S_t^j, \gamma_{X,t}^j)$ for all (j,t).

The model allows us to uniquely identify all of these inputs: (12) identifies $\gamma_{X,t}^j$ for all (j,t) as a function of observed variables $(X_{t+1}^j, X_t^j, I_t^j)$. Then, (11) identifies e_t^j for all (j,t) as a function of observed variables (I_{t+1}^j, I_t^j) and $\gamma_{X,t}^j$. Finally, (6) and (8) identify S_t^j as a function of observed variables (I_t^j, X_t^j) and e_t^j.

4. MIDIS in Selected Countries

We apply our identification strategy to a set of countries that are most seriously affected by the COVID-19 pandemic. At the first step, we select the countries with a total number of confirmed COVID-19 cases that exceeds 10,000 as of May 11, 2020. The source of our daily epidemiological data is the John Hopkins University's COVID-19 data repository (JHU, 2020). The sample includes $J = 44$ countries listed in Table 1.

Next, we apply the Gaussian filter to smooth the original epidemiological data we obtain from JHU (2020). Smoothing is a commonly followed approach in the related literature and necessary for two related reasons: First, since the model we use is deterministic, it is not suitable to capture the noise in the actual data sequences. Second, without smoothing, the identified sequences of e_t^j and $\gamma_{X,t}^j$ for some j and t are not consistent with a real-valued d_t^j term.

Finally, we assign values to the fixed parameters of the model, i.e., (α, β, μ). For α, we borrow the benchmark value from He et al. (2020) and Tang et al. (2020). Both of these papers estimate stochastic versions of a multi-compartment epidemiological model with Bayesian methods using the COVID-19 data of China. In both papers, $\alpha = 1/7$ is taken as a benchmark value that corresponds to an average incubation period of 7 days. The estimation results of He et al. (2020) additionally show that the pure probability β of transmission is equal to $\beta = 0.111$ with a standard deviation of 0.0015; we adopt this value for our benchmark results. Finally, for the scaling parameter μ, we adopt a value that normalizes the initial value of effective distancing in China to $d_0^{\mathrm{CHN}} = 0.5$. The associated value of μ satisfies $\mu = 0.2381$.

MIDIS values identified using this strategy are not much sensitive to the imposed parameter values; the qualitative properties of MIDIS sequences are not altered for plausible changes in parameters. We present a detailed analysis implemented with alternative parameter values in Appendix A.

In the remainder of this section, we present and discuss two figures. The first one pictures the absolute values of MIDIS in each of the 44 countries in our sample whereas the second one pictures the evolution of *relative* MIDIS defined as in

$$\hat{d}_t^j = \frac{d_t^j}{d_t^{\mathrm{CHN}}} \tag{15}$$

for all (j, t). Here, we take the Chinese case as a benchmark for two related reasons: First, the COVID-19 pandemic has started in China, and there is no better way to compare MIDIS across countries. Second, and more importantly, the pandemic has nearly completed its progression in China in the first half of May 2020. For instance, the smoothed sequence of confirmed cases for China indicates that, for the week ending on May 11, 2020, the average daily growth rate of confirmed cases is equal to 0.0001%.

Figure 2 shows that countries in our sample exhibit considerable variation with respect to initial values and later evolution of MIDIS during the COVID-19 pandemic.

The first thing to note is that most countries with the exceptions of the US and Spain start with an initial value that is larger than the Chinese benchmark of $d_0^{\mathrm{CHN}} = 0.5$. The initial value of the US is nearly 10 percentage points lower than the Chinese level.

The countries that achieve the highest MIDIS values at $t = 0$ of their respective samples include South Africa (0.83), Japan (0.82), Denmark (0.81), and Singapore (0.79). Initial MIDIS values lie between 0.70 and 0.79 for 14 countries, and between 0.60 and 0.69 for 19 countries. Interestingly, for some of the European countries most seriously affected from the COVID-19 pandemic, initial MIDIS values are less than 0.60. These countries are France (0.596), United Kingdom (0.586), Turkey (0.563), and Germany (0.503).

Countries differ with respect to the evolution of MIDIS during the first 30 days after the 500th case is confirmed. In some countries, MIDIS remains largely stable; these include Brazil, Colombia, Dominican Republic, Ecuador, Ireland, Mexico, Pakistan, Qatar, and Saudi Arabia.

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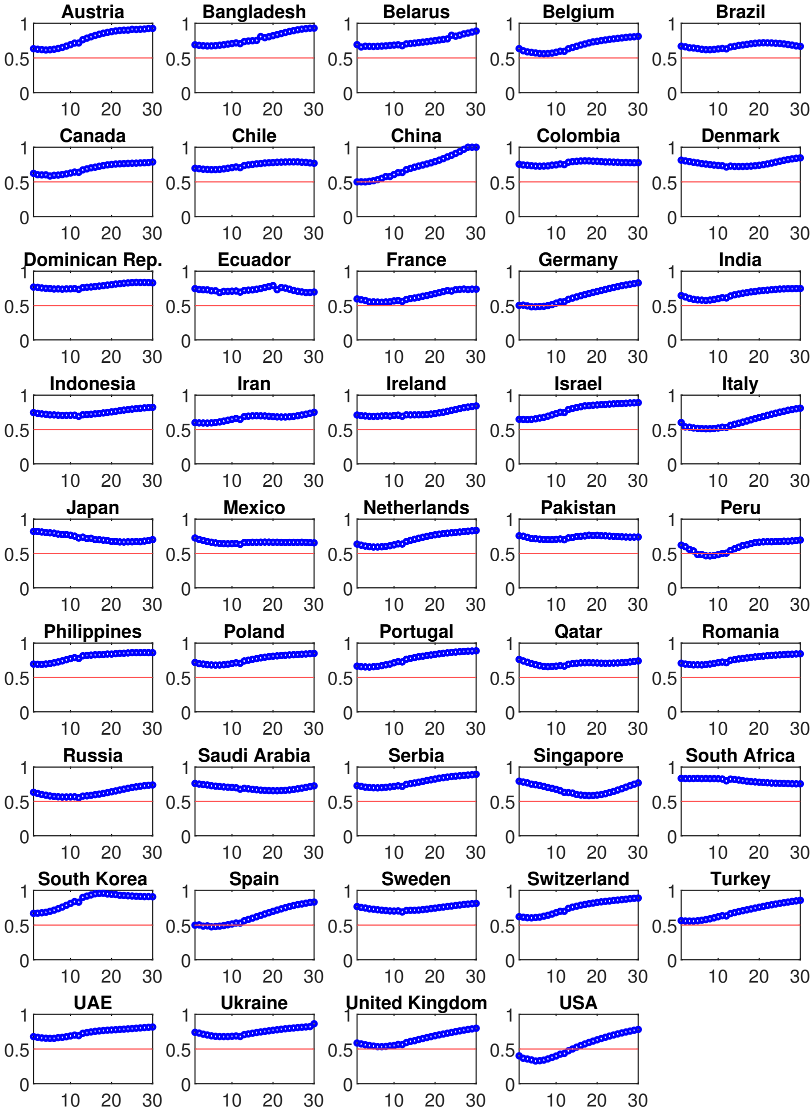

Figure 2: MIDIS: Absolute Values

$(\alpha = 1/7,\ \beta = 0.111,\ \mu = 0.2381,\ d_0^{\mathrm{CHN}} = 0.5)$

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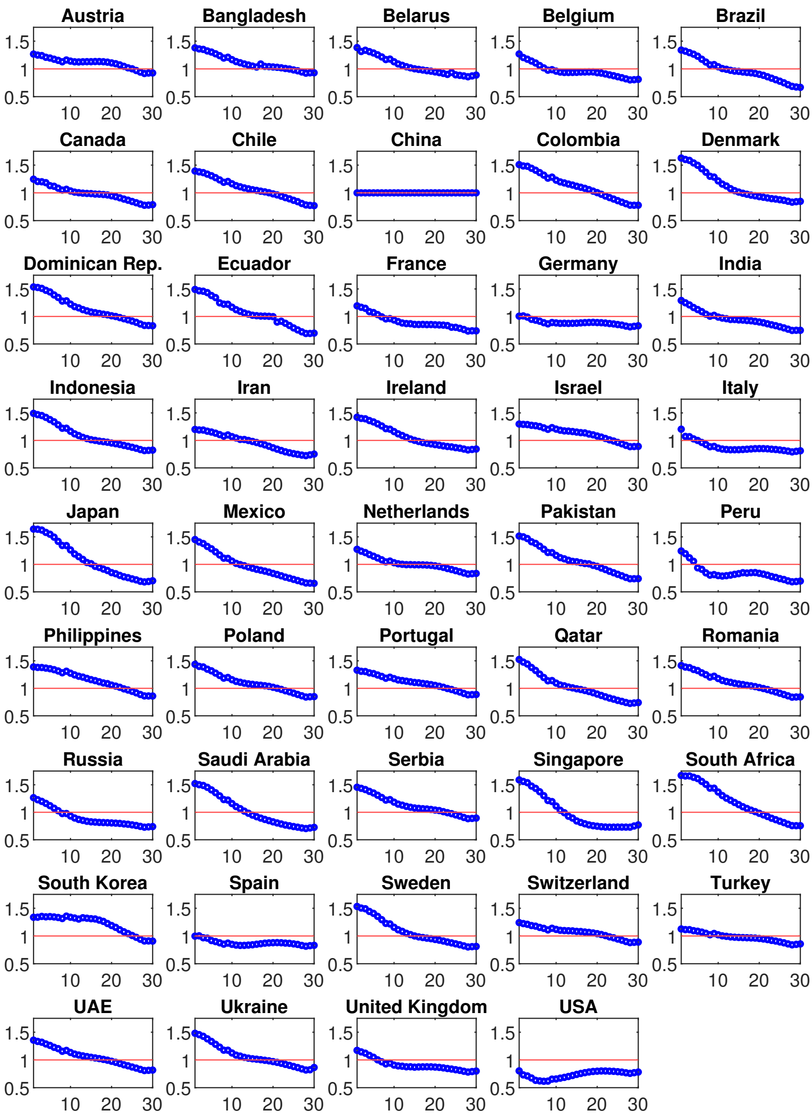

Figure 3: MIDIS: Relative to China

$(\alpha = 1/7,\ \beta = 0.111,\ \mu = 0.2381,\ d_0^{\text{CHN}} = 0.5)$

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Table 2: MIDIS: Summary Statistics

Country	init. val.	avg.	std. dev.	max.	min.	acf(1)
South Africa	0.835	0.799	0.030	0.835	0.756	0.908
Japan	0.821	0.728	0.054	0.821	0.667	0.927
Denmark	0.813	0.767	0.040	0.847	0.715	0.879
Singapore	0.794	0.674	0.068	0.794	0.584	0.886
Dominican Rep.	0.768	0.784	0.037	0.837	0.735	0.951
Sweden	0.766	0.743	0.035	0.811	0.689	0.902
Qatar	0.762	0.703	0.027	0.762	0.657	0.804
Saudi Arabia	0.761	0.695	0.031	0.761	0.655	0.874
Pakistan	0.757	0.736	0.021	0.766	0.700	0.902
Colombia	0.755	0.770	0.026	0.804	0.727	0.944
Indonesia	0.746	0.747	0.040	0.823	0.692	0.919
Ecuador	0.746	0.725	0.026	0.791	0.688	0.748
Ukraine	0.740	0.745	0.054	0.864	0.679	0.890
Serbia	0.728	0.783	0.071	0.894	0.697	0.937
Mexico	0.726	0.662	0.018	0.726	0.633	0.681
Poland	0.718	0.763	0.062	0.849	0.680	0.946
Ireland	0.711	0.736	0.048	0.843	0.691	0.892
Romania	0.707	0.764	0.059	0.844	0.682	0.941
Chile	0.697	0.741	0.043	0.789	0.677	0.957
Philippines	0.694	0.798	0.063	0.862	0.690	0.923
Belarus	0.692	0.738	0.071	0.888	0.658	0.891
Bangladesh	0.690	0.781	0.092	0.930	0.673	0.925
UAE	0.678	0.736	0.058	0.817	0.653	0.936
Brazil	0.670	0.672	0.034	0.719	0.620	0.965
South Korea	0.669	0.852	0.103	0.958	0.669	0.924
Portugal	0.665	0.776	0.087	0.887	0.651	0.935
Israel	0.649	0.788	0.092	0.891	0.645	0.929
India	0.645	0.668	0.063	0.748	0.575	0.956
Netherlands	0.637	0.709	0.088	0.835	0.594	0.944
Belgium	0.635	0.680	0.091	0.812	0.562	0.947
Austria	0.633	0.785	0.119	0.926	0.615	0.940
Russia	0.633	0.628	0.060	0.739	0.553	0.925
Canada	0.623	0.693	0.073	0.787	0.585	0.944
Peru	0.622	0.596	0.082	0.696	0.464	0.946
Switzerland	0.620	0.753	0.104	0.889	0.604	0.934
Italy	0.602	0.628	0.104	0.811	0.511	0.931
Iran	0.600	0.667	0.046	0.751	0.594	0.879
France	0.596	0.635	0.072	0.740	0.548	0.946
United Kingdom	0.586	0.644	0.091	0.799	0.533	0.934
Turkey	0.563	0.696	0.105	0.857	0.557	0.925
Germany	0.503	0.637	0.122	0.830	0.482	0.929
China	0.500	0.725	0.169	1.000	0.500	0.916
Spain	0.499	0.628	0.128	0.831	0.475	0.931
USA	0.401	0.538	0.158	0.781	0.327	0.938

Notes: Authors' calculations using the identification methodology explained in Section 3 and the JHU (2020) data. acf(1) is the sample auto-correlation function at one lag.

A pattern observed in a large number of countries features a (minor) decline of MIDIS within the first week that is followed by a persistent (slow) increase later on. Austria, Belgium, France, Germany, India, Italy, Netherlands, Peru, Poland, Russia, Spain, Switzerland, United Arab Emirates, United Kingdom, and the US exhibit such a pattern. For the US, the initial decrease in the first five days of the sample is the fastest. Hence, the US is not only the country that records the lowest initial MIDIS value; on the fifth day in the sample, the MIDIS value of the US converges to the minimum of the entire sample at 0.327. The maximum MIDIS value for the fifth day is equal to 0.834 and observed in South Africa.

The evolution of MIDIS in countries that attain the highest initial values is notably different. In Japan and South Africa, MIDIS keeps decreasing at a slow rate during the entire sample period. In Denmark and Singapore, however, there is a clear U-shaped pattern where MIDIS takes its lowest values around the middle of the 30-day period.

We observe the most distinguished pattern of MIDIS during the 30-day period in South Korea. Starting at a moderately high value of 0.67, MIDIS in South Korea increases fast and converges to over 0.90 on around the 15th day. In the second half of the episode, the country sustains a high level of MIDIS. In that second half, the average MIDIS value in South Korea is 0.93. The country also attains the highest full-sample average of 0.85 across 44 countries. Table 2 presents a detailed account of MIDIS statistics for all countries.

Figure 3 pictures the evolution of MIDIS relative to China. Some interesting messages follow from this figure as well. The common pattern is a persistent decrease below unity. Decreases are more visible in countries with larger initial MIDIS values, as expected.

An interesting observation is that there is no country that records MIDIS values larger than the Chinese levels for the entire sample. Hence, if China truly serves as a benchmark for distancing, then no country in our sample of 44 countries sustain distancing more effectively than China in the 30-day episode that follows the 500th confirmed case. The initial success in distancing is not continued, and MIDIS values decreases below unity somewhere in the second half of the 30-day episode.

The US, with an initial MIDIS value less than the Chinese benchmark, cannot forge ahead China during the entire sample period. Put differently, relative MIDIS values for the US remain lower than unity for all t. The situation is similar for Spain, Germany, Italy, Peru, and the UK whose MIDIS values decrease below the Chinese level within the first week of the sample. Hence, it is fair to state that several Western countries, most notably the US, perform least effectively in terms of distancing during the sample period.

Before concluding this section, we investigate whether the daily mobility data from Apple (2020) and Google (2020) validate our distancing measure MIDIS. In Table 3, we document various regression results where MIDIS is the dependent variable and a mobility indicator from Apple (2020) or Google (2020) is the independent variable. In these regressions, we match the calendar dates for each country, and each row presents the results of a separate regression. Clearly, the results we document here cannot be interpreted as a sign of a causal mechanism because both the mobility indicators and MIDIS quantify the very same phenomenon.

The results show that the mobility indicators are strongly correlated with MIDIS and support the validity of our identification strategy. As expected, increased mobility in resi-

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Table 3: Validating MIDIS through the Mobility Data

Independent Var.	Parameter	Robust S.E.	# of Countries	# of Obs.	R-squared
A-Driving	-0.184***	0.043	35	1,050	0.0778
A-Transit	-0.203***	0.041	18	540	0.0913
A-Walking	-0.161***	0.041	35	1,050	0.0810
G-RetailRecreation	-0.180***	0.039	40	1,200	0.0629
G-GroceryPharmacy	-0.131***	0.038	40	1,200	0.0535
G-Parks	-0.058*	0.035	40	1,200	0.0020
G-TransitStations	-0.221***	0.046	40	1,200	0.0662
G-Workplace	-0.198***	0.046	40	1,200	0.0583
G-Residential	0.377***	0.108	40	1,200	0.0349

Notes: The reported R-squared is the overall R-squared measure. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. See Table B.1 for variable definitions and data sources.

dential places are positively associated with MIDIS (the last row), and all the other mobility indicators that represent mobility in public places have a strong, inverse relationship with MIDIS. Among the indicators from Apple (2020), we estimate the largest effect for transit stations, and the magnitude of the estimated slope parameter is close to those we obtain for the mobility indicators measured for transit stations and workplace indicators using the Google (2020) data. In absolute value terms and for the nine indicators we focus on, we estimate that the largest effect originates from the mobility in residential areas, and the smallest one from mobility in parks.

5. Cross-Country Heterogeneity in MIDIS

To examine how our social distancing measure varies with a number of country characteristics along governmental, behavioral, and developmental dimensions, we estimate the following regression at the country-day level, (j, t), with each country being j and each day being t:[6]

$$\text{MIDIS}_{j,t} = \phi_0 + \phi_1 G_{j,t-1} + \phi_2 B_{j,t-1} + \phi_3 \mathbf{D}_j + \epsilon_{j,t} \tag{16}$$

Here, $\text{MIDIS}_{j,t}$ is the social distancing measure we construct in this paper at (j, t) level. We rescale this variable to vary between 0 and 100 in regressions. The next two variables are to control for the effect of NPIs on MIDIS: $G_{j,t-1}$ is governmental response to the pandemic, and $B_{j,t-1}$ is behavioral response to the pandemic by individuals. We use the lagged values of these variables to account for the time-lapse in social distancing as a response to various NPIs. $\mathbf{D}_j$ is a vector of country-specific indicators of comparative development.

First, the data for governmental response are from the Oxford COVID-19 Government Response Tracker (OxCGRT), which collects information on a multitude of containment

6 We avoid using time fixed effects in (16) since they were already taken into account in the construction of MIDIS as explained in Section 3.

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measures taken by 201 countries and territories around the globe.[7] These measures are school closures, workplace closures, cancellation of public events, bans on public transport, domestic and international travel, government information campaigns, contact tracing and extended testing. All but the last two are used to construct the COVID-19 Government Response Stringency Index, which varies between 0 and 100. We use the lagged values of this index, $stringency_{j,t-1}$, in (16) to proxy for governmental response to the COVID-19 pandemic, $G_{j,t-1}$.

Second, we use JHU (2020) epidemiological data components as proxies for behavioral response to the pandemic. It would not be hard for anyone, who consciously experienced the COVID-19 pandemic, to recall that they had to drop everything to get the news of the numbers of infected, deceased, and recovered for the COVID-19 cases in their cities, countries, and the world every day to prepare for the next day. In other words, people use daily epidemiological data, particularly the numbers of infected or deceased individuals, that headlined all types of news outlets to inform their behavior on the next day. Therefore, we utilize the lagged values of infected and deceased people, $infected_{j,t-1}$ and $deceased_{j,t-1}$, to explore the effect of behavioral response on social distancing.[8] These variables are expressed in thousands in (16).

Finally, we investigate how social distancing varies with a range of country characteristics borrowed from the comparative development literature to understand the importance of cross-country heterogeneity in geography as well as economic, social, and cultural development (e.g., Easterly and Levine, 1997; Acemoglu et al., 2001; Alesina et al., 2003; Ashraf and Galor, 2013). In particular, we use GDP per capita ($loggdppc_j$), human capital index ($humancap_j$), social progress index (spi_j), ethnolinguistic fractionalization ($ethnofrac_j$), and continent dummies. The definitions and data sources of all the variables used in the regressions are compactly presented in Table B.1, and Table B.2 reports the summary statistics.

Table 4 displays the regression results of different specifications of (16) by progressively adding variables. Column (1) explores the impact of governmental response to the pandemic. The variable $stringency_{j,t-1}$ has a significant positive impact on the level of social distancing. As governments adopt more stringent containment measures, social distancing proliferates. Indeed, a 1 point increase in stringency increases MIDIS by 1/3 of a point.

7 A detailed description of the data is provided by Hale et al. (2020) and the dataset is available at `https://covidtracker.bsg.ox.ac.uk`.

8 As in Alfaro et al. (2020), we have also used variables such as "risk taking," "patience," "reciprocity," or "altruism" from the Global Preferences Survey of Falk et al. (2018) and Falk et al. (2016). However, most probably due to very low variation in these variables for our sample of 44 counties, we could not obtain any significant results.

Table 4: Heterogeneity of MIDIS in Different Dimensions

Variables	(1) Governmental	(2) Governmental & Behavioral	(3)	(4)	(5) Governmental, Behavioral & Developmental	(6)	(7)	(8)	(9)	(10) Fixed Effects
$stringency_{j,t-1}$	0.327***			0.202***	0.202***	0.202***	0.200***	0.205***	0.197***	0.197***
	(0.061)			(0.052)	(0.052)	(0.053)	(0.052)	(0.052)	(0.050)	(0.021)
$infected_{j,t-1}$		0.247***								
		(0.078)								
$deceased_{j,t-1}$			3.862***	3.131***	3.130***	3.132***	3.142***	3.113***	3.170***	3.304***
			(0.479)	(0.454)	(0.451)	(0.448)	(0.451)	(0.450)	(0.450)	(0.222)
$humancap_j$					0.586					
					(2.167)					
spi_j						0.001				
						(0.098)				
$loggdppc_j$							-0.626			
							(1.177)			
$ethnofrac_j$								-0.001**		
								(0.000)		
$europe_j$									-3.255	
									(2.438)	
$northamerica_j$									-12.694*	
									(6.750)	
$latinamerica_j$									-4.157	
									(3.057)	
$ssafrica_j$									4.695***	
									(1.753)	
R-squared	0.114	0.029	0.019	0.100	0.100	0.100	0.104	0.149	0.170	0.643
# of Countries	43	44	44	43	43	43	43	43	43	43
# of Obs.	1,247	1,276	1,276	1,247	1,247	1,247	1,247	1,247	1,247	1,247

Notes: The reported R-squared is the overall R-squared measure. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. See Table B.1 for variable definitions and data sources.

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Columns (2) and (3) explore behavioral responses only. The former uses the number of people infected whereas the number of deceased due to the COVID19 is utilized in the latter. Both have a positive and significant impact on the level of social distancing. While 1,000 more infected people increases MIDIS by 0.25 points, 1,000 more deceased people increases MIDIS by 3.9 points. Considering the much grimmer impact of the rise in the number of deaths, it is natural to expect a higher behavioral effect from the number of deceased compared to the number of infected. In the remaining specifications, we use $deceased_{j,t-1}$ to gauge for the behavioral response; however, our results with $infected_{j,t-1}$ are qualitatively similar and available upon request. Column (4) reports governmental and behavioral dimensions together, and both parameters stay positive and significant.

In columns (5)-(8), we add the variables $humancap_j$, spi_j, $loggdppc_j$, and $ethnofrac_j$ one by one since these are highly correlated with each other as shown in Table B.3. Except for ethnolinguistic fractionalization, none of these variables are significant in explaining MIDIS. Very little cross-country variation in these variables in our 30-day sample with only 44 countries may be the culprit here. However, it may also indicate that the virus—hence social distancing—does not differentiate between developed or otherwise and can manifest itself in unexpected ways compared to our conventional wisdom. When we add continent dummies in column (9), however, it is seen that while the level of social distancing in Europe and North America is lower compared to Asia (the excluded category), it is higher in Sub-Saharan Africa. This is in line with results discussed in Section 4.

Variables measuring governmental and behavioral responses to the COVID-19 pandemic are robustly positive and significant in columns (5)-(9). The last specification reported in the column (10) of Table 4 shows that, even when we use country fixed effects, the effects of governmental and behavioral responses on MIDIS remain to be robust. As expected, the fixed effects model returns a much higher *R-squared* value.

6. MIDIS and Output Loss

This section presents an application for the use of the social distancing measure, MIDIS, constructed in this paper. We focus on the economic costs of social distancing triggered by the COVID-19 pandemic.

Baldwin and Weder di Mauro (2020a) clearly explain the types of economic shocks created by the COVID-19 pandemic that cause reduced economic activity. Among these, we concentrate on output loss. Following these authors' general guidelines, we can say that, on the one hand, even with no response at all to the pandemic, there is output loss due to sick people not being able to produce (a medical shock). On the other hand, social distancing caused by governmental and behavioral responses to the pandemic creates distances between workers and work as well as consumers and consumption, which results in further output losses.

The link between output loss and social distancing can best be explained by the help of a diagram that is now familiar to many. Figure 4 shows the epidemiological curves—bell shaped curves of the number of new cases over time—with (blue) and without (red) social

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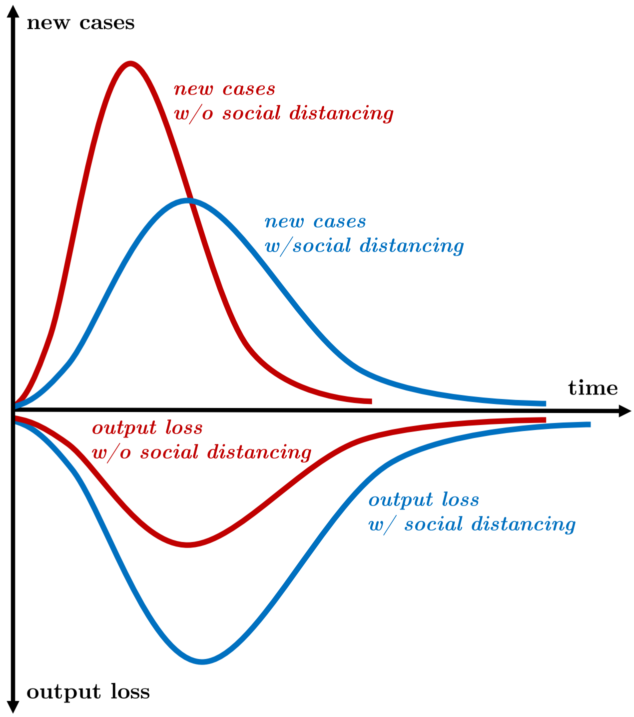

Figure 4: Social Distancing, Epidemiological Curve and Output Loss

Source: Authors' elaboration, inspired by Baldwin and Weder di Mauro's (2020b) illustration

distancing in the top panel, and the corresponding output loss curves in the bottom panel.

Considering the fact that COVID-19 is an extremely infectious killer that causes higher death rates when the patients are not well cared for, it is obvious that social distancing does not directly save people from dying but saves their lives by preventing congestion in healthcare facilities. So, the top panel of Figure 4 implies that COVID-19 kills many people, but it kills less with social distancing. This is what is meant by "flattening the curve" by epidemiologists. The bottom panel, however, illustrates that existence and/or stringency of social distancing measures proliferates output losses during a pandemic (Gourinchas, 2020).

Even though in our subsequent analysis we choose to stay oblivious to the exact channels of output loss during the COVID-19 pandemic, it is important to briefly mention them here for the sake of argument. There are demand and supply side components of output loss experienced during the pandemic. The main channels of demand disruptions are (i)

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a direct hit to aggregate demand components due to the medical shock as well as social distancing and (ii) an expectation shock to consumption and investment due to wait-and-see type delays by consumers and firms. The main channels of supply disruptions are (i) a direct hit to aggregate supply through reduced production capability resulting from the medical shock as well as social distancing and (ii) a supply-chain contagion as the disease jumps from one country to the other against the background of internationally fragmented production structure across the globe.

6.1. Proxying for Output Loss

Unlike epidemiological data, it is impossible to come by daily data for output, which makes using a proxy instead a necessity. Therefore, we use the Bruegel Electricity Tracker (BET) of COVID-19 Lockdown Effects compiled and calculated by McWilliams and Zachmann (2020) to approximate output loss experienced during the pandemic based on the premise that much economic activity heavily relies on the use of electricity. BET reports the temperature-adjusted daily sums of peak-hour electricity consumption (08:00-18:00) as a measure of economic activity owing to the intensity of economic activity within these hours. BET sample spanned 20 countries[9] between March 4-May 13, 2020 in the time of writing this paper.[10]

Let relative output be the ratio of daily peak-hour electricity consumption in 2020 to that in 2019 and state it as a percentage:

$$\text{relative output}_{j,t} = \left(\frac{\text{output}_{j,t}^{2020}}{\text{output}_{j,t}^{2019}}\right) \times 100 \tag{17}$$

Here, we calculate relative output for country j on day t by aligning each week in 2020 with the corresponding week in 2019. In our analysis, we include only working days (ignoring weekends and public holidays from our sample of 30 days for which MIDIS is calculated), which leaves us with 20-22 days for each country.

Figure 5 illustrates the evolution of relative output (blue points) and MIDIS (black points) in these 30 days along with a hypothetical red line that shows the case of no output loss by crossing the vertical axis at the value of 100.

The first observation from Figure 5 is that, with the exceptions of Denmark, Japan, and Sweden, all countries experienced a visible decline in their output levels relative to 2019. For many countries in the sample, there is output loss either for the entirety or the majority of the days considered. In Austria, India, Netherlands, Poland, and Switzerland, for instance, relative output is less than 100 percent for all the days in their respective samples.

The closer inspection of Figure 5 also reveals that there might exist a scale effect from MIDIS to relative output in the sense that output losses remain minuscule as long as MIDIS remains sufficiently low. The cases of the US, Spain, Germany, and Italy—and of the UK to

9 Austria, Belgium, Denmark, France, Germany, India, Ireland, Italy, Japan, Netherlands, Poland, Portugal, Romania, Serbia, Spain, Sweden, Switzerland, Ukraine, the UK and the US.

10 A detailed description of the temperature adjustment methodology is provided at the Bruegel website.

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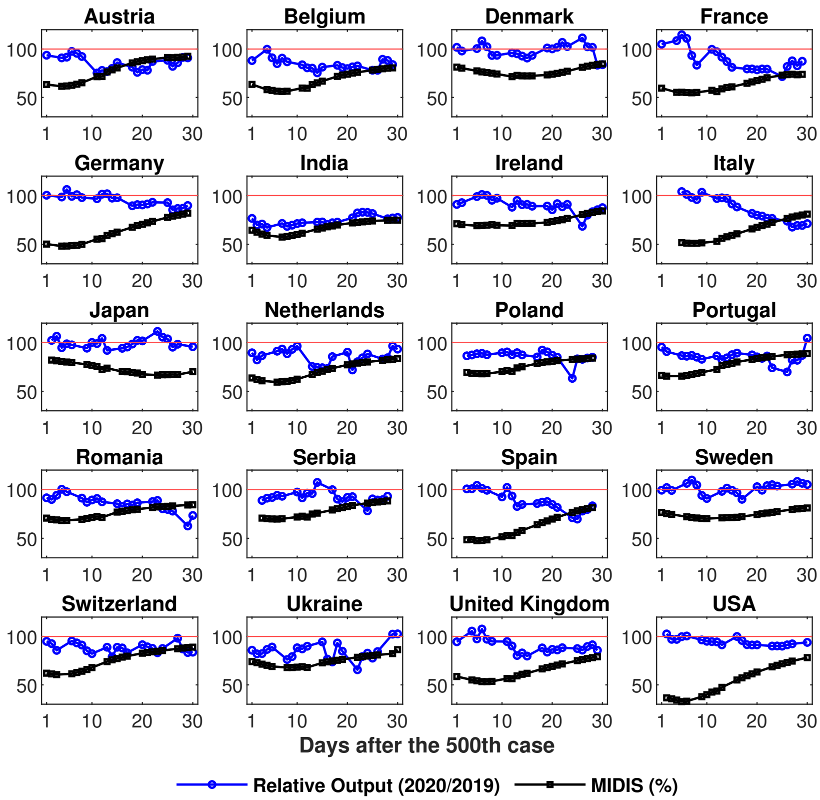

Figure 5: MIDIS and Relative Output

a lesser extent—suggest that countries that enter the 30-day episode with a MIDIS level less than or very close to 50 percent do not face (sizable) drops in relative output. In all of these countries, the decline of relative output seems to have required sufficiently large increases in MIDIS after a particular date.

Figure 5 also shows that the relationship between MIDIS and relative output is not uniform across countries and days. Some countries such as France, Italy, and Spain exemplify the strong negative association, but the relationship turns out be less visible in some countries after a particular date. For instance, in Austria, there seems to be a counterintuitively positive association between relative output and MIDIS after the 10th day. The same is true for Spain for the fourth quarter of the 30-day episode. In some countries, the continuing increase in MIDIS within a particular episode is observed along with a trendless movement of relative output. In Belgium after the 10th day, for instance, MIDIS increases from around

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Table 5: MIDIS and Output Loss

	Weekends Excluded			Weekends & Holidays Excluded		
MIDIS	0.233***	0.372***	0.342***	0.219***	0.358***	0.366***
	(0.036)	(0.038)	(0.061)	(0.035)	(0.037)	(0.059)
Country FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
R-squared	0.072	0.535	0.590	0.066	0.578	0.638
# of Countries	20	20	20	20	20	20
# of Obs.	425	425	425	407	407	407

Notes: The reported R-squared is the adjusted R-squared measure. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. See Table B.1 for variable definitions and data sources.

50 percent to 80 percent but relative output fluctuates within the proximity of 80 percent.

We observe an example of non-uniformity from the other direction as well. In Ireland, the trendless movement of MIDIS within the neighborhood of 70 percent for the entire episode is accompanied by successive episodes of slow increase, slow decrease, stability, sharp decrease, and sharp increase.

Overall, however, there exists a moderately strong, inverse relationship between MIDIS and relative output. For each country, the correlation coefficient is negative. These correlation coefficients range between -0.21 and -0.73, with an average of -0.36, and all of them are statistically significant at 5 percent confidence level.

6.2. Estimation Results

To explore the relationship between social distancing and output loss, we estimate a very basic regression specification at the country-day level, (j, t), with each country being j and each day being t:

$$\text{output loss}_{j,t} = \phi \text{MIDIS}_{j,t} + \eta_j + \delta_t + \epsilon_{j,t} \tag{18}$$

where $\text{output loss}_{j,t} = 100 - \text{relative output}_{j,t}$, and η_j and δ_t denote country and day fixed effects, respectively. Here, ϕ can be interpreted as the social distancing elasticity of output loss given that both MIDIS and output loss are expressed in percentages.

Table 5 reports the estimation results for (18) using different fixed effects structures. The left panel is for the sample excluding weekends and the right panel for the sample excluding both weekends and public holidays. The results indicate a robust positive impact of MIDIS on output loss. In other words, an escalation in social distancing increases output loss. Indeed, the social distancing elasticity of output loss vary between 0.22 and 0.37 depending on the specification. Put it another way, a 10 percent increase in social distancing causes 2.2-3.7 percent increase in output loss, which is large in any account.

In short, the social distancing measure implied by the SEIRD model and daily epidemiological data explains output losses experienced during the COVID-19 pandemic in a meaningful way. Clearly, the effects of MIDIS on output loss that we document in Table 5 do

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not identify the structural mechanisms, but the regression serves as a reduced-form device that allows us to see the quantifiable output impact of distancing.[11]

7. Concluding Remarks

In this paper, we make a first attempt to identify a social distancing term for each country and each day within the framework of the SEIRD model to be able to construct a distancing measure with minimum data requirements. This is critical in the context of the current COVID-19 pandemic because until a vaccine or an effective antiviral treatment is developed, policymakers as well as individuals will be in the midst of the tension between *necessity* and *tolerability* of social distancing. On the one hand, there is a need to sufficiently contain the spread of the disease through social distancing to prevent an overrun on the healthcare facilities. On the other hand, it will be impossible to continue social distancing—either through governmental or individual measures—indefinitely, since people's livelihoods depend on being able to work. As a result, to inform their decision making process, it would be desirable for policymakers as well as individuals to have access to a relatively reliable and robust distancing measure with a minimum requirement of high-frequency data. The social distancing term we identify in this paper (MIDIS) may be a candidate for that role.

When we take MIDIS to data, our results successfully exhibit the cross-country and over-time heterogeneity in social distancing during the COVID-19 pandemic. We also show that MIDIS is highly correlated with the mobility data, and it embeds both governmental and behavioral responses to the pandemic. Furthermore, when we use MIDIS to explain output losses experienced during the pandemic, we are able to show a robust positive correlation between the two—with sizable economic effects.

In sum, we consider our paper as an initial attempt to improve the SEIRD model and a contribution to the intense debate on the effects of the COVID-19 pandemic. We expect our qualitative results to be informative and useful. However, due to the highly stylized nature of the underlying epidemiological model we use to construct MIDIS, we urge our readers to interpret our quantitative results with care. Since the world governments are taking steps in easing lockdown restrictions in the time of writing this paper, we can safely say that there is much to change in the near future in regards to social distancing and its diverse effects on the lives of people. Our hope is to continue this line of work to incorporate what we miss in the current version and the new developments in the pandemic as they arise.

11 The strong relationship between distancing and output loss is expected to hold in the very short run, e.g., a month, and it may weaken and be reversed in the longer run. This is because both the centralized/optimal distancing policies and decentralized/individual distancing practices are time-dependent—changing daily—as demonstrated in the related literature (Bethune and Korinek, 2020; Farboodi et al., 2020). We thank an anonymous reviewer for pointing this out.

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References

Acemoglu, D., V. Chernozhukov, I. Werning, and M. D. Whinston (2020): "Optimal Targeted Lockdowns in a Multi-Group SIR Model," Working Paper 27102, National Bureau of Economic Research, 10.3386/w27102.

Acemoglu, D., S. Johnson, and J. A. Robinson (2001): "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review*, 91 (5), 1369–1401.

Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003): "Fractionalization," *Journal of Economic growth*, 8 (2), 155–194.

Alfaro, L., E. Faia, N. Lamersdorf, and F. Saidi (2020): "Social Interactions in Pandemics: Fear, Altruism, and Reciprocity," Working Paper 27134, National Bureau of Economic Research, 10.3386/w27134.

Alvarez, F. E., D. Argente, and F. Lippi (2020): "A Simple Planning Problem for COVID-19 Lockdown," *Covid Economics: Vetted and Real-Time Papers* (14).

Apple (2020): "Mobility Trends Reports," `https://www.apple.com/covid19/mobility`.

Argentieri Mariani, L., J. Gagete-Miranda, and P. Rettl (2020): "Words can hurt: How political communication can change the pace of an epidemic," *Covid Economics: Vetted and Real-Time Papers*, 1 (12).

Ashraf, Q., and O. Galor (2013): "The 'Out of Africa' Hypothesis, Human Genetic Diversity, and Comparative Economic Development," *American Economic Review*, 103 (1), 1–46.

Askitas, N., K. Tatsiramos, and B. Verheyden (2020): "Lockdown strategies, mobility patterns and Covid-19," *Covid Economics: Vetted and Real-Time Papers*, 1 (23).

Avery, C., W. Bossert, A. T. Clark, G. Ellison, and S. F. Ellison (2020): "Policy implications of models of the spread of coronavirus: Perspectives and opportunities for economists," *Covid Economics: Vetted and Real-Time Papers*, 1 (12).

Baldwin, R., and B. Weder di Mauro (2020a): *Economics in the Time of COVID-19*, VoxEU.org Book, London: Centre for Economic Policy Research.

——— (2020b): *Mitigating the COVID economic crisis: Act fast and do whatever it takes*, VoxEU.org Book, London: Centre for Economic Policy Research.

Berger, D. W., K. F. Herkenhoff, and S. Mongey (2020): "An SEIR Infectious Disease Model with Testing and Conditional Quarantine," Working Paper 26901, National Bureau of Economic Research, 10.3386/w26901.

Bethune, Z., and A. Korinek (2020): "COVID-19 infection externalities: Pursuing herd immunity or containment?" *Covid Economics: Vetted and Real-Time Papers*, 1 (11).

Brzezinski, A., G. Deiana, V. Kecht, and D. V. Dijcke (2020): "Government versus community action across the United States," *Covid Economics: Vetted and Real-Time Papers*, 1 (7).

Castex, G., E. Dechter, and M. Lorca (2020): "COVID-19: Cross-country heterogeneity in effectiveness of non-pharmaceutical interventions," *Covid Economics: Vetted and Real-Time Papers*, 1 (14).

Chang, R., and A. Velasco (2020): "Economic policy incentives to preserve lives and livelihoods," *Covid Economics: Vetted and Real-Time Papers*, 1 (14).

Chen, X., and Z. Qiu (2020): "Scenario analysis of non-pharmaceutical interventions on global Covid-19 transmissions," *Covid Economics: Vetted and Real-Time Papers*, 1 (7).

Chowell, G., P. W. Fenimore, M. A. Castillo-Garsow, and C. Castillo-Chavez (2003): "SARS outbreaks in Ontario, Hong Kong and Singapore: the role of diagnosis and isolation as a control mechanism," *Journal of Theoretical Biology*, 224 (1), 1–8, 10.1016/s0022-5193(03)00228-5.

Chudik, A., M. H. Pesaran, and A. Rebucci (2020): "Voluntary and mandatory social distancing: Evidence on Covid-19 exposure rates from Chinese provinces and selected countries," *Covid Economics: Vetted and Real-Time Papers*, 1 (15).

Cochrane, J. H. (2020): "An SIR Model with Behavior," https://johnhcochrane.blogspot.com/2020/05/an-sir-model-with-behavior.html, The Grumpy Economist Blog.

Coven, J., and A. Gupta (2020): "Disparities in Mobility Responses to COVID-19,"Technical report, NYU Stern Working Paper.

Deb, P., D. Furceri, J. D. Ostry, , and N. Tawk (2020): "The effect of containment measures on the COVID-19 pandemic," *Covid Economics: Vetted and Real-Time Papers*, 1 (19).

Degue, K. H., and J. Le Ny (2018): "An Interval Observer for Discrete-Time SEIR Epidemic Models," in *2018 Annual American Control Conference (ACC)*, 5934–5939.

Doganoglu, T., and E. Ozdenoren (2020): "Should I stay or should I go (out): The role of trust and norms in disease prevention during pandemics," *Covid Economics: Vetted and Real-Time Papers*, 1 (16).

Drazanova, L. (2019): "Historical Index of Ethnic Fractionalization Dataset (HIEF)," 10.7910/DVN/4JQRCL.

Durante, R., L. Guiso, and G. Gulino (2020): "Civic Capital and Social Distancing: Evidence from Italians' Response to COVID-19," *VoxEU Column*.

Easterly, W., and R. Levine (1997): "Africa's growth tragedy: policies and ethnic divisions," *Quarterly Journal of Economics*, 112 (4), 1203–1250.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020): "The Macroeconomics of Epidemics," Working Paper 26882, National Bureau of Economic Research, 10.3386/w26882.

Engle, S., J. Stromme, and A. Zhou (2020): "Staying at home: Mobility effects of Covid-19," *Covid Economics: Vetted and Real-Time Papers*, 1 (4).

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde (2018): "Global evidence on economic preferences," *Quarterly Journal of Economics*, 133 (4), 1645–1692.

Falk, A., A. Becker, T. J. Dohmen, D. Huffman, and U. Sunde (2016): "The preference survey module: A validated instrument for measuring risk, time, and social preferences," IZA Discussion Paper No. 9674 https://github.com/CSSEGISandData/COVID-19.

Farboodi, M., G. Jarosch, and R. Shimer (2020): "Internal and external effects of social distancing in a pandemics," *Covid Economics: Vetted and Real-Time Papers*, 1 (9).

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015): "The Next Generation of the Penn World Table," *American Economic Review*, 105 (10), 3150–82, 10.1257/aer.20130954.

Feng, Z. (2007): "Final and peak epidemic sizes for SEIR models with quarantine and isolation," *Mathematical Biosciences & Engineering*, 4 (4), 675–686.

Fernández-Villaverde, J., and C. I. Jones (2020): "Estimating and Simulating a SIRD Model of COVID-19 for Many Countries, States, and Cities,"Technical report, National Bureau of Economic Research.

Google (2020): "COVID-19 Community Mobility Results," https://www.google.com/covid19/mobility/.

Gourinchas, P.-O. (2020): "Flattening the Pandemic and Recession Curves," in *Mitigating the COVID economic crisis: Act fast and do whatever it takes* ed. by Baldwin, R., and Weder di Mauro, B. London: Centre for Economic Policy Research, 31–40.

Hale, T., N. Angrist, B. Kira, A. Petherick, T. Phillips, and S. Webster (2020): "Variation in government responses to COVID-19," BSG Working Paper Series 2020/032, https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

He, S., S. Tang, and L. Rong (2020): "A Discrete Stochastic Model of the COVID-19 Outbreak: Forecast and Control," *Mathematical Biosciences and Engineering*, 17 (4), 2792–2804.

JHU (2020): "COVID-19 Data Repository," https://github.com/CSSEGISandData/COVID-19.

Kaplan, G., B. Moll, and G. Violante (2020): "Pandemics According to HANK," https://benjaminmoll.com/wp-content/uploads/2020/03/HANK_pandemic.pdf.

Kermack, W. O., and A. G. McKendrick (1927): "A Contribution to the Mathematical Theory of Epidemics," *Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character*, 115 (772), 700–721.

Kmenta, J. (1991): "Latent Variables in Econometrics," *Statistica Neerlandica*, 45 (2), 73–84.

Lekone, P. E., and B. F. Finkenstädt (2006): "Statistical inference in a stochastic epidemic SEIR model with control intervention: Ebola as a case study," *Biometrics*, 62 (4), 1170–1177, 10.1111/j.1541-0420.2006.00609.x.

Maloney, W., and T. Taskin (2020): "Determinants of social distancing and economic activity during COVID-19: A global view," *Covid Economics: Vetted and Real-Time Papers*, 1 (13).

McWilliams, B., and G. Zachmann (2020): "Bruegel electricity tracker of COVID-19 lockdown effects," https://www.bruegel.org/publications/datasets/bruegel-electricity-tracker-of-covid-19-lockdown-effects/, Bruegel Datasets.

Painter, M. O., and T. Qiu (2020): "Political beliefs affect compliance with Covid-19 social distancing orders," *Covid Economics: Vetted and Real-Time Papers*, 1 (4).

SPI (2019): "Social Progress Index," https://www.socialprogress.org/, Social Progress Imperative.

Tang, B., X. Wang, Q. Li, N. L. Bragazzi, S. Tang, Y. Xiao, and J. Wu (2020): "Estimation of the Transmission Risk of the 2019-nCoV and Its Implication for Public Health Interventions," *Journal of Clinical Medicine*, 9(2) (462), 1–13.

Toxvaerd, F. (2020): "Equilibrium Social Distancing," *Covid Economics: Vetted and Real-Time Papers*, 1 (15).

World Bank (2020): "World Development Indicators," https://databank.worldbank.org/source/world-development-indicators.

Zhou, Y., Z. Ma, and F. Brauer (2004): "A discrete epidemic model for SARS transmission and control in China," *Mathematical and Computer Modelling*, 40 (13), 1491 – 1506, https://doi.org/10.1016/j.mcm.2005.01.007.

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Appendix A. MIDIS under Alternative Parameter Values

In this appendix, we investigate whether and to what extent the distancing measure MIDIS we identify is sensitive to the parameter values adopted for the benchmark results. We present results for China, South Korea, and the US for space considerations. We choose to focus on South Korea and the US since these are the countries with the highest and lowest average MIDIS values, respectively. The full set of sensitivity results are available upon request.

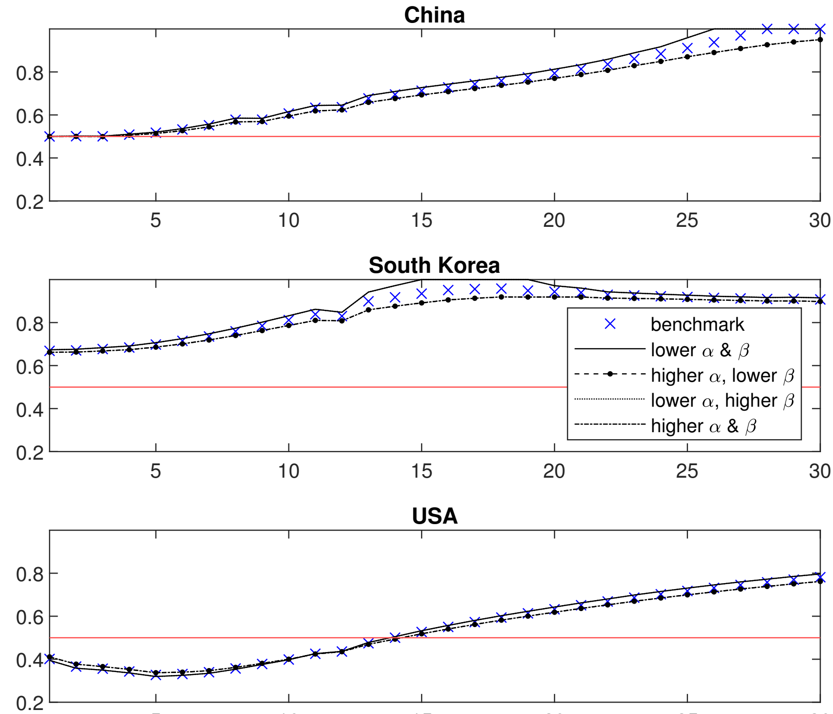

Figure A.1: MIDIS under Alternative (α, β) Values: μ is re-calibrated

Notes: This figure pictures the evolution of MIDIS for China, South Korea, and the US under alternative values of α and β and with a re-calibrated value of μ in each case. For α, the lower and higher values are $1/9$ and $1/5$, respectively. These correspond to 9 and 5 days of incubation. For β, the lower and higher values are $\beta - 2\hat{\sigma}_\beta = 0.1080$ and $\beta + 2\hat{\sigma}_\beta = 0.1140$, respectively, where $\hat{\sigma}_\beta = 0.0015$ as estimated by He et al. (2020).

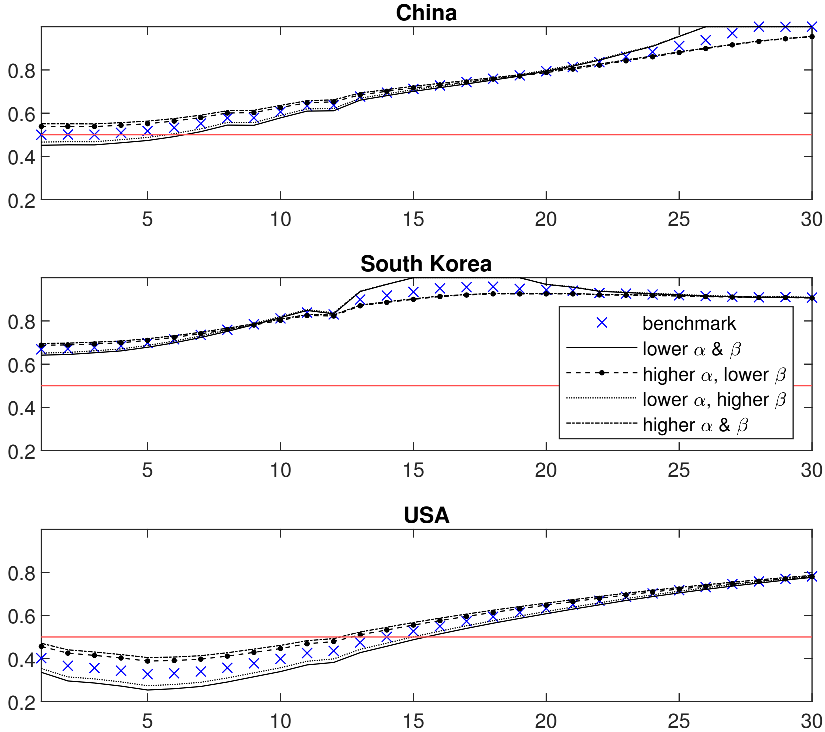

Figure A.2: MIDIS under Alternative (α, β) Values: μ is not re-calibrated

Notes: This figure pictures the evolution of MIDIS for China, South Korea, and the US under alternative values of α and β. For α, the lower and higher values are $1/9$ and $1/5$, respectively. These correspond to 9 and 5 days of incubation. For β, the lower and higher values are $\beta - 2\hat{\sigma}_\beta = 0.1080$ and $\beta + 2\hat{\sigma}_\beta = 0.1140$, respectively, where $\beta = 0.111$ is the benchmark value, and $\hat{\sigma}_\beta = 0.0015$ is the standard error, both being estimated by He et al. (2020).

Recall that the model has three parameters; β as the pure probability of transmission, α as the inverse of average incubation period, and μ as a free parameter that we adjust by normalizing the initial MIDIS value of China to $d_0^{\mathrm{CHN}} = 0.5$. The benchmark values of these parameters are $\beta = 0.111$, $\alpha = 1/7$, and $\mu = 0.2381$.

For all the scenarios we consider here, we set lower and higher values for both α and β. For the former, the lower value is characterized by 9 days of incubation, and the higher value by 5 days. For the latter, we use the standard error estimated by He et al. (2020) in assigning the lower and higher values to β. Specifically, with the estimated benchmark value of $\beta = 0.111$ and the estimated standard error of $\hat{\sigma}_\beta = 0.0015$, we assign the lower and higher values by constructing a confidence band of 2 standard errors, i.e., $\beta - 2\hat{\sigma}_\beta = 0.1080$

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and $\beta + 2\hat{\sigma}_\beta = 0.1140$.

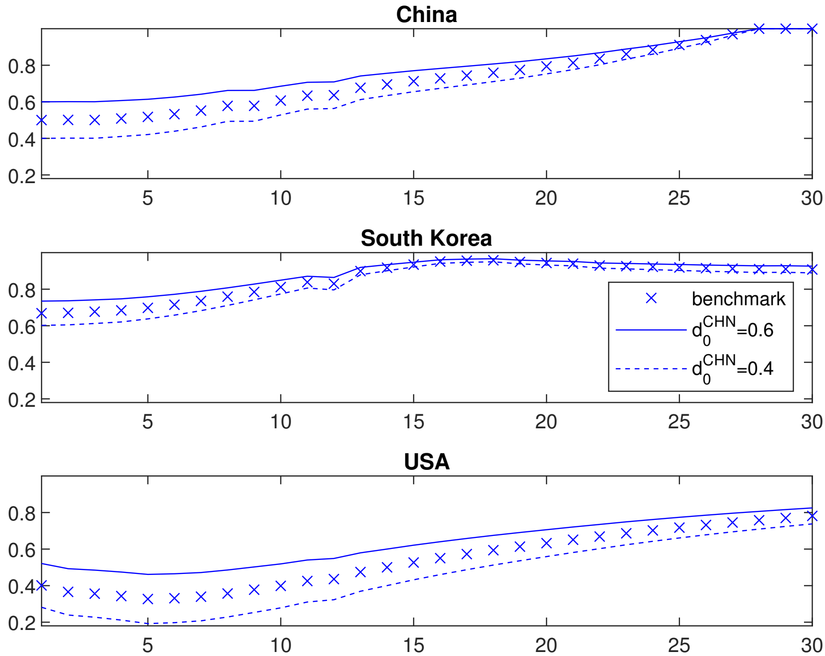

Figure A.3: MIDIS under Alternative d_0^{CHN} Values

Notes: This figure pictures the evolution of MIDIS for China, South Korea, and the US under alternative values of the normalized initial value for China, i.e., $d_0^{\text{CHN}} = 0.5$. Hence, the figure re-calibrates μ for each of the cases. For $d_0^{\text{CHN}} = 0.4$, the re-calibrated value is $\mu = 0.2857$, and, for $d_0^{\text{CHN}} = 0.6$, it is equal to $\mu = 0.1904$.

In the first stage of the sensitivity analysis, we run the algorithm for four different scenarios:

- $\alpha = 1/9$ and $\beta = 0.1080$
- $\alpha = 1/5$ and $\beta = 0.1080$
- $\alpha = 1/9$ and $\beta = 0.1140$
- $\alpha = 1/5$ and $\beta = 0.1140$

Figures A.1 and A.2 picture the results of these scenarios under two sub-scenarios. In the former, we re-calibrate μ to normalize the initial MIDIS value of China to $d_0^{\text{CHN}} = 0.5$ as in the benchmark case. These re-calibrated values are $\mu_1 = 0.2170$, $\mu_2 = 0.2579$, $\mu_3 = 0.2230$, and $\mu_4 = 0.2650$, respectively. In Figure A.2, however, we allow d_0^{CHN} to be different from 0.5 by keeping μ at its benchmark value of $\mu = 0.2381$.

Both figures show that the evolution of MIDIS is not much sensitive to the changes in parameter values. In fact, when we re-calibrate μ, this sterilizes the effect of changes in β, and only the value of α matter for the evolution of MIDIS.

Inspecting Figure A.2 also reveals that the separate effects of α and β on the magnitude of MIDIS for any t are closer to each other in size, but the effect of α is slightly larger.

In the second stage of sensitivity analysis, we investigate whether the normalized MIDIS value for China at $t = 0$ has an effect on the identified MIDIS sequences. In this exercise, we keep α and β at their benchmark levels, but change the target level of d_0^{CHN} and re-calibrate μ. The resulting values of μ for $d_0^{\text{CHN}} = 0.4$ and $d_0^{\text{CHN}} = 0.6$ are $\mu_5 = 0.2857$ and $\mu_6 = 0.1904$, respectively.

Figure A.3 pictures the associated MIDIS values along with the benchmark sequence. Once again, the evolution of MIDIS for the selected countries are qualitatively similar with that of the benchmark. For the three countries considered here, effects are symmetric with respect to the benchmark, and largest for the US and smallest for South Korea.

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Appendix B. Statistical Appendix

Table B.1: Variable Definitions and Data Sources

Variable	Definition	*Source*
stringency	Stringency Index, score, (0-100) a composite of various government responses	*Source*: Hale et al. (2020)
infected	Total number of confirmed COVID-19 cases	
deceased	Total number of individuals deceased because of COVID-19 in 1,000s	*Source*: JHU (2020)
humancap	Human Capital per person, indexed, 2017 values based on years of schooling & returns to education	*Source*: Feenstra et al. (2015)
spi	Social Progress Index, score, (0-100) based on more than 50 development indicators	*Source*: SPI (2019)
gdppc	GDP per capita, 2018 values purchasing power parity, constant 2017 international dollars	*Source*: World Bank (2020)
ethnofrac	Ethnolinguistic Fractionalization, score, (0-100) probability that two randomly drawn individuals within a country are not from the same ethnic group	*Source*: Drazanova (2019)
A-Driving	Map requests for driving route directions (relative to Jan 13, 2020, %)	
A-Transit	Map requests for transit directions (relative to Jan 13, 2020, %)	
A-Walking	Map requests for walking route directions (relative to Jan 13, 2020, %)	*Source*: Apple (2020)
G-RetailRecreation	Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters (relative to Jan 3-Feb 6, 2020, %)	
G-GroceryPharmacy	Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies (relative to Jan 3-Feb 6, 2020, %)	
G-Parks	Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens (relative to Jan 3-Feb 6, 2020, %)	
G-TransitStations	Mobility trends for places like public transport hubs such as subway, bus, and train stations (relative to Jan 3-Feb 6, 2020, %)	
G-Workplace	Mobility trends for places of work (relative to Jan 3-Feb 6, 2020, %)	
G-Residential	Mobility trends for places of residence (relative to Jan 3-Feb 6, 2020, %)	*Source*: Google (2020)
Relative Output	Peak-hour daily electricity consumption in 2020 (relative to 2019 values, %, excluding weekends and holidays)	*Source*: McWilliams and Zachmann (2020)

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Table B.2: Summary Statistics

Variable	# of Obs.	# of Countries	mean	std. dev.	min	max
MIDIS (%)	1,320	44	71.62	9.97	32.69	100.00
stringency	1,290	43	78.75	17.32	14.29	97.14
infected (in 1,000s)	1,320	44	11.98	26.65	0.50	366.32
deceased (in 1,000s)	1,320	44	0.51	1.46	0.00	13.89
humancap	1,290	43	3.05	0.52	1.77	3.97
spi	1,320	44	76.39	11.31	49.18	89.97
gdppc	1,320	44	35,776.08	23,690.32	4,441.42	96,477.22
ethnofrac	1,320	44	45.02	24.54	1.90	95.80
europe	1,320	44	0.43	0.49	0	1
northamerica	1,320	44	0.05	0.21	0	1
latinamerica	1,320	44	0.16	0.36	0	1
ssafrica	1,320	44	0.02	0.15	0	1
A-Driving	1,050	35	46.17	24.41	9.82	161.59
A-Transit	540	18	36.06	29.04	7.04	155.51
A-Walking	1,050	35	41.84	24.46	5.82	178.42
G-RetailRecreation	1,320	44	47.40	28.62	3.00	117.00
G-GroceryPharmacy	1,320	44	74.13	24.48	3.00	146.00
G-Parks	1,320	44	70.67	37.63	9.00	288.00
G-TransitStations	1,320	44	46.08	26.28	5.00	108.00
G-Workplace	1,320	44	57.12	24.42	8.00	104.00
G-Residential	1,320	44	119.42	11.20	98.00	153.00
Relative Output	425	20	89.30	9.55	62.66	114.77

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Table B.3: Correlation Coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) MIDIS	1.000											
(2) stringency	0.320	1.000										
(3) infected	0.155	0.021	1.000									
(4) deceased	0.133	0.052	0.806	1.000								
(5) humancap	-0.065	-0.350	0.107	0.079	1.000							
(6) spi	-0.085	-0.428	0.128	0.173	0.818	1.000						
(7) loggdppc	-0.128	-0.350	0.129	0.119	0.717	0.824	1.000					
(8) ethnofrac	-0.180	0.148	0.042	0.057	-0.362	-0.360	-0.284	1.000				
(9) europe	-0.038	-0.097	0.037	0.139	0.410	0.553	0.367	-0.370	1.000			
(10) northamerica	-0.222	-0.163	0.338	0.160	0.281	0.199	0.190	0.159	-0.190	1.000		
(11) latinamerica	-0.038	0.183	-0.107	-0.084	-0.211	-0.190	-0.294	0.170	-0.379	-0.095	1.000	
(12) ssafrica	0.128	0.103	-0.057	-0.051	-0.072	-0.140	-0.148	0.252	-0.133	-0.033	-0.066	1.000

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The Covid-19 crisis response helps the poor: The distributional and budgetary consequences of the UK lockdown

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We nowcast the economic effects of the Covid-19 pandemic and related lockdown measures in the UK and then analyse the distributional and budgetary effects of the estimated individual income shocks, distinguishing between the effects of automatic stabilisers and those of the emergency policy responses. Under conservative assumptions about the exit strategy and recovery phase, we predict that the rescue package will increase the cost of the crisis for the public budget by an additional £26 billion, totalling over £60 billion. However, it will allow to contain the reduction in the average household disposable income to 1 percentage point, and will reduce poverty rate by 1.1 percentage points (at a constant poverty line), with respect to the pre-Covid situation. We also show that this progressive effect is due to the increased generosity of Universal Credit, which accounts for only 20% of the cost of the rescue package.

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1. Introduction

The objective of this paper is to nowcast the effects of the Covid-19 lock-down on the UK economy, in terms of lost income, budgetary impact, and distributional consequences.

On Monday March 23, 2020, the UK Government followed a long list of countries and enforced drastic lock-down measures to limit and delay the spread of Covid-19. These included home confinement but for a limited list of exceptions, bans of public gatherings of more than two people, and closure of all retailers selling non-essential goods (essential shops include food retailers, pharmacies, hardware stores, corner shops, petrol stations, shops in hospital, post offices, banks, newsagents, laundrettes and pet shops). Schools were ordered to close a few days before, taking effect on that same Monday. The first phase of strict lock-down continued until May 13, when the Government allowed workers unable to work from home to return to their workplace provided social distancing was ensured at work, among other measures (HM Government, 2020).

There are no doubts that the effects of this forced breaks imposed on the economy, for the UK as well for the other countries following similar trajectories will be massive. Expert forecasts – reviewed in Hughes et al. (2020) – vary around a central estimate of around 2% GDP loss for each month of strict lock-down (see also OECD, 2020). The Office for Budget Responsibility's own forecasts lie on the pessimistic side, with a projected drop in the second quarter GDP of 35%, for a three-month lock-down (OBR, 2020).

In order to cushion the effects of the lock-down, the Government has introduced emergency income-support measures. These include a Coronavirus Job Retention Scheme, covering 80% of the wage costs of furloughed employees up to a maximum of £2,500 a month, a Self-Employment Income Support Scheme, allowing to claim a taxable grant worth 80% of trading profits up to a maximum of £2,500 a month, plus modified conditions for Universal Credit and Local Housing Allowance, among other auxiliary measures. The furlough scheme was extended at the end of the first phase of the lock-down until the end of October, with part-time working allowed from August.

The OBR forecasts that the impact of reduced economic activity and increased spending on the public budget will amount to around £220 billion (OBR, 2020), or 12% of GDP, split between £130 billion of lower receipts (a reduction of 15% with respect to the Budget), and almost £90 billion of increased spending (+9% with respect to the budget).

In this paper we go beyond these aggregate estimates, characterise the groups most affected by the lock-down, identify who benefits from the emergency support measures and by how much, and the consequences in terms of poverty and the government budget. We do this by using UKMOD, the EUROMOD-based tax-benefit model for the four UK nations developed at ISER, University of Essex.[1] Tax-benefit microsimulation models apply the fiscal legislation to an observed input population, typically coming from survey data (the Family Resource Survey for UKMOD). The most recent input data for UKMOD is for the financial year 2017/18. To model the effects of the lockdown, these data need to be updated. Lacking timely data on sectoral activity and employment, we employ an input-output (IO) model based on the supply-use tables published by the Office for National Statistics and referring to 2016, parameterised with the results of a consensus analysis of the opinions of a large number of UK-based economists. We allow the lock-down measures to impact final demand by sector, and also model supply-side constraints originating from the government guidelines. An important result from our IO model is that 75% of the effect originates from demand-side constraints originating from restrictions preventing final consumers from physically visiting sellers in lock-down, reduction in the demand from importers, or difficulties to get the goods and services through the border. Supply-side constraints, due to social distancing and smart working measures reducing the output of intermediate

[1] See https://www.iser.essex.ac.uk/research/projects/ukmod.

goods and services, which producers sell to other producers, account for only 25% of the overall macro effect of the crisis according to our estimates.

Overall, our baseline scenario predicts a loss of 7.3 million jobs (22.3% of the total), once the economy is in the lock-down equilibrium. This is in line with other forecasts indicating a contraction of 25% of GDP approximately after a two-month lock-down (e.g. Pichler et al., 2020). In our analysis we assume that the economy rapidly adjusts downwards to the Covid-19 shock, consistently with the preliminary evidence available. We also assume that the first phase of the crisis lasts for 2 months, followed by a further two months where the shock is reduced to 50%, and another four months where the shock is reduced to 25%. After that, we make the conservative assumption –in terms of the estimated impact of the crisis– that the economy goes back to the previous equilibrium.

The IO model allows us to differentiate the employment effects of the lock-down by industry. To distribute the income shock to workers within industries, we estimate individual relative probabilities of transitioning from employment to non-employment, on LFS data. We then analyse the effects of the estimated individual income shocks with UKMOD.

We show that the rescue package will add a net £26 billion bill to the £35 billion cost that the crisis would have entailed for the public budget, totalling £61 billion. However, it will allow to contain the reduction in the average household disposable income to 1 percentage point, and will reduce poverty rate by 1.1 percentage points (at a constant poverty line), with respect to the pre-Covid situation. We also show that this progressive effect is due to the increased generosity of Universal Credit, which accounts for around one fifth of the cost of the rescue package.

In our analysis we assume that there are no behavioural responses to the income shocks, with respect to labour supply behaviour. This is of course a simplification, which however is probably less dramatic than one would expect given the size of the shocks. This is because the crisis unfolded very rapidly and the emergency measures caught the economy entirely by surprise, being unconceivable just a few weeks before they were implemented. Moreover, they are coercive in nature and left very limited room for individual adjustment. Finally, they are generally understood to be limited in time. Hence, we argue that behavioural responses can be largely ignored, at least during the acute phase of the crisis.

Our paper belongs to a growing number of exercises trying to understand the distributional consequences of Covid-19.[2] Other contributions include Figari and Fiorio (2020), who perform the analysis on Italy, Beirne et al. (2020) for Ireland, O'Donoghue et al. (2020) also for Ireland, and we are aware of ongoing work in other countries. Figari and Fiorio use a legislation-based approach to identify what occupations should be affected by the regulation. Beirne and co-authors consider arbitrary employment scenarios. O'Donoghue et al. also start from a scenario analysis for sectoral shocks, and then distribute these shocks based on an income generation model.

The rest of the paper is structured as follows. Section 2 describes our dynamic IO model. Section 3 presents our parameterisation and quantification of the macroeconomic shock for the UK. Section 4 discusses the estimation of the employment transition model. Section 5 applies UKMOD and derives our main results. Section 6 summarises and concludes.

2. The macro model

Attempts to predict the macro-effects of the lockdown are more numerous than those looking at distributional consequences. Most exercises rely on aggregate macro models (e.g. Eichenbaum et al., 2020), with fewer making use of input-output (IO) models, often also fairly aggregated (e.g. to two sectors as in Bodenstein et al., 2020). IO models are typically of the Leontief (1936) or Gosh (1958)

[2] Gender issues of the Covid-19 epidemics are discussed, but not estimated, in Alon et al. (2020).

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type. In the Leontief model, output depends on final demand, and a shock to demand for one sector reverberates its effects upwards in the production process through sectoral interdependencies. In the Gosh model, output depends on value added, and a shock to productivity in one sector reverberates its effects downwards in the production process through sectoral interdependencies.[3]

In both cases, standard applications assume that no substitution among inputs is possible in the production of any good or service (Christ, 1955): production is then scaled up or down to meet final demand or supply constraints using the same optimal production plan, with a fixed mix of inputs in nominal terms.

Applications of the Leontief model to disaster impact assessment have led to the so-called Inoperability IO model, which follows a very similar logic (Dietzenbacher and Miller, 2015). The Inoperability model assumes that, when an entire sector or sub-sector is shut down or drastically impacted, the demand for that sector is picked up by imports. As such, the assumption that there is only one process used for the production of each output is maintained.[4] An alternative to assuming perfect substitutability between domestic intermediate inputs and imports is to consider a Cobb-Douglas specification with constant returns to scale both for production functions (supply side) and utility functions (demand side), as in Acemoglu et al. (2016).[5] This assumption ensures that income and substitution effects exactly offset each other, and the optimal mixes of intermediate inputs and final demand depend only on technological and utility parameters respectively, and not on prices nor quantities. Acemoglu et al. show that, under those assumptions, demand shocks are only propagated upwards and supply shocks only propagated downwards.

Both approaches allow in principle for contemporaneous demand and supply shocks, but are not particularly well suited for analysing the disruptions caused by Covid-19. Starting from the Inoperability model, the assumption that imports can compensate for shortfalls of intermediate inputs looks unsatisfactory, given that imports are also affected, either by lock-down measures in the producing countries or by trade restrictions. The Cobb-Douglas assumption is also problematic in the Covid context, as it implies constant expenditure shares. This means, for instance, that if a company routinely uses low fare airlines to allow its managers to visit production facilities, and airlines cease to operate, it will hire a private plane to allow at least some managers to visit some plants, some of the time, so that the proportion of the budget that goes to travelling remains unchanged. This seems implausible in the current circumstances.

Most contributions trying to predict the effects of Covid-19 on the economy follow the standard IO literature without optimisation. They typically deal with the problem of reconciling demand and supply shocks by computing the effects of the two shocks separately, and then considering the biggest of the two. This is for instance the approach of del Rio-Chanona et al. (2020), who construct their own measure of supply shocks for the US based on detailed occupation-specific considerations, while taking the Congressional Budget Office scenarios for the demand shocks.[6] Dorn et al. (2020) supposedly follow a similar approach in providing growth estimates for Germany, although they do not fully describe their

[3] The dual nature of the demand-driven Leontief model and the supply-driven Gosh model and their mathematical equivalence between the Leontief and Gosh model has been proposed (Dietzenbacher, 1997) and, while debated (de Mesnard, 2009), is generally accepted in the literature (see also Manresa and Sancho, 2019).
[4] Again, the implicit assumption that prices do not change or that they are perfectly offset by changes in quantity is made.
[5] To be noted, Acemoglu et al. do not estimate production function and utility parameters, but rather use their theoretical framework to inform a reduced form econometric specification, estimated using past shocks (variation from the exogenous components of imports from China, changes in federal government spending, total factor productivity shocks and variation in foreign-industry patents).
[6] The OECD (2020) works out its scenarios in an even simpler manner, by either looking at supply shocks (i.e. reductions in production) or demand shocks (i.e. reductions in sales), without working out their effects throughout the IO matrix.

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methods. On the other hand, Pichler et al. (2020) allow for a reorganisation of production plans by adopting a hybrid Leontief + linear production function, where they distinguish between essential and non-essential inputs in production based on ad-hoc survey of market analysts. They also allow substitutability in household final demand by estimating consumption functions. Here we develop an IO model that – although less sophisticated than Pichler et al. (2020), also considers the joint effects of demand side and supply side shocks. Interestingly, we get to similar results in terms of the macroeconomic effects of the crisis.

Let $y = [y_i]$ be the total output of each industry, $Z = [z_{i,j}]$ the matrix of intermediary inputs supplied by industry i to industry j, and $f = [f_i]$ the final demand for each industry. We have

$$y = Z + f, \tag{1}$$

where y is supply (production), and $Z + f$ is demand (sales). Inventories (included in the final demand) guarantee that the accounting identity production = sales holds, from which we obtain the familiar expression

$$Z = Ay \tag{2}$$

where A is a matrix of technical coefficients, assumed to remain constant. In a standard IO approach, a change in the final demand Δf is transmitted upwards and leads to a change in total production equal to

$$\Delta y = (1 - A)^{-1} \Delta f, \tag{2}$$

while a change in production of Δy is transmitted downwards and leads to a change in final demand equal to

$$\Delta f = (1 - A) \Delta y. \tag{2'}$$

There is however no way to allow contemporaneous demand and supply shocks to all industries. The fundamental problem is that if the equation demand = supply is to hold, one of the three terms A, y or f needs to be endogenously determined. We solve this problem by allowing A to change endogenously. Ideally, this could be rationalised under the assumption of constant elasticity of substitution (CES) production functions, to be separately estimated by sectors. CES production functions nest the three cases of Leontief (no substitutability), Cobb-Douglas (constant shares) and linear production functions (full substitutability). However, CES production functions are not simple to estimate on UK data, and estimates for many sectors do not converge (Richiardi and Valenzuela, 2020). We therefore proceed by making the extreme assumption of full substitutability. While this assumption might work for some inputs, that are dependable at least in the short term (think of air travels), it is clearly inadequate for others, which are essential in the production process (for instance, iron ore for metalwork). We defend it with two arguments: first, Covid-19 restrictions mostly involve the production and consumption of non-essential goods and services; second, our approach puts us on the safe side, by providing a lower bound of the estimated effect of the lock-down on the UK economy.

Our modelling assumptions are best described in dynamic terms. We assume a linear production function in intermediate inputs z, imports m and labour l:

$$y_i^S = \sum_{j=1}^{J} z_{j,i} + m_i + l_i. \tag{3}$$

Production is sold to other industries and final customers (including households, government, foreign markets and inventories):

$$y_i^D = \sum_{j=1}^{J} z_{i,j} + f_i. \quad (3)$$

Because of the disruptions caused by Covid-19, final demand is reduced to $\hat{f_i} = \alpha_i f_i$.[7] We assume that in a first period production plans are potentially affected by disruptions in supply, but otherwise continue unchanged even in the face of reduced final demand. Disruptions in supply, due to either an inability of firms to buy all the intermediate inputs originally planned, or to a diminished productivity of labour, reduce production to $\hat{y_i}^S = \beta_i y_i^S$. In absence of supply-side constraints, a reduction in final demand leads to over-production, which goes to inventories.[8] On the other hand, in absence of demand effects, a reduction in supply leads to under-production. We make the assumption that intermediate customers are served first, so that under-production leads to a reduction in sales to final customers.

Now, the subsequent dynamics is very different depending on whether there is over- or under-production in any given industry. In the first case, production is reduced to bring it in line with sales, meaning that the demand of all intermediate inputs is proportionally and uniformly reduced. This triggers further effects, as it worsen supply constraints in industries that are net buyers from industry *i*, and worsen demand constraints in industries that are net sellers to industry *i*.

Note that the symmetry between demand and supply shocks is broken because production is not allowed to expand in presence of supply-side constraints. Note also that supply-side constraints interact with final demand constraints by making the adjustment faster: if supply is reduced at the same time when demand is reduced, the economy remains closer to an equilibrium, although at a lower level of activity.

Finally, our model maintains the original input mix as far as demand shocks are considered. It's only supply shocks that affect the composition of intermediary inputs.

3. Scenario assumptions and the size of the employment shocks

Equipped with our dynamic IO model, we need scenario parameters for the supply and demand shocks. We get these from a consensus analysis of an ad-hoc survey of 2,644 economists with UK affiliations and complete personal profiles in RePEc, realised between April 24 and May 1, 2020. The questionnaire asked for the expected change, at the industry level, in (i) household demand (which we assumed representative of all final demand with the exclusion for the demand for exports), (ii) supply of intermediate goods and services, and (iii) exports. Final demand is affected because consumers face limitations to buy certain goods or services. For instance, in strict lock-down beers can be ordered take-away from the local pub, and cars can be bought online without visiting a dealer, but fewer people are doing this. Supply is constrained due to the social distancing measures that producers have to put in place, or because productivity goes down due to working from home arrangements. In some sectors, distinguishing between reduction in demand and reduction in supply is difficult. This is particularly true for services requiring a personal contact: for instance, consumers can't buy a haircut in lock-down, while hairdressers cannot sell it. The distinction is more meaningful in manufacturing, wherever social distancing can be achieved in factories. Our approach is more sophisticated than some other early attempts to model the macro effects of the Covid-19 lockdown, but still disregards to a large extent substitution effects by households and producers. As discussed above for labour supply, we motivate this simplifying assumption with the consideration that the shock was large, exogenous, unexpected, and likely of short duration (a few months), hence limiting the opportunities for reorganizing production and consumption plans.

[7] We assume that in a first period intermediate demand remains unchanged. Relaxing this assumption poses no problems (but also makes very little difference to our empirical results).
[8] So, technically, final demand remains unchanged, and only its composition is affected.

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Filling in scenario assumptions on all the three dimensions cited above for the 64 industries used by the IO tables provided by the Office for National Statistics would have required asking for 192 different values. We have therefore opted for selecting key industries only: 23 industries most relevant for household demand, and 11 industries most relevant for exports and intermediate inputs (Appendix 1, Table A1). This brought down the number of industries on which the respondents were asked to focus to 34, and the single values on which they were asked for an opinion to 45. We obtained a 378 valid responses, for a response rate of 14.3%. Removing surveys in which no questions were answered and surveys in which respondents did not consent to the study, we obtain a sample of 257 responses with 81% of complete responses (208 completed surveys and 49 partially completed surveys).[9] The distribution of the responses are reported in Appendix 1, Figures A1-A3.

We then created a mapping between the 192 parameters required, and the 45 obtained (Appendix 1, Table A2). On the basis of this mapping, we identify a baseline scenario with median values of the responses: feeding the IO model with these parameters leads to reduction in GDP of 22.6%, in the lock-down equilibrium. Our baseline is consistent with preliminary estimates showing that the UK economy contracted by 6% in March 2020. Given that lock-down was in place only in the last week of March, this points to a total effect close to one quarter of GDP, in equilibrium, not far away from our 22% figure.

The combination of demand and supply side constraints, as discussed in Section 2, also helps to produce a rapid adjustment. The effects of such a dramatic contraction in production on employment however depend crucially on how firms respond – their specific HR policies at a time of a national emergency. The presence of quite generous government schemes, in this respect, undoubtedly takes some pressure to cushion employment responses away from companies. As a first approximation, we assume a decrease in employment proportional to the decrease in production. This leads to an equivalent of 7.3 million jobs (-22.3%), in the lock-down equilibrium.[10] Our estimated job losses are slightly more conservative than the figure of almost 8 million workers released by HM Treasury on May 20, 2020 – the advantage of the macro model of course being that our estimates are disaggregated by sector.

Figure 1 reports the predicted employment losses by macro-sectors. Sector I - Accommodation & food services is the most badly hit, with an estimated reduction in lock-down of more than 80%, followed by H - Transport & storage with -40% and C - Manufacturing (almost -30%). The least affected sectors are L - Real estate activities, A - Agriculture, forestry & fishing, Q - Human health & social work and K - Finance and insurance, all around -10%.

[9] More information on the study is available at www.euromod.ac.uk/covid-19/consensus.

[10] The results of a low-impact scenario with the p25 values, and a high-impact scenario with the p75 values are available on request, together with their distributional and budgetary consequences. In the aggregate, the employment losses go down to just above 3 million jobs (-9%) in the low-impact scenario, and shoot up to almost 13.5 million jobs (-41%) in the high-impact scenario.

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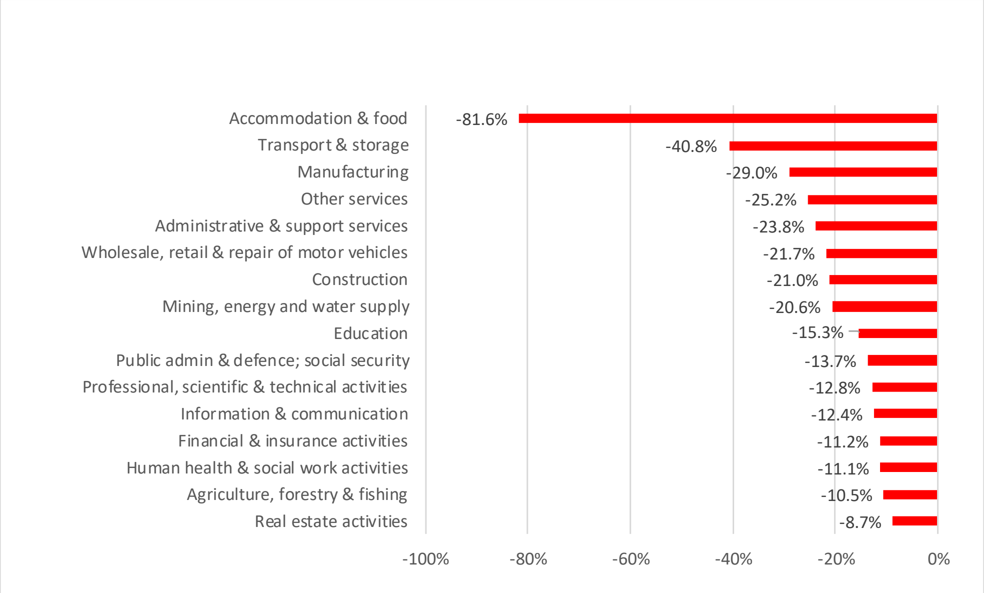
Figure 1: Employment effects by macro-sectors, baseline scenario.



Source: Our computation

The detailed employment effects predicted by our IO model by industry, which we use to adjust the input data of UKMOD, are reported in Table 1. Note that the estimated effects differ sometimes significantly from the input values obtained from the scenario analysis. For instance, final household demand for industry 39 - Telecommunication services was projected to go up 20% in the consensus analysis, but overall output and employment is estimated to go down 9% from our IO model. This is because of inter-industry linkages in the supply and demand of intermediate inputs.

Interestingly, if we shut down supply constraints we obtain a modified Baseline scenario where the contraction in employment is reduced to 5.5 million jobs, or 16.9% of total employment. Supply side constraints therefore amount to one quarter only of the total macroeconomic effect, in our model.[11]

[11] Pichler et al. (2020) show that the role of supply side vis-a'-vis demand side constraints is sensitive to the assumptions about the production function used. In particular, assuming some degree of substitutability between inputs as we do lowers, *ceteris paribus*, the overall economic effects of the initial shock, and also the role of supply side constraints. As already noted however, the aggregate results we get from our model are quite in line with those of Pichler et al. (and also other independent estimates – see the review in Hughes et al. 2020, already cited).

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Table 1: Estimated employment effects in the Baseline, High-impact and Low-impact scenarios.

	Industry		Change in Employment (%) Baseline median	High-impact p25	Low-impact p75
1	A	Products of agriculture, hunting and related services	-9	-24	-2
2	A	Products of forestry, logging and related services	-43	-65	-19
3	A	Fish and other fishing products; aquaculture products; support services to fishing	-13	-26	-2
4	BDE	Mining and quarrying	-37	-57	-19
5	C	Food products, beverages and tobacco products	-17	-30	-5
6	C	Textiles, wearing apparel and leather products	-34	-50	-17
7	C	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	-28	-46	-8
8	C	Paper and paper products	-23	-44	-2
9	C	Printing and recording services	-41	-58	-25
10	C	Coke and refined petroleum products	-27	-45	-11
11	C	Chemicals and chemical products	-22	-37	-4
12	C	Basic pharmaceutical products and pharmaceutical preparations	-12	-30	-2
13	C	Rubber and plastics products	-32	-51	-14
14	C	Other non-metallic mineral products	-26	-47	-3
15	C	Basic metals	-41	-61	-20
16	C	Fabricated metal products, except machinery and equipment	-33	-52	-15
17	C	Computer, electronic and optical products	-15	-35	-1
18	C	Electrical equipment	-27	-45	-8
19	C	Machinery and equipment n.e.c.	-41	-56	-28
20	C	Motor vehicles, trailers and semi-trailers	-53	-79	-31
21	C	Other transport equipment	-30	-48	-12
22	C	Furniture; other manufactured goods	-40	-65	-16
23	C	Repair and installation services of machinery and equipment	-17	-37	0
24	BDE	Electricity, gas, steam and air-conditioning	-18	-39	0
25	BDE	Natural water; water treatment and supply services	-16	-34	-1
26	BDE	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	-16	-35	-2
27	F	Constructions and construction works	-21	-42	0
28	G	Wholesale and retail trade and repair services of motor vehicles and motorcycles	-44	-72	-23
29	G	Wholesale trade services, except of motor vehicles and motorcycles	-13	-34	-1
30	G	Retail trade services, except of motor vehicles and motorcycles	-22	-43	-9
31	H	Land transport services and transport services via pipelines	-34	-59	-12
32	H	Water transport services	-49	-64	-30
33	H	Air transport services	-89	-96	-74
34	H	Warehousing and support services for transportation	-39	-60	-23
35	H	Postal and courier services	-10	-22	-4
36	I	Accommodation and food services	-82	-94	-51
37	J	Publishing services	-15	-41	0
38	J	Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services	-26	-40	-21
39	J	Telecommunications services	-9	-27	-1
40	J	Computer programming, consultancy and related services; information services	-8	-25	-1
41	K	Financial services, except insurance and pension funding	-11	-26	-8
42	K	Insurance, reinsurance and pension funding services, except compulsory social security	-12	-26	-9
43	K	Services auxiliary to financial services and insurance services	-9	-22	-4
44	L	Real estate services excluding imputed rents	-10	-27	0
45	L	Imputed rents of owner-occupied dwellings	-8	-25	0
46	M	Legal and accounting services; services of head offices; management consulting services	-13	-28	-6
47	M	Architectural and engineering services; technical testing and analysis services	-24	-40	-18
48	M	Scientific research and development services	-3	-18	0
49	M	Advertising and market research services	-14	-30	-6
50	M	Other professional, scientific and technical services; veterinary services	-10	-27	-2
51	N	Rental and leasing services	-12	-31	0
52	N	Employment services	-12	-31	-3
53	N	Travel agency, tour operator and other reservation services and related services	-92	-92	-92
54	N	Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services	-12	-29	-3
55	O	Public administration and defence services; compulsory social security services	-14	-32	-2
56	P	Education services	-15	-35	-7
57	Q	Human health services	-11	-29	-2
58	Q	Social work services	-11	-32	-3
59	RST	Creative, arts and entertainment services; library, archive, museum and other cultural services; gambling and betting services	-23	-54	-2
60	RST	Sporting services and amusement and recreation services	-63	-86	-34
61	RST	Services furnished by membership organisations	-10	-33	-4
62	RST	Repair services of computers and personal and household goods	-20	-42	-16
63	RST	Other personal services	-11	-34	-6
64	RST	Services of households as employers; undifferentiated goods and services produced by households for own use	-20	-50	0
		Total	**-22.3**	**-41.0**	**-9.2**

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4. The employment transition model

Having obtained from the IO model the expected contraction in employment in each of the 64 industries (as % change from the original level of employment), we need to assign the employment shocks at the individual level. Our assumptions distinguish between self-employment and dependent employment. For the self-employed, we simply assume that income is homogenously reduced proportionally to the industry-level shock. For employees, we assume that some workers remain unscathed, while others go down to 0 hours (whether because they are dismissed or furloughed, see Section 5 below). To identify the employees that make the transition to 0 hours, we model the probability of transitioning from dependent employment to non-employment between two consecutive quarters as a function of a set of individual observable characteristics X, the change in the industry-level aggregate employment ΔE_j, and a full set of industry dummies. We use the two-quarter longitudinal version of the Labour Force Survey (LFS). Due to a relatively small number of observations making the transition in any single file, we pool 11 two-quarter longitudinal datasets to cover the period from April 2014 to September 2019.[12] Removing observations with missing values in any of the variables included in X we obtain a sample of 175,475 observations on 128,702 unique individuals, all dependent employees in the first quarter observations, for a total of 4,160 transitions from employment to non-employment. Table 2 reports the estimated coefficients from a logistic regression.

Table 2: Employment transition model: Estimated coefficient (logistic regression)

	Coef.	St.Err.	
Sex of respondent (1= male)	0.011	0.039	
Age in years	-0.205	0.008	***
Age in years squared	0.003	0.000	***
% change in employment in sector	-0.096	0.008	***
2014 (omitted)	0.000	.	
2015.year	-0.010	0.060	
2016.year	-0.045	0.062	
2017.year	-0.142	0.063	**
2018.year	-0.131	0.063	**
2019.year	-0.135	0.065	**
Hours worked weekly	-0.028	0.002	***
Occupation:			
Managers (omitted)	0.000	.	
Professionals	0.000	0.070	
Technicians	-0.059	0.069	
Clerks	0.133	0.068	*
Sales	-0.003	0.068	
Trade and crafts	-0.169	0.092	*
Plant operators	0.189	0.088	**
Elementary	0.139	0.072	*
Public sector	-0.087	0.055	
Marital status:			
Single (omitted)	0.000	.	
Married	-0.317	0.048	***
Separated	-0.481	0.128	***
Divorced	-0.250	0.073	***
Widowed	-0.308	0.123	**
Education level:			
Low (omitted)	0.000	.	
Medium	-0.011	0.049	
High	0.089	0.062	
Tenure in months	-0.002	0.000	***
Industry dummies	Yes		
Constant	1.558	0.248	***

Mean dependent var	0.024	SD dependent var	0.152
Pseudo r-squared	0.082	Number of obs	175,475
Chi-square	3644.319	Prob > chi2	0.000
Akaike crit. (AIC)	36261.174	Bayesian crit. (BIC)	37137.721

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors reported are clustered at individual level.
Source: Our computation on LFS two-quarter longitudinal data, April 2014 to September 2019.

[12] Descriptive statistics for our sample are reported in Appendix 1, table A2.

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5. Distributional and budgetary consequences

We finally analyse the distributional and budgetary consequences of the employment shocks estimated above, and of the associated policy responses.

We utilise the tax-benefit microsimulation model UKMOD, the UK component of EUROMOD (Sutherland & Figari, 2013; Sutherland 2018). We use UKMOD version A1.5+, released in April 2020 to calculate disposable (net) household incomes, given individual (gross) market incomes and personal/household characteristics.[13] UKMOD runs on the Family Resources Survey (FRS), the latest data available being the 2017/18 wave with the different income components uprated to 2020 values.

UKMOD A1.5+ includes the changes announced in the Scottish and UK budgets of this year as well as Covid-19 policy measures, except for the Job Retention Scheme (JRS) and the Self-employment Income Support Scheme (SEISS), which we jointly label Market Income Support Schemes (MISS) and simulate directly.[14] Besides MISS, the main policy changes in response to the Covid-19 crisis are:

- an increase in the yearly basic element of the Working Tax Credit (WTC) of £1,045;
- an increase in the weekly housing benefit disregard of £20;
- an increase in the monthly standard Universal Credit (UC) allowance of £86.67;
- the removal of the minimum income floor for self-employed within the UC calculation;
- an increase in the weekly local housing allowance of £14.86 (on average across regions and accommodation types).

We modify the input data to simulate the effects of the Covid-19 income shock (see Appendix 2). With respect to the *size* of the income shock, we distinguish, as described in Section 4, between self-employed and dependent employees. For self-employed, we consider a homogenous reduction in earnings proportional to the projected reduction in output of their respective industry; for employees, we randomly put workers to 0 hours on the basis of the estimated probabilities coming out of the employment transition model.[15] With respect to the *duration* of the income shock, we assume 2 months of strict lock-down at 100% of the estimated effects, 2 months of partial lock-down at 50% of the estimated effect, and a further 4 months of recovery phase at 25% of the estimated effect. In the recovery phase, self-employed see a reduction in their income loss, while a proportion of the dependent employees that were sent to 0 hours are allowed to get back to their previous employment status.

Our analysis is based on a comparison between three counterfactuals:

1. A "pre-Covid" scenario (referred to as 'Scenario 1'), corresponding to the income distribution and fiscal position that would have occurred in the absence of the Covid-19 crisis and related policy changes;
2. A "post-Covid employment, pre-Covid policies" scenario (referred to as 'Scenario 2'), corresponding to the impact of the Covid-19 crisis in the absence of policy changes, where only the automatic stabilisers already embedded in the tax-benefit system operate. In this scenario, the employed individuals who would stop working in lock-down receive

[13] More information can be found in the UKMOD country report available at https://www.iser.essex.ac.uk/files/projects/UKMOD/EUROMOD_country_report.pdf.
[14] The JRS covers employment income, employer National Insurance contributions and employer pension contributions. UKMOD does not simulate the latter, which are therefore excluded from our impact assessment.
[15] Because of the non-linearity of the logistic model, and given that the projected Covid-19 shocks are much larger than the observed quarter-to-quarter employment changes, we further normalise the individual predicted probabilities by the industry shocks, so that the reduction in industry-level employment matches the projected industry-level shocks.

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contribution-based Job's Seekers Allowance (Cb-JSA) and other pre-Covid benefits, if they become eligible.[16]

3. A "post-Covid employment, post-Covid policies" scenario (referred to as 'Scenario 3'), corresponding to the combined impact of the Covid-19 crisis and all policy changes.

Comparing Scenario 2 with Scenario 1 gives the un-mitigated socio-economic impact of Covid-19, and the cost that this would have entailed for the public budget due to lower tax revenues and increased benefit payments. Comparing Scenario 3 with Scenario 1 gives the mitigated socio-economic impact of Covid-19, and its overall effect on the public budget. Comparing scenario 3 with scenario 2 gives the additional costs and benefits of the emergency measures.

A crucial assumption in Scenario 3 concerns the take-up rate of MISS. We calibrate this using the latest data released by ONS on the number of people claiming benefits primarily for the reason of being unemployed (19 May 2020). These show an increase from 1.2 million in March 2020 to 2.1 million in April.[17] Considering that the adjustment to the lock-down equilibrium – although fast – could have been still incomplete at the end of April, we assume that 1 million dependent employees become unemployed, rather than being furloughed, and are then checked for eligibility for the less generous contribution-based and income-based JSA and Universal Credit.[18][19] On the other hand, we assume that all self-employed have access to the Self-Employment Income Support Scheme for their lost profits.

Comparing Scenarios 1 and 2, we see that in the absence of any policy change the Covid-19 crisis would have increased the number of claimants of unemployment benefits by 4.8 million, increased the poverty rate – at a constant poverty line – by 1.2 percentage points (pp), and decreased mean equivalised disposable income by 3%, with a more pronounced effect at the top half of the income distribution (Table 3).

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[16] UKMOD checks the eligibility condition for contribution-based JSA by looking at the entire individual work history rather than the last two fiscal years, due to difficulties in approximating the amount of contributions paid. This makes it easier to become eligible for contribution-based JSA in UKMOD. We plan to improve on this approximation in future releases.

[17] The ONS Claimant Count (series K02000001 UK) is a combination of claimants of Jobseeker's Allowance (JSA) and claimants of Universal Credit (UC) who fall within the UC 'searching for work' conditionality.

[18] This is more conservative than the 2 million unemployment figure considered by the Office for Budget Responsibility, which also considers a bigger contraction in GDP. Robustness analysis to this assumption is available upon request.

[19] Brewer and Handscomb (2020) show that the median effective replacement rate for the Job Retention Scheme is over 90%, compared to 53% for those who do not qualify (the reason why the replacement rate is over the 80% threshold is that many people will pay lower taxes after a 20 per cent fall in earnings, and might also qualify for other benefits – these effects are also included in our simulations).

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Table 3: Distributional consequences of Covid-19

	Scenario 1	Scenario 2	Δ[2-1]	Scenario 3	Δ[3-1]
Poverty					
Rate	17.4%	18.6%	1.2pp	16.3%	-1.1pp
Fixed Poverty Line	£ 982.10				
Mean equivalised household income					
Decile 1	£ 613.02	£ 603.33	-2%	£ 630.20	3%
Decile 2	£ 935.34	£ 913.46	-2%	£ 955.82	2%
Decile 3	£1,129.70	£1,106.59	-2%	£1,146.46	1%
Decile 4	£1,322.55	£1,288.74	-3%	£1,328.06	0%
Decile 5	£1,529.15	£1,486.79	-3%	£1,524.97	0%
Decile 6	£1,757.29	£1,694.99	-4%	£1,739.52	-1%
Decile 7	£2,025.91	£1,955.69	-3%	£2,000.07	-1%
Decile 8	£2,359.14	£2,273.16	-4%	£2,327.18	-1%
Decile 9	£2,859.04	£2,752.04	-4%	£2,807.83	-2%
Decile 10	£4,554.44	£4,394.29	-4%	£4,451.20	-2%
All	£1,908.28	£1,846.64	-3%	£1,890.86	-1%

Notes: Income figures are monthly averages over the year. Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 2 is a counterfactual exercise that considers "post-Covid employment, pre-Covid policies". Scenario 3 is our estimate of the real effect of the Covid-19 crisis, with "post-Covid employment, post-Covid policies".
Source: Our computation based on UKMOD A1.5+.

To understand the specific income components driving the changes, we decompose the percentage change in mean equivalised income for each decile looking at the contribution of different income sources (Figure 2). We find that the drop in market incomes (MI) hits proportionally harder at the top half of the income distribution: this is due to (i) many people not having market incomes in the first place, in the lowest deciles, (ii) the distribution of income by industries, and (iii) the distribution of the individual employment transition probabilities within industries.[20] We also confirm that JSA tends to be somewhat progressive due to its flat nature.

[20] There is also a fourth, mechanical effect, as any given percentage drop in market income reduces household disposable income differently in different part of the income distribution, due to the rules of the tax-benefit system. The direction of this effect depends on the effective marginal tax rate, with losses for high incomes reducing taxes proportionally more than for low incomes, but triggering lower increases in benefits.

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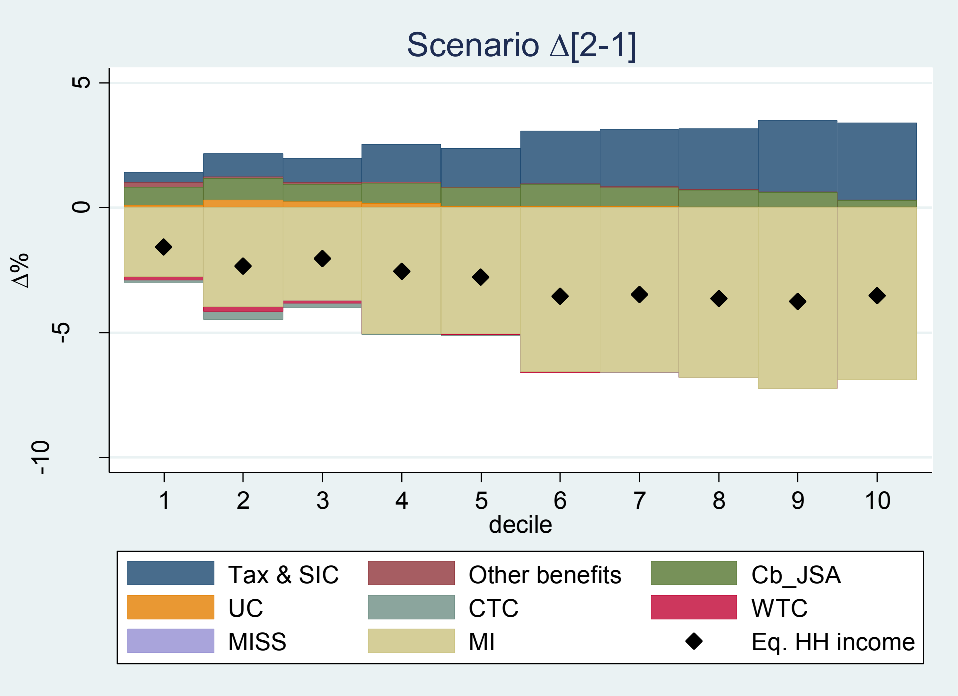
Figure 2: Decomposition of percentage change in mean equivalised income by income component, effects of income shock only (difference between Scenario 2 and Scenario 1).



Notes: Cb_JSA = contribution-based Job Seekers Allowance, UC = Universal Credit, CTC = Child Tax Credit, WTC = Working Tax Credit, MI = Market Income, MISS = MI Support Schemes.
Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 2 is a counterfactual exercise that considers "post-Covid employment, pre-Covid policies". The figure reports a decomposition of the percentage change between Scenario 2 and Scenario 1.
Source: Our computation based on UKMOD A1.5+.

From the perspective of public finances (Table 4), this counterfactual scenario would have resulted in a drop in government revenues (taxes and social insurance contributions) of more than 28 billion pounds or 7.5% with respect to the baseline, and an increase in government expenditure on social transfers of more than 6 billion pounds. Due to the way eligibility conditions for contribution-based JSA are modelled in UKMOD (see footnote 17), this increase in social transfers is mostly concentrated in contribution-based JSA – as also visible in Figure 2 – while in reality we would expect more people falling into means-tested benefits such as Universal Credit, income-based Job Seekers Allowance and Income Support.

Overall, the increase in expenditures and the decrease in revenues would have caused a 20% deterioration in the total net revenues, or 35 billion pounds.

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Table 4: Budgetary consequences of Covid-19 (yearly, million £)

	Scenario 1	Scenario 2	Δ[2-1]	Scenario 3	Δ[3-1]	Δ[3-2]
Total market incomes	£1,104,502	£1,044,386	-£ 60,116	£1,044,386	-£ 60,116	£ -
... income from (self) employment	£ 954,334	£ 894,218	-£ 60,116	£ 894,218	-£ 60,116	£ -
... other sources	£ 150,168	£ 150,168	£ 0	£ 150,168	£ 0	£ -
Government expenditure supporting market incomes	£ -	£ -	£ -	£ 32,939	£ 32,939	£ 32,939
Government expenditure on social transfers	£ 205,315	£ 211,747	£ 6,433	£ 212,964	£ 7,649	£ 1,216
... contribution-based Job Seekers Allowance	£ 164	£ 6,188	£ 6,024	£ 1,265	£ 1,101	-£ 4,923
... WorkingTax Credit	£ 1,101	£ 861	-£ 240	£ 1,469	£ 367	£ 608
... Family Tax Credit	£ 4,511	£ 4,184	-£ 327	£ 4,674	£ 163	£ 489
... Universal Credit	£ 32,362	£ 32,958	£ 596	£ 38,123	£ 5,762	£ 5,165
... other benefits	£ 75,807	£ 76,293	£ 486	£ 76,424	£ 617	£ 131
Government revenue through taxes and social insurance contributions	£ 381,473	£ 352,832	-£ 28,641	£ 360,960	-£ 20,513	£ 8,128
... Direct taxes and (self) employee social insurance contributions	£ 301,749	£ 279,721	-£ 22,027	£ 291,198	-£ 10,551	£ 11,477
... employer social insurance contributions (not part of disposable income)	£ 79,725	£ 73,111	-£ 6,614	£ 73,111	-£ 6,614	£ -
... employer social insurance contributions paid by Job Retention Scheme	£ -	£ -	£ -	-£ 3,349	-£ 3,349	-£ 3,349
Total net revenue (revenue - expenditure)	£ 176,158	£ 141,085	-£ 35,074	£ 115,057	-£ 61,102	-£ 26,028

Notes: Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 2 is a counterfactual exercise that considers "post-Covid employment, pre-Covid policies". Scenario 3 is our estimate of the real effect of the Covid-19 crisis, with "post-Covid employment, post-Covid policies".

Contribution-based Job Seekers Allowance is over-simulated due to lack of data in UKMOD. Claimants must have paid a minimum amount of National Insurance contributions in the two previous tax years. UKMOD does not have this information and approximates it using the number of years in work. Improving on this approximation would result in fewer unemployed individuals being entitled to this benefit and more households receiving other means-tested benefits such as Universal Credit, income-based Job Seekers Allowance and Income Support.

Source: Our computation based on UKMOD A1.5+.

Once we consider the policy changes in Scenario 3, we see that the effects of the Covid-19 crisis become progressive, with positive changes in equivalised household incomes up to the fifth decile, and negative changes in the deciles above (Table 3).[21] The poverty rate consequently goes down from 17.4% in the baseline (Scenario 1) to 16.3%, travelling practically the same distance than in Scenario 2 (a change of 1.1 pp) but in the opposite direction.

The result that the policy response to the crisis reduces poverty is mainly driven by the increase in the means-tested Universal Credit (UC) in the lowest part of the distribution (Figure 3). Note that MISS, with their 80% baseline replacement rate, mirror the distribution of losses in market incomes (which are the same as in Scenario 2), but for the cap at £2,500 per month which introduces some progressivity (this can be seen looking at the ratio between MISS and MI which goes down in absolute terms in the highest deciles). Because (i) MISS only covers 80% of the lost salaries and profits, (ii) some employees go into unemployment rather than being furloughed, and (iii) the rules for Universal Credit have become more generous, more people are now covered by the latter scheme. Moreover, people without labour income already on UC are net gainers from the Covid-19 crisis, as they benefit from the increased generosity of the scheme without suffering from market losses.

[21] While inequality is reduced, changes in the Gini coefficients are too small to be noticeable.

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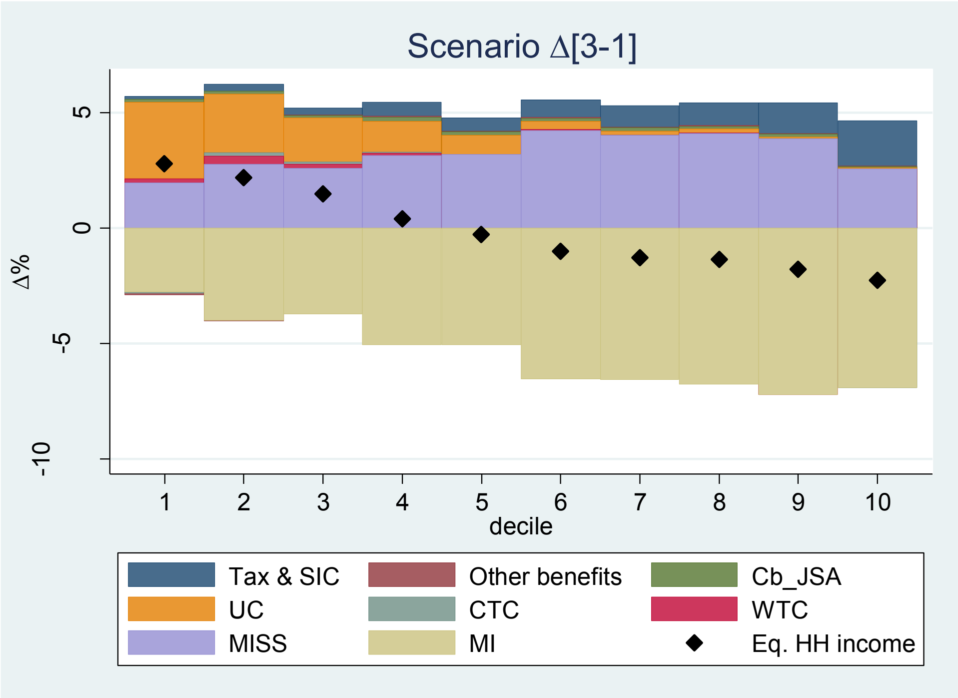
Figure 3: Decomposition of percentage change in mean equivalised income by income component, effects of income shock and policy responses (difference between Scenario 3 and Scenario 1).



Notes: Cb_JSA = contribution-based Job Seekers Allowance, UC = Universal Credit, CTC = Child Tax Credit, WTC = Working Tax Credit, MI = Market Income, MISS = MI Support Schemes.

Employer National Insurance contributions paid by the government under the JRS are included as negative contributions (or credits) in the employer social insurance contributions category.

Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 3 is our estimate of the real effect of the Covid-19 crisis, with "post-Covid employment, post-Covid policies". The figure reports a decomposition of the percentage change between Scenario 3 and Scenario 1.

Source: Our computation based on UKMOD A1.5+.

Finally, Figures 4 and 5 show the socio-economic groups most affected by the Covid-19 crisis in terms of both lost market incomes, and changes to household disposable income (lost market incomes are the same in Scenarios 2 and 3, while the change in equivalised household disposable income showed refer to Scenario 3, which includes the Government rescue package).

The figures show that the most affected groups in terms of lost market income are low-skilled people and people in elementary occupations. In particular, the losses for professionals and clerks are half the size, in percentage terms, than the losses for elementary occupations, craft and trade workers. This is the combined result of (i) the distribution of earnings by industries, and (ii) the distribution of the individual employment transition probabilities within industries. The working of the tax-benefit system reduces the losses, and eliminates most differences between groups. The gender, age, household type and country of origin gradients are less pronounced, while with the exception of Northern Ireland (marginally less affected) there are no regional differences. Changes in after tax and benefits equivalised incomes are positive for inactive people of working age, and for single with children. These groups

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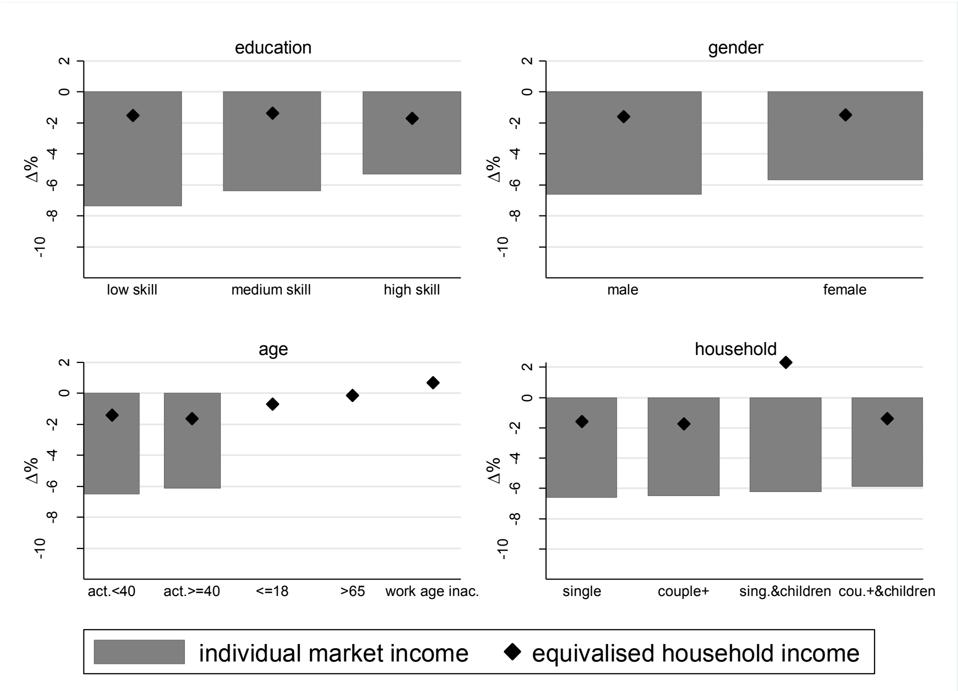
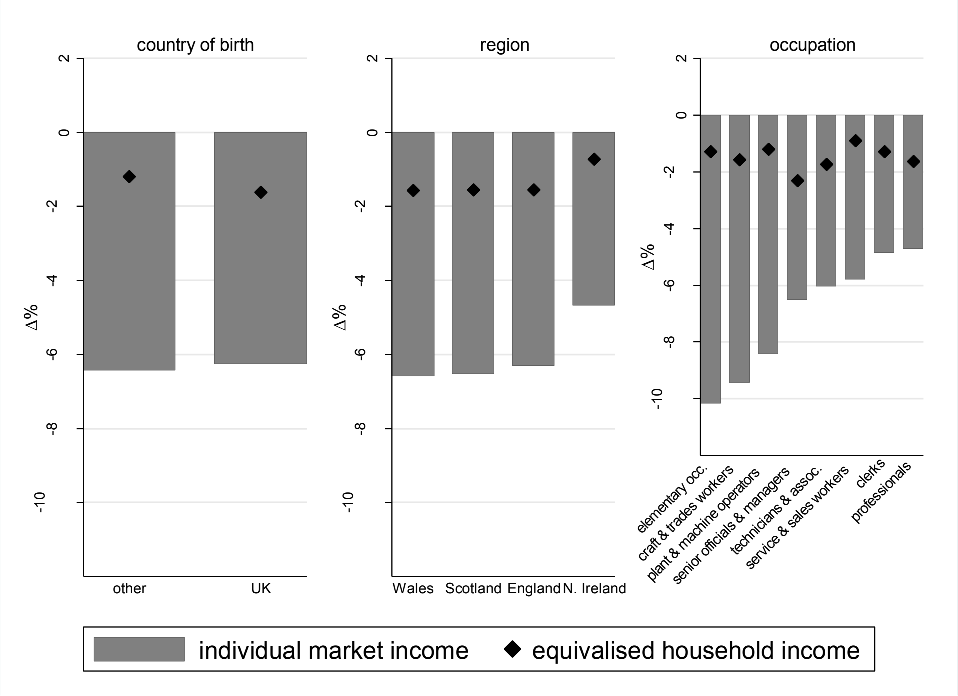
include many individuals with no market incomes and already on Universal Credit, who as noted above are net beneficiaries from the increased generosity of the system.

Figure 4: Mean income lost by education, gender, age and household composition.



Note: To make market and household incomes more comparable, the means only include people with positive market incomes, except for inactive people in the chart by age (there are few under-18 and elderly people with market incomes, and they are excluded from the graph).
. low skill = not completed primary, primary & lower secondary education, medium skill= upper secondary & post-secondary, high skill = tertiary. act. = working age with positive market income. couple+ = couple or more adults.
Source: Our computation based on UKMOD A1.5+.

Figure 5: Mean income lost by country of origin, region and occupation.



Note: To make market and household incomes more comparable, the means only include people with positive market incomes. The regions of England are put together.
Source: Our computation based on UKMOD A1.5+.

The lifeline that the Government has given to the economy obviously comes at a high cost for the budget, with the rescue package expected to cause an extra deficit of 26 billion pounds in 2020 with respect to Scenario 2 (Table 4, last column), bringing the overall reduction in total net revenues for the government due to the pandemic to over £60 billion (-35%). This is mostly due to MISS, with an expected direct cost of 36 billion pounds (£33 billion in income support plus £3 billion in employer social insurance contributions paid by the Government), partly offset by an increase in taxes and employee social insurance contributions (+11 billions).

In Scenario 3 fewer people go on unemployment benefits with respect to Scenario 2, with a consequent reduction in expenditure from 6 billion to just over 1 billion. This expenditure however is replaced by an increased expenditure for Universal Credits, which are now more generous (+£5 billion).

To be noted, this relatively minor component of the rescue package (£5 billion out of £25 billion, or 20%) does the bulk of the work in reverting the distributional consequences of the crisis. This is not surprising, as Universal Credits are a highly targeted measure.[22]

[22] The positive role of Universal Credit in the crisis is also noted in Brewer and Handscomb (2020).

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6. Conclusions

In this paper we have provided an assessment of the distributional and budgetary impact of the Covid-19 crisis and associated policy responses, in the UK. Due to lack of timely data on the employment effects of the crisis, we have nowcasted the market income shocks by means of a dynamic IO model calibrated to the 2016 IO tables and parameterised with the results of a consensus analysis of over 250 UK-based economists to predict macro effects by industry, and a probabilistic model estimated on LFS data to predict employment-to-non-employment transitions within industry. Our macro results point to a reduction in GDP/employment of almost 25% in the lock-down equilibrium, with demand-side constraints accounting for 75% of this effect and supply-side constraints for the remaining 25%. These macro effects are in line with most of the expectations and preliminary estimates available for advanced economies, which roughly point to a 2% yearly GDP loss per month of full lock-down. Having distributed this macro shock between industries, and within industries to each individual worker, we have used the UKMOD tax-benefit model to analyse the distributional and budgetary impact of the crisis, distinguishing between the impact of the shock *per se*, as cushioned by the tax-benefit system in its pre-Covid configuration, and the impact of the emergency measures put in place during the crisis. We have shown that the extra intervention has contained the reduction in the average household disposable income from -3% to -1%. More importantly, we predict that the rescue package has reverted the distributional impact of the pandemic, *reducing* poverty by more than 1 percentage point with respect to the pre-Covid situation. This is mostly due the increased role of Universal Credit, which however accounts only for 20% of the total cost of the emergency rescue package (£26 billion).

A few considerations need to be made here.

First, in this study we examine the income effects of the crisis, and we do not say anything with respect to the increased health inequalities that have been documented elsewhere (e.g. Bibby et al., 2020; Coronini-Cronberg et al., 2020) – nor with respect to how health inequalities interact with income inequality (Baker, 2019).

Second, it is perhaps not surprising that at a time of a national emergency the country comes together and implements steps that reduce inequality, especially given that those more at risk from a health perspective come from more disadvantaged socio-economic group.[23] This is often seen in wars, for instance (Obinger et al., 2018).

Third, 80% of the emergency package goes to policy measures – the Job Retention Scheme and the Self-Employment Income Support Scheme – that are regressive for the lowest deciles and only mildly progressive at the top of the income distribution, while the bulk of the redistribution is operated by the increased generosity of Universal Credit, that accounts only for 20% of the rescue package. This does not mean that these Market Income Support Schemes are a bad use of public money, as they are explicitly motivated by a desire to maintain as much as possible the pre-Covid status quo. Indeed, in their absence the shock to disposable incomes would have caused significant distributional consequences, with workers in some sectors affected much more than in others, and an overall increase in poverty. Moreover, the Market Income Support Schemes might serve other purposes, for instance help the economy bounce back to the previous equilibrium quicker.

Forth, and related, the issue of whether the Job Retention Scheme and the Self-employment Income Support Scheme will be maintained in place throughout the crisis is crucial. This is particularly true for some sectors, (e.g. hospitality and the travel industry) where the shock has been greater.

[23] Between March and April 2020, the age-standardised mortality rate of deaths involving COVID-19 in the most deprived areas of England was 55.1 deaths per 100,000 population compared with 25.3 deaths per 100,000 population in the least deprived areas, according to the ONS.

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Finally, the overall cost of the crisis for the public deficit is massive – with a 35% projected decrease in total net revenues for the Government (£61 billion pounds). This raises the issue of how the increased debt will be managed in the years ahead, and in particular if the advances that have been achieved, most notably with an expansion in Universal Credit, will be maintained.

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References

Acemoglu D, Akcigit U, Kerr w (2016). Networks and the Macroeconomy: An Empirical Exploration. NBER Macroeconomics Annual, University of Chicago Press, 30(1): 273-335.

Alon T, Doepke M, Olmstead-Rumsey J, Tertilt M (2020). The impact of Covid-19 on gender equality. Covid Economics 4: 62-85.

Baker C (2019). Health inequalities: Income deprivation and north/south divides. House of Commons Library, 22 January 2019 (available at https://commonslibrary.parliament.uk/insights/health-inequalities-income-deprivation-and-north-south-divides/).

Barrot J-N, Grassi B, Sauvagnat J (2020). Sectoral Effects of Social Distancing. Covid Economics 3: 85-102.

Beirne K, Doorley K, Regan M, Roantree B, Tuda D (2020). The Potential Costs and Distributional Effect of Covid-19 Related Unemployment in Ireland. EUROMOD Working Papers Series, forthcoming.

Bibby J, Everest G, Abbs I (2020). Will COVID-19 be a watershed moment for health inequalities? Health Foundation Long Read 7 May 2020, Health Foundation.

Bodenstein M, Corsetti G, Guerrieri L (2020). Social distancing and supply disruptions in a pandemic. CEPR Discussion Paper No. DP14629.

Brewer M, Handscomb K (2020). This time is different – Universal Credit's first recession. Assessing the welfare system and its effect on living standards during the coronavirus epidemic. Resolution Foundation, May 2020.

Coronini-Cronberg S, Maile EJ, Majeed A (2020). Health inequalities: the hidden cost of COVID-19 in NHS hospital trusts? Journal of the Royal Society of Medicine 113(5): 179–-84.

de Mesnard L (2009). Is the Ghosh Model Interesting. Journal of Regional Science 49(2): 361-372.

Dietzenbacher, E. (1997) 'In Vindication of the Ghosh Model: A Reinterpretation as a Price Model', Journal of Regional Science,Vol. 37, No. 4: 629-651.

Dingel J, Neiman B (2020). How many jobs can be done at home? Covid Economics 1: 16-24.

Dorn F, Fuest C, Göttert M, Krolage C, Lautenbacher S, Link S, Peichl A, Reif M, Sauer S, Stöckli M, Wohlrabe K, Wollmershäuser T(2020). The Economic Costs of the Coronavirus Shutdown for Germany: A Scenario Calculation. EconPol Policy Brief 3(21).

Eichenbaum MS, Rebelo S, Trabandt M (2020). The macroeconomics of epidemics. NBER WP 26882.

Figari F, Fiorio C (2020). Welfare resilience in the first month of Covid-19 pandemic in Italy. EUROMOD Working Papers Series, forthcoming.

Ghosh A (1958). Input-Output Approach in an Allocation System. Economica, 58-64.

HM Government (2020). Our Plan to Rebuild: The UK Government's Covid-19 recovery strategy. UK Government.

Hughes R, Leslie J, McCurdy C, Pacitti C, Smith J, Tomlinson D (2020). Doing more of what it takes. Next steps in the economic response to coronavirus. Resolution Foundation, April 2020.

Inoue H, Todo Y (2020). The propagation of the economic impact through supply chains: The case of a mega-city lockdown to contain the spread of Covid-19. Covid Economics 2: 43-59.

Manresa A, Sancho F (2020) A follow-up note on the plausibility of the Leontief and Ghosh closed models. Economic Systems Research, 32(1): 166-172.

Obinger H, Petersen K, Starke P (2018). Warfare and Welfare. Military Conflict and Welfare State Development in Western Countries. Oxford University Press.

Office for Budget Responsibility (OBR) (2020). Commentary on the OBR coronavirus reference scenario, 14 April 2020.

OECD (2020). Evaluating the initial impact of COVID-19 containment measures on economic activity. OECD, Paris.

Oosterhaven J (1996). Leontief versus Ghoshian Price and Quantity Models. Southern Economic Journal, 62(3): 750-759.

Pichler A, Pangallo M, del Rio-Chanona RM, Lafond F, Farmer JD (2020). Production networks and epidemic spreading: How to restart the UK economy? INET Oxford Working Paper No. 2020-12.

Sutherland H, Figari F (2013). EUROMOD: the European Union tax-benefit microsimulation model. International Journal of Microsimulation, (1): 4-26.

Sutherland H (2018). Quality Assessment of Microsimulation Models The Case of EUROMOD. International Journal of Microsimulation, 11(1): 198-223.

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Appendix 1: Additional tables and figures

Table A1: Industries included in the questionnaire

Industry	Ref	Industry	Ref
Food and beverages	F1	Coke and refined petroleum products	X1 / Z1
Electricity, water, sewage	F2	Chemicals and chemical products	X2 / Z2
Textiles, wearing apparel and leather products	F3	Basic pharmaceutical products and pharmaceutical preparations	X3 / Z3
Furniture	F4	Other manufacturing	X4 / Z4
Motor vehicles	F5	Constructions and construction works	X5 /Z5
Computer, electronic and optical products	F6	Mining and quarrying	X6 / Z6
Wholesale and retailing	F7	Land and water transport	X7 / Z7
Hotels, restaurants, pubs, etc.	F8	Advertising	X8 / Z8
Air transport	F9	Other professional, scientific and technical services	X9 / Z9
Public transport	F10	Scientific research and development	X10 / Z10
Telecommunication services	F11	Public administration	X11 / Z11
Postal and courier services	F12		
Financial, insurance and legal services	F13		
Rents	F14		
Other real estate services	F15		
Compulsory education	F16		
Non-compulsory education	F17		
Public health services	F18		
Private health services	F19		
Services of households as employers	F20		
Arts and culture (both live and digital)	F21		
Sports	F22		
Other services	F23		

Note: Industries in the left column were considered for final household demand, with values of the responses being referred to as F1-F23; industries in the right column were considered for exports and supply of intermediate goods and services, with values of the responses being referred to as X1-X11 and Z1-Z11 respectively.

Table A2: Mapping from results of the consensus analysis to parameters used for the macro model.

		Industry	Direct Multiplier of Lockdown on Final Consumption (Exports ecluded)	Direct Multiplier of Lockdown on Exports	Direct Multiplier of Lockdown on Supply of Intermediate Inputs
1	A	Products of agriculture, hunting and related services	F1	F1	F1
2	A	Products of forestry, logging and related services	Z4	X4	Z4
3	A	Fish and other fishing products; aquaculture products; support services to fishing	F1	F1	F1
4	BDE	Mining and quarrying	Z6	X6	Z6
5	C	Food products, beverages and tobacco products	F1	F1	F1
6	C	Textiles, wearing apparel and leather products	F3	X4	Z4
7	C	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	Z4	X4	Z4
8	C	Paper and paper products	Z4	X4	Z4
9	C	Printing and recording services	Z4	X4	Z4
10	C	Coke and refined petroleum products	Z1	X1	Z1
11	C	Chemicals and chemical products	Z2	X2	Z2
12	C	Basic pharmaceutical products and pharmaceutical preparations	Z3	X3	Z3
13	C	Rubber and plastics products	Z4	X4	Z4
14	C	Other non-metallic mineral products	Z4	X4	Z4
15	C	Basic metals	Z4	X4	Z4
16	C	Fabricated metal products, except machinery and equipment	Z4	X4	Z4
17	C	Computer, electronic and optical products	F6	F6	Z4
18	C	Electrical equipment	Z4	X4	Z4
19	C	Machinery and equipment n.e.c.	Z4	X4	Z4
20	C	Motor vehicles, trailers and semi-trailers	F5	F5	Z4
21	C	Other transport equipment	Z4	Z4	Z4
22	C	Furniture; other manufactured goods	F4	F4	Z4
23	C	Repair and installation services of machinery and equipment	Z4	X4	Z4
24	BDE	Electricity, gas, steam and air-conditioning	F2	X6	Z6
25	BDE	Natural water; water treatment and supply services	F2	X6	Z6
26	BDE	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	F2	Z4	Z4
27	F	Constructions and construction works	Z5	X5	Z5
28	G	Wholesale and retail trade and repair services of motor vehicles and motorcycles	F5	F7	F7
29	G	Wholesale trade services, except of motor vehicles and motorcycles	F7	F7	F7
30	G	Retail trade services, except of motor vehicles and motorcycles	F7	F7	F7
31	H	Land transport services and transport services via pipelines	F10	X7	Z7
32	H	Water transport services	F9	X7	Z7
33	H	Air transport services	F9	F9	F9
34	H	Warehousing and support services for transportation	Z7	X7	Z7
35	H	Postal and courier services	F12	F12	F12
36	I	Accommodation and food services	F8	F8	F8
37	J	Publishing services	F21	X9	Z9
38	J	Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services	Z9	X9	Z9
39	J	Telecommunications services	F11	F11	F11
40	J	Computer programming, consultancy and related services; information services	Z9	X9	Z9
41	K	Financial services, except insurance and pension funding	F13	F13	F13
42	K	Insurance, reinsurance and pension funding services, except compulsory social	F13	F13	F13
43	K	Services auxiliary to financial services and insurance services	F13	F13	F13
44	L	Real estate services excluding imputed rents	(F14+F15/2)	(F14+F15/2)	(F14+F15/2)
45	L	Imputed rents of owner-occupied dwellings			
46	M	Legal and accounting services; services of head offices; management consulting	F13	F13	F13
47	M	Architectural and engineering services; technical testing and analysis services	F23	X9	Z9
48	M	Scientific research and development services	Z10	X10	Z10
49	M	Advertising and market research services	Z8	X8	Z8
50	M	Other professional, scientific and technical services; veterinary services	Z9	X9	Z9
51	N	Rental and leasing services	Z9	X9	Z9
52	N	Employment services	Z9	X9	Z9
53	N	Travel agency, tour operator and other reservation services and related services			
54	N	Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services	Z9	X9	Z9
55	O	Public administration and defence services; compulsory social security services	Z11	X11	Z11
56	P	Education services	(F16+F17)/2	(F16+F17)/2	(F16+F17)/2
57	Q	Human health services	(F18+F19)/2	(F18+F19)/2	(F18+F19)/2
58	Q	Social work services	F23	F23	F23
59	RST	Creative, arts and entertainment services; library, archive, museum and other cultural services; gambling and betting services	F21	F21	F21
60	RST	Sporting services and amusement and recreation services	F22	F22	F22
61	RST	Services furnished by membership organisations	F23	F23	F23
62	RST	Repair services of computers and personal and household goods	F23	F23	F23
63	RST	Other personal services	F23	F23	F23
64	RST	Services of households as employers; undifferentiated goods and services produced by households for own use	F20	F20	F20

Note: Values referred to as per Table A1.

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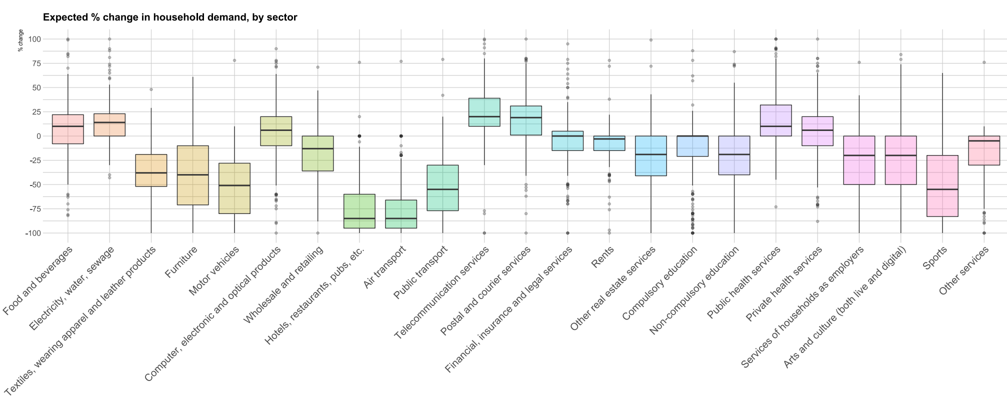
Table A3: Employment transition model: Descriptive statistics

Variable	mean	sd	min	max
Employment to Non-employment transition = 1	0.0237		0	1
Age	43.19	12.77	16	69
Sex (1 = Male)	0.482		0	1
Single	0.324		0	1
Married	0.555		0	1
Separated	0.025		0	1
Divorced	0.082		0	1
Widowed	0.014		0	1
Total usual hours worked in main job (incl. overtime)	36.00	12.73	0	97
Months continuously employed	109.4	110.2	0	696
Public sector = 1	0.290		0	1
% change in employment in industry	0.469	2.372	-16.67	36.36

Figure A1: Box-plot for the expected change in household demand, by sector



Responses to the question: Please provide your estimates of the effects on final household demand for goods and services of the Covid-19 related lock-down measures implemented by the UK Government on March 23: these are due to constraints preventing consumers from physically visiting sellers.

Note: Statistics based on 257 valid responses to this question.

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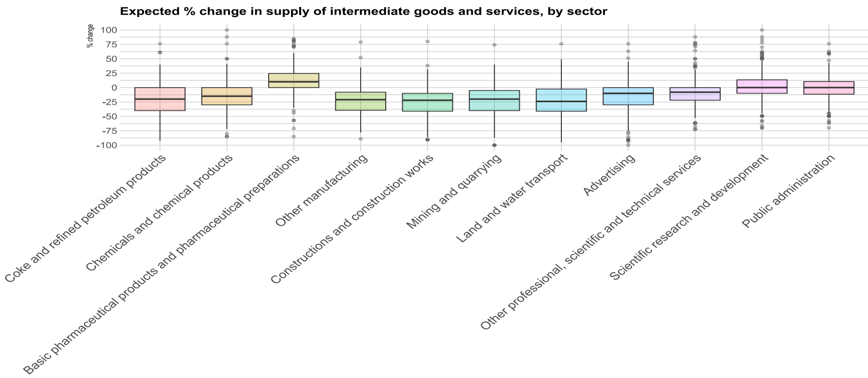
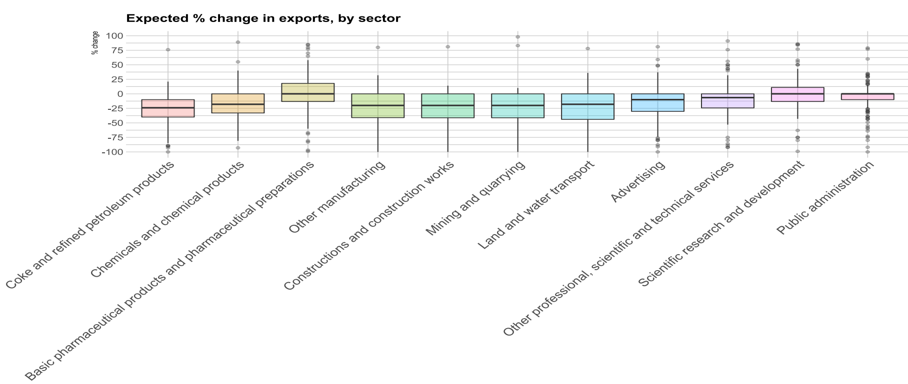
Figure A2: Box-plot for the expected change in supply of intermediate goods and services, by sector



Responses to the question: Please provide your estimates of the effects on the supply of intermediate goods and services to businesses of the Covid-19 related lock-down measures implemented by the UK Government on March 23: these are due to social distancing and smart working measures reducing the output of intermediate goods and services, which producers sell to other producers.

Note: Statistics based on 223 valid responses to this question.

Figure A3: Box-plot for the expected change in export of intermediate and final goods and services, by sector



Responses to the question: Please provide your estimates of the effects on the supply of intermediate and final goods and services of the Covid-19 related lock-down measures implemented by the UK Government on March 23: these are due to due to reduction in the demand from importers, or to difficulties to get the goods and services through the border.

Note: Statistics based on 208 valid responses to this question.

Appendix 2: Modifications to UKMOD input data and modelling assumptions

UKMOD runs on the Family Resources Survey (FRS). This survey contains weekly information on incomes. For most analyses, incomes are simply extrapolated to months in UKMOD (and to years in our fiscal overview). Since we are simulating that the COVID-19 crisis lasts for part of the year, we modify incomes from employment (yem), self-employment (yse) and contributory-based Job Seekers Allowance (bunct_s) to obtain weighted average amounts that reflects the months during and after the crisis (while we do not modify hours of work), as detailed in Table A4.

We consider as employed (self-employed) individuals, people with positive employment (self-employment) income and whose incomes from this source are higher than those from self-employment (employment).

Table A4: Changes to UKMOD variables.

<table>
<tr><th>Var</th><th>Scenario 1</th><th>Scenario 2</th><th>Scenario 3</th></tr>
<tr><td rowspan="2">yem</td><td rowspan="2">yem</td><td rowspan="2">yem*(8/12)</td><td>MISS=1 → as in Scenario 2
+ min(0.8*yem,2500)*(4/12)</td></tr>
<tr><td>MISS=0 → as in Scenario 2</td></tr>
<tr><td>yse</td><td>yse</td><td>yse*(8/12) +
new_emp*yse*(4/12)</td><td>as in Scenario 2
+ min(0.8*(yse-new_emp*yse), 2500) *(4/12)</td></tr>
<tr><td rowspan="2">bunct_s</td><td rowspan="2">0</td><td rowspan="2">bunct_s *(4/12)
[this & yem removed from disregard]</td><td>MISS=1 → 0</td></tr>
<tr><td>MISS=0 → bunct_s *(4/12) [as in Scenario 2]</td></tr>
<tr><td>lhw</td><td>lhw</td><td>(not modified)</td><td>(not modified)</td></tr>
</table>

Job Retention Scheme (JRS)

JRS is a grant that covers 80% of usual monthly wage costs, up to £2,500 a month, plus the associated Employer National Insurance contributions and pension contributions (up to the level of the minimum automatic enrolment employer pension contribution). UKMOD does not simulate employer pension contributions; therefore, we do not assess their impact of revenue changes. Employees pay the taxes they normally pay, which includes automatic pension contributions, unless the employee has opted out or stopped saving into their pension. We do not have information on the latter, and therefore assume they continue to pay pension contributions. Employer National Insurance contributions are paid by the government instead of the employers under the JRS. Accordingly, for the fiscal overview we made those contributions negative.

$$yem = yem*(8/12) + \min(0.8*yem, 2500)*(4/12) \tag{A1}$$

Self-Employment Income Support Scheme (SEISS)

SEISS is taxable grant of 80% of average monthly trading profits, paid out in a single instalment covering 3 months, and capped at £7,500 altogether. UKMOD uses the FRS variable on gross earnings from self-employed Opt 2 (yse). SEISS is subject to Income Tax and self-employed National Insurance. The pseudo-code for the implementation of this policy is:

$$yse = yse*(8/12) + income\_reduction\_coeff*yse*(4/12) + \min(0.8*(yse - income\_reduction\_coeff*yse), 2500)*(4/12) \tag{A2}$$

Contribution-based Job Seekers Allowance (Cb-JSA)

UKMOD includes a Labour Market Adjustment (LMA) add-on to transition people across employment statuses. When transitioning people to unemployment during the crisis, we modify income from employment (in the LMA

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add-on) and contribution-based Job Seekers Allowance (in UKMOD) as in Table A4. In addition, for those transitioning we remove income from employment from the base for disregards in UKMOD (otherwise the income earned after the crisis would be part of this base). Furthermore, for the (very few) people considered as employed that also have some self-employment incomes, the latter incomes are maintained (and not put to 0 as by the default in the LMA add-on).

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Pandemic Catch-22: How effective are mobility restrictions in halting the spread of COVID-19 in developing countries?

Tushar Bharati[1] and Adnan M. S. Fakir[2]

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Countries across the world responded to the COVID-19 pandemic with what might well be the set of biggest state-led mobility and activity restrictions in the history of mankind. But how effective were these measures across countries? Compared to multiple recent studies that document an association between such restrictions and the control of the contagion, we use an instrumental variable approach to estimate the causal effect of these restrictions on mobility, and the growth rate of confirmed cases and deaths attributed to COVID-19. Using the level of stringency in the rest of the world to predict the level of stringency of the restriction measures in a country, we show while stricter contemporaneous measures affected mobility, stringency in seven to fourteen days mattered for containing the contagion. Heterogeneity analysis reveal that even though the restrictions reduced mobility more in relatively less-developed countries, the causal effect of a reduction in mobility was higher in more developed countries. We propose several explanations. Our results highlight the need to complement mobility and activity restrictions with other health and information measures, especially in less-developed countries, to combat the COVID-19 pandemic effectively.

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1 Introduction

By May 30, 2020, the COVID-19 pandemic had infected close to six million people and claimed over 365,000 lives. Countries across the world have responded with what might well be the set of biggest state-led mobility and activity restrictions in the history of mankind. The hope is to reduce contagion and congestion in health-care utilization. Besides being controversial and costly, such measures may not always be successful in containing the spread and can, sometimes, worsen the situation.[1] The situation is especially dire for many developing countries. In the absence of of proper social security support, they face a catch-22 situation where strict mobility and activity restrictions, especially if ineffective, will unnecessarily increase the economic cost through lost livelihoods. The natural question that then follows is whether such measures have been effective in controlling the COVID-19 contagion. If yes, then what factors contribute to their effectiveness?

Multiple recent studies have submitted that there exists a negative association between such restrictions and the contagion (Anderson et al. (2020); Fang et al. (2020); Greenstone and Nigam (2020); Jinjarak et al. (2020); Qiu et al. (2020); Villas-Boas et al. (2020); Yilmazkuday (2020)). However, much of the work either simulates counterfactual scenarios or documents association between the restrictions and the contagion. With studies suggesting a steep economic cost of such restrictions, to be able to design optimal mitigation policy for COVID-19 and future pandemics, it is crucial to understand whether, when, where, and how much do these restrictions have a causal effect on containing the contagion (Glover et al. (2020)). Few studies attempt to identify causal effects of the restrictions using a difference-in-differences (DiD) design - comparing regions with high and low levels of restrictions (Fang et al. (2020); Villas-Boas et al. (2020); Yilmazkuday (2020)). But the restrictions were often in response to disease situation. Areas with worse contagion or more watchful population might have enacted stringent restrictions relatively early. Since these factors must have also affected the evolution of the disease scenario, the assumption of parallel trends underlying the DiD methodology comes into question.

First, we propose an instrumental variable approach to estimate the causal effect that the level of stringency of the restrictions had on human mobility and the rate of growth of the contagion. In deciding whether to impose restrictions, national and local governments took into account not only the prevailing disease situation in the country (the factor that confounds DiD estimates) but also what they expected would happen in the future in the presence and absence of such restrictions. Lacking perfect foresight, they made predictions based on their observations of the condition in

[1] See, among others, Markel (1999), Cetron and Landwirth (2005), World Health Organization Writing Group (2006), Coker et al. (2007), Tognotti (2013), McNeil Jr (2014), Onishi (2014), Towers et al. (2014), Bell (2016), and Espinoza et al. (2016))

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the rest of the world. Governments that witnessed a rapid increase in the number of COVID-19 cases and subsequent mobility and activity restrictions in the rest of the world, in the days following the first confirmed case in their own country, sprung into action swiftly and imposed stricter restrictions. Building on this insight, we use the day-to-day changes in the stringency of the restrictions in the rest of the world to instrument how stringent a country's internal mobility and activity restrictions were.

We conduct our analysis combining high-frequency measures of mobility data from Google's daily mobility reports, country-date-level information on the stringency of restrictions in response to the pandemic from Oxford's Coronavirus Government Response Tracker (OxCGRT), and daily data on people tested, confirmed cases, recovery and deaths attributed to COVID-19 from Our World In Data and the Johns Hopkins Center for Systems Science and Engineering (CSSE). Using the instrumental variable technique, we estimate large causal effects of stricter restrictions on mobility and on the weekly growth rate of recorded cases and deaths attributed to COVID-19. In comparison, we find that more stringent restrictions have weak marginal effects on the growth rate of tests conducted and recoveries. Consistent with the current scientific understanding that an infected human can infect another human up till 14 days since being infected, we find that the level of stringency of the restrictions in the previous two weeks matter more than contemporaneous level or level of restrictions 3 weeks in the past.[2] We also document considerable differences between the correlation and causal estimates that raise concerns over the use of the association estimates from previous studies to evaluate the costs and benefits of the restrictions.

Next, we show that the effectiveness of the restrictions vary significantly across countries. In particular, more stringent measures help more in richer, more educated, more democratic, and less corrupt countries with older, healthier populations and more effective governments. Finally, we draw attention to the observation that announcing restrictions does not necessarily imply a reduction in mobility; it depends on the level of compliance. The estimated reduced-form effects of stringency on the growth rate of cases, deaths, and recoveries incorporates the differential compliance across countries. Taking a ratio of the causal effect of restriction stringency on the growth rate of cases or deaths, to the effect on mobility, we show that even though the stricter restrictions had a larger negative effect on mobility in relatively less-developed countries, they were more effective in containing the contagion in more developed countries. Consistent with the heterogeneity results, these results indicate that imposing mobility restrictions is not enough to contain the contagion in developing countries, and the benefits reaped from high stringency is lower relative to developed nations. The restrictions should be effectively complemented with other policy measures,

[2]See Qiu et al. (2020), and the studies they cite for a discussion of the incubation and the infection period.

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such as raising awareness about best-practices when these restrictions are imposed, and health and economic assistance for those affected (Chang and Velasco (2020); Lin and Meissner (2020)).

The findings have important policy implications. COVID-19 is not the first and will not be the last epidemic to afflict humanity. Better future preparedness requires a better understanding of when and how to act in times of such crises. If the 2002–2004 SARS outbreak is any guide, it might be years before we develop a vaccine against COVID-19. Understanding the effectiveness of mobility and activity restrictions in containing contagions will not only help us optimize our current response to COVID-19 but also prepare us better to face future disease outbreaks. The heterogeneity analysis suggests that increasing stringency alone might not be enough, especially in developing countries where labour market conditions, lacking in health infrastructure, and constraints on implementation infrastructure might limit the effectiveness of these restrictions. Since the economic downturn can negatively affect the health and welfare outcomes in poorer countries more than in rich countries, where transition into work from home is relatively easier, this raises serious concerns about health cost-effectiveness of stringent mobility and activity restrictions in the absence of complementary policies. The results call for a country-specific policy response suited to the institutional capacity and socio-economic circumstances of the country.

2 Data and Empirical Specification

2.1 Data and Summary Statistics

For our analyses, we collate and link country-level daily data from the following sources:

2.1.1 Google Community Mobility Reports

In lieu of various nationwide and local lockdown decisions to promote social distancing to reduce the transmission of the COVID-19 contagion, Google has released publicly daily aggregated data on changes in mobility across six key high-level location categories in 131 countries. The mobility measures reflect how busy these places are. The six location categories are groceries and pharmacies, retail and recreation sites, parks, transit stations, workplaces, and residences. We source the mobility data from these reports from the 15th of February to the 09th of May reflecting daily percentage changes in reference to a baseline. The baseline is the median value of mobility for the corresponding day of the week during the 5-week period of January 3, 2020 to February 6, 2020. These measures of changes in mobility across the six location categories serve as our first set of outcome variables.

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While a reasonable measure of the extent of compliance to the restrictions, the data comes with certain caveats. The reports are generated using a technology similar to the real-time anonymized Google Maps traffic data, and as such are reflective of only those users who have their location history setting turned on in their Google account (Aktay et al. (2020)). Therefore, while the data is impressive, it is not representative of the population at large. Another important aspect to note is that while the residential category shows relative change in daily time spent at home, the other measures reflect respective daily relative changes in the number of individual visits. So, the residential category carries a different unit of measurement than the other categories and thus should be interpreted as such.

2.1.2 Oxford COVID-19 Government Response Tracker (OxCGRT)

OxCGRT provides a comprehensive and systematic country-level daily stringency index, constructed on the basis of common policy responses implemented by governments to combat COVID-19 (Hale et al. (2020)). Stringency is measured as a composite score, equally weighted and normalized between 0 and 100 for each country (with 100 being the strictest response), using eight ordinal indicators of containment, movement restriction and closure policies, and a ninth indicator measuring the coordinated presence of public awareness campaigns on the pandemic. The containment indicators include school closures, workplace closure, cancellation of public events, restrictions on gatherings, public transport closure, stay at home requirements, internal movement restrictions, and international travel controls.

Since the stringency index further tracks how quickly governments implemented or rolled out such their policy measures, we use the index as our primary independent variable of interest. As contemporary stringency measures would affect mobility but its affect on the growth of the pandemic would be observable only days after, we also use 7-day and 14-day lagged values of the index in our analyses. While the index provides a numerical score to the strictness of the policies enacted, it does not reflect the compliance or effectiveness of the stringency put in place. Hence, while a higher score in the index reflects a willingness for greater stringency, it does not translate to a country's response being better than countries with a lower score.

2.1.3 COVID-19 Outbreak Data

We source COVID-19 country-specific daily data on confirmed cases per million, deaths attributed to COVID-19 per million, and recoveries per million from the Johns Hopkins Center for Systems Science and Engineering (CSSE) COVID-19 data repository (Johns Hopkins CSSE (2019)). We

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combine this with tests per million population data collated by Our World In Data (OWID). Since it takes some time for delayed reporting to be reflected in the dataset, we restrict our focus to events between February 15, 2020 to May 9, 2020. OWID collects testing data from country-specific official government reports and is available only from 85 countries. We then construct daily growth rates for the four outbreak variables – cases, deaths, recoveries and tests – and use them as our second set of outcomes. We limit our analysis to the 117 (78 for testing) countries that we have mobility, stringency, cases, deaths, and recovery data for. The countries are listed in Table A1.

Several studies and media outlets have reported that due to country-specific differences in testing rates, data aggregation, and reporting quality, the number of cases, deaths and recovery are potentially under-reported (Vogel (2020); Bendavid et al. (2020); Burn-Murdoch et al. (2020)). Testing data, when available, has strong selection bias with many countries screening and testing only those people who presented symptoms. The extent of this selection bias might be systematically related to country-specific characteristics. While we control for country fixed effects in our empirical specifications, it will not account for systematic changes in selection bias over time across countries. Therefore, this study, like all studies utilizing the CSSE and the OWID data, should be interpreted with a healthy dose of skepticism.

2.1.4 Heterogeneity Variables

In order to investigate the heterogeneity in the impact of the restrictions across developing and developed countries, we link our data with various pre-COVID-19 country-specific demographic, health, and governance factors, that may aid or hinder the stringency effect on people's mobility and the spread of the disease. Along the demography dimension, we examine heterogeneity by population density, education, poverty head count, inequality (Gini index), share of population aged 65 years of above, and air pollution per capita (measured by the concentration of suspended particulate matter in the air with a diameter of 2.5 micrometers or less, PM2.5). We also examine heterogeneity by available hospital beds per 100 thousand population (a proxy of available healthcare infrastructure), share of the population with hand-washing facilities on premises (a proxy for availability of tools to combating the growth in transmissions), and death rate form cardiovascular diseases (CVD) as proxy for share of immune-compromised population who face higher risks from COVID-19.

Finally, we examine heterogeneity along country's governance indicators using the Economist Intelligence Unit (EIU) democracy index, government effectiveness from the Worldwide Governance Indicators (WGI) project by Kaufmann and Kraay (2007), and the corruption perception index (CPI) developed by Transparency International (TI), where larger values represent cleaner countries. The vast majority of data from the demography and health dimensions are sourced from the World Development Indicators (WDI), United Nations Population Division or the Global Burden of Disease Collaboration Network. Table A2 in the appendix provides details of the sources for each of the variables used, and Table 1 presents the summary statistics.

Table 1: Summary Statistics

	N	Mean	SD	Median	Min	Max
Oxford Government Response Tracker						
Stringency Index	9901	55.04	34.44	67.06	0.00	100.00
Google Mobility Measures						
Retail and Recreation (% change)	10115	-34.17	31.00	-33.00	-97.00	37.00
Grocery and Pharmacy (% change)	10111	-17.03	23.90	-11.00	-97.00	76.00
Parks (% change)	10115	-17.49	33.37	-13.00	-95.00	226.00
Transit Stations (% change)	10115	-35.51	30.67	-37.00	-95.00	31.00
Workplaces (% change)	10115	-25.99	27.84	-24.00	-92.00	56.00
Residential (% change)	10063	12.97	11.83	12.00	-5.00	55.00
Outbreak Variables						
Tests (Growth Rate)	4339	0.11	0.68	0.05	-0.08	39.78
Confirmed Cases (Growth Rate)	7783	0.15	0.45	0.05	-0.08	14.00
Deaths (Growth Rate)	5416	0.11	0.27	0.03	0.00	4.60
Recoveries (Growth Rate)	6292	0.30	4.48	0.03	-1.00	17.09
Days since first case (by Country)	10030	23.76	27.70	24.00	-55.00	84.00
Heterogeneity Variables						
Population Density	10030	286.60	976.95	86.23	1.98	7915.73
Primary Education	6545	79.51	22.26	87.54	13.87	100.00
Poverty Headcount (2011 PPP)	8925	10.05	16.41	1.60	0.00	62.90
Gini Index	8840	38.23	8.19	36.55	24.20	63.00
Population Aged 65 or older	10030	9.88	6.62	7.40	1.14	27.05
PM2.5 (2010-2017 Average)	9860	28.56	19.76	23.67	6.46	98.25
Hospital Beds per 100k Population	9180	3.07	2.51	2.36	0.10	13.05
Handwashing Facilities	4590	57.61	29.79	59.58	2.74	98.99
CVD Death Rate	9945	230.20	113.56	208.26	79.37	597.03
Democracy Score	9520	6.04	2.07	6.42	1.93	9.87
Governance Effectiveness	10030	0.22	0.96	0.11	-2.24	2.23
Corruption Perception Index	9520	47.22	19.57	41.00	14.00	88.00

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The stringency index appears to be skewed to the left with a mean value of 55 below the median of 67, meaning there is a relatively long tail of days with lower stringency scores. All the mobility measures, excluding residential mobility, show a percentage decrease in the visits with the decrease being greatest at about 35.5 percent at transit stations, followed closely by mobility around retail and recreation sites. On the other hand, the percentage change of time spent at home increases by about 13 percent. Segregating the measures by developing vis-à-vis developed countries, reported in Table A3 in the appendix, reveal that compliance to mobility restrictions has been, expectedly, overall lower in developing countries (for example, while transit stations see a decrease of 29 percent in developing countries, developed countries see a 38.6 percent decrease).

Mean cumulative daily growth rates of tests, cases, and deaths are 11.2, 14.8, and 11.4 percent, respectively, and that of recoveries is greater at 30 percent. Finally, while the mean statistic of the variables provide a snapshot of the overall sample, developing countries are significantly less educated, poorer, younger, more polluted, lack adequate health infrastructure, face greater corruption, and have poorer levels of democracy and government effectiveness (see Table A3).

2.2 Empirical Specification

Investigating the causal impact of the level of stringency on the mobility indicators, and COVID-19 outbreak growth rate variables, presents a few empirical challenges. First, governments around the world enacted these measures in response to the disease situation in their countries. Therefore, ordinary least squares estimation (OLS) of the associations between stringency of the measures and the outbreak growth rate could be driven by the reverse causality - countries with worse disease situations had to enact more stringent measures to control the contagion. Similarly, even without the announced restrictions, countries with a higher proportion of circumspect population might see a decrease in both mobility and disease spread. The governments in these countries might have responded to the expectation this placed on the government to support their citizens. It is also possible that the outcome measures suffer from non-classical measurement errors. For example, less educated countries might be less stringent and might also have larger measurement errors in recording cases, deaths, and recoveries. All these factors will bias the OLS estimates.

In order to address these concerns, we opt an instrumental variable (IV) approach. We use the level of stringency in countries other than country c on date t, to predict the level of stringency of the restrictions in country c on date t. The rationale is that governments, in deciding the level of stringency of the restriction, looked not only at the disease condition in their own country but also what they expected would happen if they did not impose stricter measures. Since there was no way for them to predict the counterfactual scenario, they looked to the state of other countries. In

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particular, they observed the actions other countries in the world were taking. If a country observed that all other countries in the world were imposing strict restrictions, it was under greater pressure to enact stricter restrictions regardless of the disease situation at home.[3] So, the level of stringency of the measures in a country c at time t must be correlated with the stringency of the measures in the rest of the world, satisfying the relevance requirement for the IV. While the day-to-day variations in the extent of governments-imposed restrictions in the rest of the world might influence a country's propensity to impose mobility and activity restrictions, it should not, at least in the short-run, affect the level of activity and the growth rate of confirmed cases in the country through other channels. Therefore, the exclusion restriction is likely to hold.

The first stage of our 2SLS specification is as follows:

$$\text{First Stage: } Stringency_{c,t} = a + b \times Stringency_{w-c,t} + \theta_c + \delta_{t-i} + \varepsilon_{c,t} \tag{1}$$

where, $Stringency_{c,t}$ is the level of stringency of the measures at time t in country c. $Stringency_{w-c,t}$ measures the average level of stringency at time t in countries in our sample excluding country c. In some specifications, we exclude all countries in the same region or sub-region as country c to minimize any spillovers of infections across borders.[4] In our preferred specification, we exclude all countries in the sub-region while calculating $Stringency_{w-c,t}$.[5] γ_c controls for time-invariant differences across countries that capture factors like differential measurement errors in outcomes variables, levels of health and health infrastructure, times at which the first case was detected in different countries, and so on. θ_{i-t} controls for affects that are associated with days since the first confirmed case in the country. We believe θ_{i-t} does a better job at capturing the time varying unobservable factors that might affect stringency across countries, since how the disease spreads within a country depends on when the first confirmed case was detected. For example, since the first confirmed case in China was much earlier than in the United States of America, there is no reason why both countries will have a similar level of unobservable factors affecting $Stringency_{c,t}$ on February 15, 2020.

We then use the predicted values of $Stringency_{c,t}$ in:

$$\text{Second Stage: } Y_{c,t} = \alpha + \beta \times \widehat{Stringency}_{c,t} + \gamma_c + \tau_{i-t} + \varepsilon_{c,t} \tag{2}$$

[3]Since a country did not observe the private signal of other countries about how bad they expected the situation to become, the country used the observable decision of other countries to inform its own decision.

[4]We use the World Bank's classification of world regions and sub-regions

[5]Other definitions we use are: (1) World stringency minus country stringency, (2) Region stringency minus country stringency, (3) Sub-region stringency minus country stringency, and (4) World stringency minus region stringency. The results using these alternative instruments are reported in the appendix.

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where $Y_{c,t}$ is any of the mobility or outbreak growth rate outcomes for country c at time t. In some of our second stage specifications, we replace $\widehat{Stringency}_{c,t}$ with $\widehat{Stringency}_{c,t-7}$, $\widehat{Stringency}_{c,t-14}$, or $\widehat{Stringency}_{c,t-21}$ to account for possibility that the impact of a change in stringency on the number of confirmed cases, deaths, and recovery might show up after a lag. We cluster the standards errors at the level of the country.

3 Results

The mobility and activity restrictions enacted by countries around the world aimed at containing the contagion by limiting human-to-human contact. However, it is not obvious whether these restrictions actually limited mobility and activity; it depended on people's will and ability to observe these restrictions and their government's ability to enforce it. For example, multiple factors including, but not limited to, the level of education, trust in the government, and ability to maintain basic consumption expenditure without working, affect the extent to which citizens of a country might observe the restrictions. In Table 2, we begin by examining the impact of these restrictions on mobility.

The dependent variables in columns (1) to (6) are the percentage changes in mobility in areas of the country as compared to the median value for the corresponding day of the week, during the 5-week period of January 3, 2020 to February 6, 2020. The first four panels of the table present the association between these dependent variables and the stringency of the restrictions in the country at distinct points in time. The estimated coefficient for Stringency Index (Lag 0) reports the association between mobility and contemporaneous restrictions. Similarly, coefficients for Stringency Index (Lag 7), Stringency Index (Lag 14), Stringency Index (Lag 21) report the association of the mobility measures with the stringency of the restrictions seven, fourteen, and twenty one days ago, respectively. All specifications include country fixed effects and the number of days since the first case fixed effect, and we cluster the standard errors at the country level. Two observations stand out. First, the restrictions had the intended impact - countries with stricter restrictions observed higher reduction in mobility in public areas and an increase in time spent in residential areas.[6] Second, as expected, contemporaneous restrictions matter more than past restrictions. In fact, the mobility measures had no significant association with the level of stringency of the restrictions twenty-one days prior. This suggests that the stringency varies a lot over time even within countries.

[6]Here, our results are consistent with Jinjarak et al. (2020), Fang et al. (2020), Villas-Boas et al. (2020), and Yilmazkuday (2020)

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Table 2: Impact of stricter restrictions on mobility

VARIABLES	(1) Retail Recreation	(2) Grocery Pharmacy	(3) Parks	(4) Transit Stations	(5) Workplaces	(6) Residential
			Ordinary Least Squares			
Stringency Index (Lag 0)	-0.8976***	-0.5629***	-0.6857***	-0.8635***	-0.7509***	0.3177***
	(0.0344)	(0.0362)	(0.0477)	(0.0309)	(0.0317)	(0.0146)
Mean of DV	-43.568	-22.383	-23.327	-44.998	-33.865	16.376
Stringency Index (Lag 7)	-0.6906***	-0.5378***	-0.5411***	-0.6667***	-0.6077***	0.2540***
	(0.0373)	(0.0367)	(0.0463)	(0.0354)	(0.0327)	(0.0144)
Mean of DV	-44.515	-22.870	-23.997	-46.047	-34.605	16.734
Stringency Index (Lag 14)	-0.2996***	-0.2760***	-0.2354***	-0.2725***	-0.2773***	0.1131***
	(0.0408)	(0.0346)	(0.0430)	(0.0397)	(0.0333)	(0.0152)
Mean of DV	-45.798	-23.569	-24.846	-47.394	-35.593	17.186
Stringency Index (Lag 21)	0.0291	-0.0241	0.0284	0.0488	0.0159	-0.0135
	(0.0470)	(0.0372)	(0.0461)	(0.0469)	(0.0400)	(0.0182)
Mean of DV	-48.342	-25.046	-26.343	-49.983	-37.705	18.090
			2SLS: Excluding Subregion IV			
Stringency Index (Lag 0)	-1.1042***	-0.6644***	-0.7332***	-1.0775***	-0.9591***	0.3805***
	(0.0448)	(0.0400)	(0.0792)	(0.0401)	(0.0361)	(0.0179)
Mean of DV	-43.567	-22.378	-23.332	-44.998	-33.861	16.376
F-Stat	303.458	303.405	303.458	303.458	303.458	302.388
Stringency Index (Lag 7)	-0.9821***	-0.7383***	-0.6374***	-0.9706***	-0.9403***	0.3651***
	(0.0491)	(0.0411)	(0.0695)	(0.0485)	(0.0449)	(0.0199)
Mean of DV	-44.514	-22.865	-24.001	-46.047	-34.600	16.734
F-Stat	306.084	306.032	306.084	306.084	306.084	303.958
Stringency Index (Lag 14)	-0.4120***	-0.4438***	-0.1999***	-0.4119***	-0.5168***	0.1831***
	(0.0529)	(0.0472)	(0.0546)	(0.0517)	(0.0487)	(0.0205)
Mean of DV	-45.797	-23.563	-24.851	-47.393	-35.588	17.185
F-Stat	299.846	299.693	299.846	299.846	299.846	297.280
Stringency Index (Lag 21)	0.0374	-0.1182	-0.2874	0.0756	-0.0125	0.0279
	(0.1457)	(0.1088)	(0.1450)	(0.2428)	(0.1272)	(0.0520)
Mean of DV	-48.340	-25.039	-26.348	-49.982	-37.699	18.089
F-Stat	59.144	59.105	59.144	59.144	59.144	59.266
Fixed Effects			Country; Days since first case			
Number of country	117	117	117	117	117	117
Observations (Lag 0)	7,701	7,697	7,701	7,701	7,701	7,655
Observations (Lag 7)	7,617	7,613	7,617	7,617	7,617	7,570
Observations (Lag 14)	7,389	7,385	7,389	7,389	7,389	7,342
Observations (Lag 21)	6,983	6,979	6,983	6,983	6,983	6,936

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

The next four panels of the table present the results from the instrumental variable (IV) approach. As we discuss in Section 2, we use the level of stringency of the restrictions in countries in

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the rest of the world to predict the level of stringency in a country.[7] We use several definitions of the instrumental variable, all of which yield similar results. We present these results using alternative instruments in Appendix Tables A4 and A5. In what follows, we present results from our most-preferred IV specification where we use the stringency in the countries outside the sub-region to which the country belongs. Excluding countries from the sub-regions minimizes the chances of the stringency in other countries affecting the mobility or spread of the disease in the country through pathways other than affecting the country's restriction stringency. Compared to the association results in the first four panels, the IV causal estimates are larger in magnitude. But the two broad observations remain unchanged - countries with stricter restrictions observed higher reduction in mobility, and contemporaneous restrictions matter more than past restrictions.

Next, in Table 3, we examine the impact of the level of stringency of the restrictions on the growth rates of the numbers of tests conducted, confirmed cases, deaths attributed to COVID-19, and recoveries across time in different countries.[8] The first four panels present the associations for comparison, but the discussion hereon will focus on the IV results. Compared to Table 2 where the contemporaneous restrictions had the largest impact on mobility, the stringency of the measures seven days and fourteen days ago have a much larger impact on the growth rate of confirmed cases and deaths attributed to COVID-19. Given the current scientific understanding that the virus has an incubation and infection period of up to fourteen days, this is expected. Second, even if we focus only on the effect of stringency in seven or fourteen days prior, there appears to be no strong effect on the number of tests. We expected this too. There is no reason why the number of tests conducted, given the testing infrastructure of a country is controlled for by the country fixed effect, would have been affected by a decrease in mobility.[9] But the more stringent the measures, the lower the growth in the number of confirmed cases and deaths attributed to COVID-19. The impact on cases and deaths suggest that stricter restrictions achieved their goal of containing the contagion. The impact on recoveries, even though sometimes large and in the right direction, is

[7]The rationale, once again, is that countries, while deciding to the on the level of stringency responded not only to the disease situation in the country but also to how it was expected to evolve. To predict how the situation would have evolved and what the optimal level of stringency might have been, every country looked at the rest of the countries in the world. Therefore, while the level of stringency in the rest of the world affected the stringency of the restrictions in a country, it did not affect the mobility and the disease situation in the country directly. That is, the exclusion restriction is likely to be satisfied.

[8]While we cannot rule out systematic (non-classical) measurement error in these outcome variables, we follow other researchers and assume that these measurement errors are classical in nature and do not add bias to the estimated coefficients.

[9]It is possible that with reduced mobility, events like accidents that require medical attention decreases reducing the pressure on the health infrastructure that could then be devoted to COVID-19 testing. However, that would have lead to an increase in testing, which is not what we observe.

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mostly statistically insignificant.

Table 3: Impact of stricter restrictions on growth rates of tests, cases, deaths, and recoveries

VARIABLES	(1) Tests	(2) Cases	(3) Deaths	(4) Recoveries
	Ordinary Least Squares			
Stringency Index (Lag 0)	-0.0023	-0.0003	0.0003	0.0178**
	(0.0018)	(0.0004)	(0.0007)	(0.0090)
Mean of DV	0.112	0.149	0.116	0.304
Stringency Index (Lag 7)	-0.0021*	-0.0028***	-0.0011**	0.0056**
	(0.0011)	(0.0004)	(0.0005)	(0.0027)
Mean of DV	0.110	0.150	0.115	0.303
Stringency Index (Lag 14)	-0.0010***	-0.0020***	-0.0018***	-0.0070
	(0.0003)	(0.0003)	(0.0004)	(0.0063)
Mean of DV	0.098	0.145	0.114	0.306
Stringency Index (Lag 21)	-0.0002	-0.0008***	-0.0019***	-0.0100*
	(0.0003)	(0.0003)	(0.0003)	(0.0054)
Mean of DV	0.092	0.134	0.112	0.314
	2SLS: Excluding Subregion IV			
Stringency Index (Lag 0)	-0.0047	-0.0009*	-0.0009	0.0168**
	(0.0030)	(0.0005)	(0.0013)	(0.0072)
Mean of DV	0.112	0.149	0.116	0.304
F-Stat	77.081	299.485	46.873	158.483
Stringency Index (Lag 7)	-0.0033*	-0.0029***	-0.0024***	0.0024
	(0.0018)	(0.0005)	(0.0007)	(0.0036)
Mean of DV	0.110	0.150	0.115	0.303
F-Stat	114.377	305.991	127.046	220.038
Stringency Index (Lag 14)	-0.0005	-0.0029***	-0.0032***	-0.0127
	(0.0006)	(0.0005)	(0.0005)	(0.0090)
Mean of DV	0.098	0.145	0.114	0.306
F-Stat	128.357	298.155	244.166	277.915
Stringency Index (Lag 21)	0.0003	0.0003	-0.0027***	-0.0140*
	(0.0008)	(0.0006)	(0.0004)	(0.0083)
Mean of DV	0.092	0.134	0.112	0.314
F-Stat	100.106	237.133	244.085	238.362
Fixed Effects	Country; Days since first case			
Number of country	72	117	108	113
Observations (Lag 0)	4,113	7,607	5,277	6,141
Observations (Lag 7)	4,063	7,525	5,333	6,081
Observations (Lag 14)	4,008	7,319	5,300	5,939
Observations (Lag 21)	3,867	6,932	5,240	5,755

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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But were restrictions equally effective across developing and developed countries, and adequate to contain the contagion? Heterogeneity analysis by demography, the status of the health infrastructure, and governance indicators will help us understand the mechanisms and the role of other institutional and cultural factors. To find out, we split the sample of countries at the median along a range of characteristics and repeat the analysis. We present the heterogeneity in the impact of stringency on mobility in Tables 4 and 5. The first and last three columns in each panel report the impact of imposing stricter restrictions on cases, deaths, and recovery in countries below and above the median along the different dimensions. Comparing column (1) with column (4), column (2) with column (5), and column (3) with column (6), stricter restrictions worked in limiting mobility better in densely populated, poorer, more unequal, more polluted countries with younger but unhealthier populations and worse health infrastructure. From their description, and affirmed by the segregated summary statistics presented in Table A3, these characteristics belong to the relatively less-developed countries in the sample. The restrictions also worked better in more democratic countries, with better government effectiveness and lower perceived levels of corruption.

However, this stronger effect of stringency on mobility does not imply that the relatively less-developed countries contained the contagion better. First, it is important to note that upon announcement of lockdowns, less-developed countries generally faced a mass migration of urban migrant workers moving back to their homes in rural areas, before the lockdown is in effect (see for example, Roy and Agarwal (2020) for the case in India). With limited mobility (or mobility not captured in the Google data) in their rural homes, this can contribute to the stronger stringency effect on mobility for less-developed countries, but does not translate to better contagion containment. Second, it is entirely possible that people in more developed countries were already socially distancing even in the absence of these restrictions (Maloney and Taskin (2020)). Similarly, it is also possible that countries with population in better health and adequate health infrastructure, handled the infections better, even if the restrictions were not stringent or if the populations were lax about observing them.[10]

[10]Examples include Sweden, Norway, and Germany.

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Table 4: Heterogenous impact of stricter restrictions on mobility 01

VARIABLES	(1) Transit Stations	(2) Workplaces	(3) Residential	(4) Transit Stations	(5) Workplaces	(6) Residential
		< Median			> Median	
			Population Density			
Stringency Index (Lag 14)	-0.3893***	-0.5110***	0.1621***	-0.5251***	-0.5097***	0.1965***
	(0.0777)	(0.0756)	(0.0306)	(0.0723)	(0.0645)	(0.0276)
Observations	3,513	3,513	3,499	3,878	3,878	3,845
Number of country	58	58	58	59	59	59
Mean of DV	-45.481	-33.615	16.332	-49.126	-37.375	17.961
F-Stat	155.829	155.829	153.769	125.467	125.467	125.219
			Primary Education			
Stringency Index (Lag 14)	-0.3679***	-0.4488***	0.1750***	-0.5428***	-0.5568***	0.2927***
	(0.0819)	(0.0748)	(0.0323)	(0.0663)	(0.0634)	(0.0257)
Observations	2,345	2,345	2,332	5,046	5,046	5,012
Number of country	38	38	38	79	79	79
Mean of DV	-51.445	-37.950	19.637	-45.511	-34.490	16.044
F-Stat	173.657	173.657	173.474	168.153	168.153	166.004
			Poverty Head Count			
Stringency Index (Lag 14)	-0.3438***	-0.4193***	0.1557***	-0.5512***	-0.6424***	0.2392***
	(0.0817)	(0.0696)	(0.0303)	(0.0749)	(0.0730)	(0.0309)
Observations	3,441	3,441	3,439	3,950	3,950	3,905
Number of country	51	51	51	66	66	66
Mean of DV	-47.607	-37.839	16.281	-47.207	-33.627	17.981
F-Stat	126.350	126.350	126.203	154.908	154.908	152.585
			Gini Index			
Stringency Index (Lag 14)	-0.3976***	-0.4974***	0.1666***	-0.4734***	-0.5590***	0.2161***
	(0.0834)	(0.0803)	(0.0289)	(0.0703)	(0.0650)	(0.0297)
Observations	3,480	3,480	3,478	3,911	3,911	3,866
Number of country	52	52	52	65	65	65
Mean of DV	-44.932	-34.470	14.497	-49.584	-36.582	19.603
F-Stat	98.720	98.720	98.593	199.702	199.702	197.319
			Age 65 & Older			
Stringency Index (Lag 14)	-0.5122***	-0.5472***	0.2133***	-0.3741***	-0.5166***	0.1818***
	(0.0767)	(0.0704)	(0.0310)	(0.0744)	(0.0701)	(0.0290)
Observations	3,512	3,512	3,485	3,879	3,879	3,859
Number of country	59	59	59	58	58	58
Mean of DV	-46.549	-32.707	17.672	-48.158	-38.196	16.745
F-Stat	133.420	133.420	132.017	135.047	135.047	137.220
			PM2.5			
Stringency Index (Lag 14)	-0.4022***	-0.5205***	0.1860***	-0.4789***	-0.5449***	0.2032***
	(0.0690)	(0.0666)	(0.0297)	(0.0795)	(0.0744)	(0.0311)
Observations	3,761	3,761	3,752	3,630	3,630	3,592
Number of country	57	57	57	60	60	60
Mean of DV	-48.224	-37.724	17.266	-46.533	-33.375	17.101
F-Stat	176.502	176.502	175.536	119.232	119.232	117.192
FE			Country; Days since first case			

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Heterogenous impact of stricter restrictions on mobility 02

VARIABLES	(1) Transit Stations	(2) Workplaces	(3) Residential	(4) Transit Stations	(5) Workplaces	(6) Residential
		< Median			> Median	
			Hospital Beds per 100k			
Stringency Index (Lag 14)	-0.4501***	-0.5076***	0.1894***	-0.4025***	-0.5276***	0.1859***
	(0.0717)	(0.0665)	(0.0285)	(0.0705)	(0.0668)	(0.0275)
Observations	3,271	3,271	3,251	4,120	4,120	4,093
Number of country	54	54	54	63	63	63
Mean of DV	-47.988	-34.815	18.474	-46.922	-36.201	16.161
F-Stat	189.553	189.553	187.191	130.292	130.292	130.560
			Handwashing Facilities			
Stringency Index (Lag 14)	-0.8003***	-0.7785***	0.3288***	-0.3398***	-0.4575***	0.1550***
	(0.1494)	(0.1435)	(0.0646)	(0.0520)	(0.0500)	(0.0204)
Observations	1,530	1,530	1,530	5,861	5,861	5,814
Number of country	27	27	27	90	90	90
Mean of DV	-41.393	-29.052	16.808	-48.960	-37.294	17.284
F-Stat	73.924	73.924	73.924	226.589	226.589	224.396
			Cardiovascular Diseases Death Rate			
Stringency Index (Lag 14)	-0.3991***	-0.5182***	0.1814***	-0.4492***	-0.5290***	0.1915***
	(0.0679)	(0.0646)	(0.0271)	(0.0794)	(0.0763)	(0.0308)
Observations	3,790	3,790	3,764	3,601	3,601	3,580
Number of country	58	58	58	59	59	59
Mean of DV	-49.565	-38.488	18.567	-45.108	-32.536	15.732
F-Stat	174.289	174.289	169.300	109.755	109.755	109.745
			Democracy Score			
Stringency Index (Lag 14)	-0.4281***	-0.3849***	0.1814***	-0.4700***	-0.5942***	0.2168***
	(0.0789)	(0.0757)	(0.0309)	(0.0702)	(0.0641)	(0.0280)
Observations	3,344	3,344	3,337	4,047	4,047	4,007
Number of country	55	55	55	62	62	62
Mean of DV	-45.116	-32.235	16.751	-49.276	-38.358	17.546
F-Stat	129.313	129.313	128.962	137.939	137.939	135.267
			Government Effectiveness			
Stringency Index (Lag 14)	-0.4161***	-0.3741***	0.1750***	-0.4926***	-0.6096***	0.2211***
	(0.0762)	(0.0731)	(0.0300)	(0.0784)	(0.0744)	(0.0322)
Observations	3,518	3,518	3,504	3,873	3,873	3,840
Number of country	59	59	59	58	58	58
Mean of DV	-45.882	-34.003	17.370	-48.766	-37.028	17.016
F-Stat	119.758	119.758	118.808	138.460	138.460	136.651
			Corruption Perception Index			
Stringency Index (Lag 14)	-0.3993***	-0.3361***	0.1597***	-0.4951***	-0.6195***	0.2283***
	(0.0814)	(0.0756)	(0.0311)	(0.0692)	(0.0644)	(0.0282)
Observations	3,060	3,060	3,053	4,331	4,331	4,291
Number of country	51	51	51	66	66	66
Mean of DV	-45.422	-33.445	17.427	-48.787	-37.102	17.013
F-Stat	104.360	104.360	104.185	175.311	175.311	172.424
FE			Country; Days since first case			

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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We see this in Tables 6 and 7. As opposed to the results in Tables 4 and 5, stricter measures for containing the contagion did better in richer, more equal, less-polluted countries with older but healthier populations and better health infrastructure. From the description, the country characteristics reflect relatively more developed countries in the sample.[11] Not surprisingly, the restrictions also worked better in more democratic countries, with better government effectiveness and lower perceived levels of corruption. The results from tables 4, 5, 6, and 7 taken together suggest that even though stricter restrictions worked better at limiting mobility in relatively less developed countries, it did not translate into better control of the contagion. To see this, note that:

$$\frac{d\,(growth\ rate\ of\ cases\ or\ deaths)}{d\,(Mobility)} = \frac{\frac{d\,(growth\ rate\ of\ cases\ or\ deaths)}{d\,(Stringency\ Index)}}{\frac{d\,(Mobility)}{d\,(Stringency\ Index)}}$$

That is, the ratio of the causal IV estimate of the impact of the stringency index on the growth rates to the impact of the stringency index on mobility, is an estimate of how mobility affected the growth rates of cases or deaths in different countries. We present these ratios in 8.[12] We use the estimated effect on the mobility at public transport transit stations as the denominator to calculate these ratios. Using alternative measures of mobility produce similar results.

For the sake of completeness, we also present in table 8 the ratio of the impact on recovery to impact on mobility at transit stations. However, since the impact of stricter restrictions on recovery are almost always insignificant, we focus on the ratios for cases and deaths. Comparing the ratios in column (1) with column (4) and column (2) with column (5), it is clear that the decrease in mobility had a larger effect in more developed countries with better health infrastructure and governance. For example, a unit decrease in mobility in countries with more than the median number of hospital beds per 100,000 people causes a 0.006 unit decrease in the growth of deaths attributed to COVID-19. The corresponding figure for countries with less than median number of hospital beds per 100,000 people is 0.002. With relatively few exceptions, the results suggest that developed countries benefited more from reduction in mobility than developing countries.[13]

[11]These results are in partly in contrast with association results from Jinjarak et al. (2020) that finds that the correlation between stricter pandemic policies and lower future mortality growth was more pronounced in countries with a greater proportion of the elderly population, higher density, greater proportion of employees in vulnerable occupations, greater democratic freedom, more international travels, and further distance from the equator. The differences in our findings highly the need to distinguish causal effects of these restrictions from associations.

[12]A more methodological sound approach is to use the 3-Stages Least Square Methodology. But it comes with additional assumptions. Similarly, we can add level of significance and standard errors to these ratios. But the point we wish to make can be made simply by comparing these ratios.

[13]This result is consistent with Barnett-Howell and Mobarak (2020) who also report much lower estimated benefits of social distancing and social suppression in low-income countries.

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Table 6: Heterogenous impact of stricter restrictions on growth rates of cases, deaths, and recoveries 01

VARIABLES	(1) Cases	(2) Deaths	(3) Recovery	(4) Cases	(5) Deaths	(6) Recovery
		< Median			> Median	
			Population Density			
Stringency Index (Lag 14)	-0.0027***	-0.0026**	0.0117**	-0.0041***	-0.0028**	-0.0034
	(0.0007)	(0.0010)	(0.0047)	(0.0007)	(0.0010)	(0.0042)
Observations	3,518	2,422	2,671	4,009	2,914	3,413
Number of country	58	53	56	59	55	57
Mean of DV	0.150	0.114	0.263	0.151	0.116	0.334
F-Stat	184.961	134.058	164.411	122.684	55.175	94.257
			Primary Education			
Stringency Index (Lag 14)	-0.0010	-0.0009	0.0041**	-0.0036***	-0.0025***	0.0038
	(0.0009)	(0.0015)	(0.0020)	(0.0006)	(0.0008)	(0.0053)
Observations	2,366	1,640	1,929	5,161	3,696	4,155
Number of country	38	34	38	79	74	75
Mean of DV	0.161	0.108	0.200	0.145	0.118	0.350
F-Stat	197.516	88.825	225.520	184.958	82.043	128.590
			Poverty Head Count			
Stringency Index (Lag 14)	-0.0040***	-0.0019**	0.0018	-0.0020**	-0.0020	0.0020
	(0.0005)	(0.0009)	(0.0060)	(0.0008)	(0.0013)	(0.0027)
Observations	3,556	2,723	3,088	3,971	2,613	2,996
Number of country	51	50	51	66	58	62
Mean of DV	0.154	0.131	0.411	0.147	0.098	0.191
F-Stat	170.724	94.956	152.729	123.444	22.485	62.173
			Gini Index			
Stringency Index (Lag 14)	-0.0025***	-0.0017**	0.0040***	-0.0026***	-0.0014	-0.0018
	(0.0007)	(0.0009)	(0.0009)	(0.0008)	(0.0015)	(0.0071)
Observations	3,595	2,590	3,075	3,932	2,746	3,009
Number of country	52	48	51	65	60	62
Mean of DV	0.149	0.131	0.418	0.151	0.100	0.185
F-Stat	132.052	85.478	126.623	149.001	25.938	76.008
			Age 65 & Older			
Stringency Index (Lag 14)	-0.0022**	-0.0018*	0.0018	-0.0032***	-0.0019**	0.0022
	(0.0010)	(0.0010)	(0.0023)	(0.0005)	(0.0010)	(0.0069)
Observations	3,532	2,238	2,738	3,995	3,098	3,346
Number of country	59	50	57	58	58	56
Mean of DV	0.150	0.099	0.182	0.151	0.127	0.401
F-Stat	156.680	87.763	146.525	126.848	71.324	94.809
			PM2.5			
Stringency Index (Lag 14)	-0.0032***	-0.0029***	0.0009	-0.0026**	-0.0007	0.0016
	(0.0004)	(0.0010)	(0.0066)	(0.0010)	(0.0006)	(0.0022)
Observations	3,848	2,960	3,204	3,679	2,376	2,880
Number of country	57	55	55	60	53	58
Mean of DV	0.152	0.131	0.414	0.149	0.096	0.179
F-Stat	201.158	110.374	142.214	120.273	23.316	89.538
FE			Country; Days since first case			

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Heterogenous impact of stricter restrictions on growth rates of cases, deaths, and recoveries 02

VARIABLES	(1) Cases	(2) Deaths	(3) Recovery	(4) Cases	(5) Deaths	(6) Recovery
	< Median			> Median		
	Hospital Beds per 100k					
Stringency Index (Lag 14)	-0.0028***	-0.0009	0.0022	-0.0028***	-0.0025***	0.0027
	(0.0009)	(0.0006)	(0.0026)	(0.0005)	(0.0005)	(0.0063)
Observations	3,311	2,335	2,600	4,216	3,001	3,484
Number of country	54	50	53	63	58	60
Mean of DV	0.157	0.106	0.208	0.145	0.122	0.373
F-Stat	215.723	102.682	225.611	132.499	73.230	103.493
	Handwashing Facilities					
Stringency Index (Lag 14)	-0.0007	-0.0012	0.0041**	-0.0030***	-0.0022***	0.0013
	(0.0009)	(0.0013)	(0.0017)	(0.0005)	(0.0008)	(0.0047)
Observations	1,529	876	1,174	5,998	4,460	4,910
Number of country	27	21	27	90	87	86
Mean of DV	0.147	0.100	0.164	0.151	0.118	0.336
F-Stat	86.892	133.378	275.484	236.312	109.709	166.313
	Cardiovascular Diseases Death Rate					
Stringency Index (Lag 14)	-0.0035***	-0.0034**	0.0041	-0.0022**	-0.0019*	0.0014
	(0.0005)	(0.0009)	(0.0063)	(0.0009)	(0.0011)	(0.0021)
Observations	3,909	3,039	3,244	3,618	2,297	2,840
Number of country	58	57	56	59	51	57
Mean of DV	0.155	0.123	0.415	0.145	0.104	0.174
F-Stat	166.194	79.668	101.821	122.073	85.867	112.774
	Democracy Score					
Stringency Index (Lag 14)	-0.0010	-0.0007	0.0018	-0.0035***	-0.0026***	0.0033
	(0.0010)	(0.0009)	(0.0023)	(0.0005)	(0.0009)	(0.0062)
Observations	3,376	2,131	2,684	4,151	3,205	3,400
Number of country	55	48	54	62	60	59
Mean of DV	0.152	0.099	0.174	0.149	0.126	0.404
F-Stat	118.138	79.102	87.654	166.684	81.403	116.450
	Government Effectiveness					
Stringency Index (Lag 14)	-0.0022***	-0.0006	0.0027	-0.0032***	-0.0024***	0.0004
	(0.0004)	(0.0010)	(0.0029)	(0.0005)	(0.0007)	(0.0060)
Observations	3,524	2,323	2,710	4,003	3,013	3,374
Number of country	59	51	57	58	57	56
Mean of DV	0.153	0.108	0.207	0.148	0.120	0.380
F-Stat	129.661	135.962	92.951	142.381	58.642	106.264
	Corruption Perception Index					
Stringency Index (Lag 14)	-0.0019**	-0.0011	0.0024	-0.0035***	-0.0032***	0.0011
	(0.0008)	(0.0010)	(0.0029)	(0.0005)	(0.0009)	(0.0061)
Observations	3,079	2,076	2,404	4,448	3,260	3,680
Number of country	51	44	50	66	64	63
Mean of DV	0.152	0.105	0.205	0.149	0.121	0.366
F-Stat	123.339	118.122	120.891	169.900	64.596	110.002
FE	Country; Days since first case					

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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Table 8: Ratio of the estimated effect on growth rates to the estimated effect on mobility

VARIABLES	(1) Cases	(2) Deaths	(3) Recovery	(4) Cases	(5) Deaths	(6) Recovery
	< Median			> Median		
Population Density	0.007	0.007	-0.030	0.008	0.005	0.006
Primary Education	0.003	0.002	-0.011	0.007	0.004	-0.007
Poverty Head Count	0.012	0.006	-0.005	0.004	0.004	-0.004
Gini Index	0.006	0.004	-0.010	0.005	0.003	0.004
Age 65 & Older	0.004	0.004	-0.004	0.009	0.005	-0.006
PM2.5	0.008	0.007	-0.002	0.005	0.001	-0.003
Hospital Beds per 100k	0.006	0.002	-0.005	0.007	0.006	-0.007
Handwashing Facilities	0.001	0.002	-0.005	0.009	0.006	-0.004
Cardiovascular Diseases Death Rate	0.009	0.009	-0.010	0.005	0.004	-0.003
Democracy Score	0.002	0.002	-0.004	0.007	0.006	-0.007
Government Effectiveness	0.005	0.001	-0.006	0.007	0.005	-0.001
Corruption Perception Index	0.005	0.003	-0.006	0.007	0.006	0.002

The heterogeneity results provide some elucidation to the possible reasons. Given that the population, on average, in relatively less-developed countries is more immunocompromised, fewer people are able to fight off the infections.[14] Stringency measures are unable to counter the rise in cases and deaths, catalyzed by immunodeficiency. This is further aggravated by the fact that stringent mobility measures lower disease rise at the cost of people's economic opportunities. With high poverty rates, poor people will thus place greater value on their livelihoods relative to contracting the infection. The reduction in economic activity due to the restrictions could directly affect the daily consumption of poorer people, further compromising their immune system. Lack of access to adequate handwashing facilities also further hinders their ability to combat the virus, even in the

[14]There is a growing amount of scientific evidence that point towards people with better immune systems being able to fight SARS-CoV-2 infection better. See, for example Shi et al. (2020). People who are able to fight off the viral infection are possibly being less diagnosed, due to shorter incubation period.

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presence of greater stringency.

The idea of instilling mobility restrictions is to flatten the curve and thereby lower the disease burden on the health infrastructure. However, most less-developed countries have limited number of hospital beds and ventilators. If these are already over-whelmed and inaccessible, flattening the curve is only marginally useful compared to countries with better and accessible health infrastructure, and the effect of stringcy measures would be, accordingly, much lower. Furthermore, the higher population density in less-developed countries could mean a higher rate of human-to-human contact and transfer even with lower mobility than richer countries. Finally, another reason could be that less-developed countries lacked the knowledge of best-practices to follow when a person who tested positive was isolated either at home or at the hospital. Poorer government effectiveness and more corruption also means sluggish enforcement of recommended best-practices.

Whatever be the reason(s), one clear inference from this final result is that mobility measures alone were not and will not be sufficient to contain the contagion in developing countries. What is worse is that on top of the relatively worse performance of decrease in mobility in controlling the spread, the economic cost of these restrictions are also higher in these countries. With weaker social security support and reliance on daily wages for consumption, restrictions on economic activity mean that poorer countries face a catch-22 much worse than the richer countries. Finding a solution could be difficult without external support.

4 Conclusion

Some have claimed that governments across the world have responded slowly and insufficiently to the COVID-19 pandemic (The Lancet (2020)). Others have highlighted the real threats of stricter restrictions (Ravallion (2020)). It is, therefore, imperative to understand how effective the restrictions implemented by the countries across the world are. Compared to earlier evaluations of these restrictions that document a strong negative association between the stringency of the restrictions and the spread of the disease, we use an instrumental variable approach to estimate the causal effect of the restrictions.

We find that while the restrictions implemented affected mobility and the spread of the disease, there was considerably heterogeneity across countries. While stricter measures reduce mobility more in less-developed countries, it does not contain the contagion as effectively as it does in developed countries. Thus, it would seem less-developed countries have less to gain from stricter mobility restrictions. This could result from the lower levels of awareness, poorer health conditions and practices, and worse economic conditions in these countries. The results highlight the need to

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complement restriction policies with awareness, economic and health assistance schemes.

It is, however, unclear what these complementary policies could be. From direct monetary help to only partial shutdowns, there is a range of policies to choose from. Future research should investigate the effectiveness of these alternative complementary policies in increasing the effectiveness of the mobility and activity restrictions in developing nations.

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References

Aktay, A., Bavadekar, S., Cossoul, G., Davis, J., Desfontaines, D., Fabrikant, A., Gabrilovich, E., Gadepalli, K., Gipson, B., Guevara, M., et al. (2020). Google COVID-19 community mobility reports: Anonymization process description (version 1.0). *arXiv preprint arXiv:2004.04145*.

Anderson, R. M., Heesterbeek, H., Klinkenberg, D., and Hollingsworth, T. D. (2020). How will country-based mitigation measures influence the course of the COVID-19 epidemic? *The Lancet*, 395(10228):931–934.

Barnett-Howell, Z. and Mobarak, A. M. (2020). Should low-income countries impose the same social distancing guidelines as europe and north america to halt the spread of covid-19? *Yale School of Management, New Haven, CT. http://yrise. yale. edu/wp-content/uploads/2020/04/covid19_in_low_income_countries. pdf*.

Bell, B. P. (2016). Overview, control strategies, and lessons learned in the CDC response to the 2014–2016 Ebola epidemic. *MMWR Supplements*, 65.

Bendavid, E., Mulaney, B., Sood, N., Shah, S., Ling, E., Bromley-Dulfano, R., Lai, C., Weissberg, Z., Saavedra, R., Tedrow, J., et al. (2020). COVID-19 antibody seroprevalence in Santa Clara County, California. *MedRxiv*.

Burn-Murdoch, J., Romei, V., and Giles, C. (2020). Global coronavirus death toll could be 60% higher than reported. *Financial Times*.

Cetron, M. and Landwirth, J. (2005). Public health and ethical considerations in planning for quarantine. *The Yale Journal of Biology and Medicine*, 78(5):329.

Chang, R. and Velasco, A. (2020). Economic policy incentives to preserve lives and livelihoods. Technical report, National Bureau of Economic Research.

Coker, R., Thomas, M., Lock, K., and Martin, R. (2007). Detention and the evolving threat of tuberculosis: Evidence, ethics, and law. *The Journal of Law, Medicine & Ethics*, 35(4):609–615.

Espinoza, B., Moreno, V., Bichara, D., and Castillo-Chavez, C. (2016). Assessing the efficiency of movement restriction as a control strategy of Ebola. In *Mathematical and Statistical Modeling for Emerging and Re-emerging Infectious Diseases*, pages 123–145. Springer.

Fang, H., Wang, L., and Yang, Y. (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-nCoV) in China. Technical report, National Bureau of Economic Research.

Covid Economics 26, 5 June 2020: 107-136

Glover, A., Heathcote, J., Krueger, D., and Ríos-Rull, J.-V. (2020). Health versus wealth: On the distributional effects of controlling a pandemic. Technical report, National Bureau of Economic Research.

Greenstone, M. and Nigam, V. (2020). Does social distancing matter? *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-26).

Hale, T., Petherick, A., Phillips, T., and Webster, S. (2020). Variation in government responses to COVID-19. *Blavatnik School of Government Working Paper*, 31.

Jinjarak, Y., Ahmed, R., Nair-Desai, S., Xin, W., and Aizenman, J. (2020). Accounting for global COVID-19 diffusion patterns, January-April 2020. Technical report, National Bureau of Economic Research.

Johns Hopkins CSSE (2019). 2019-nCoV Data Repository by Johns Hopkins CSSE. *Retrieved from https://github. com/CSSEGISandData/COVID-19 on*.

Kaufmann, D. and Kraay, A. (2007). *Governance indicators: where are we, where should we be going?* The World Bank.

Lin, Z. and Meissner, C. M. (2020). Health vs. wealth? Public health policies and the economy during COVID-19. Technical report, National Bureau of Economic Research.

Maloney, W. F. and Taskin, T. (2020). Determinants of social distancing and economic activity during covid-19: A global view. *World Bank Policy Research Working Paper*, (9242).

Markel, H. (1999). *Quarantine!: East-European Jewish immigrants and the New York City epidemics of 1892*. JHU Press.

McNeil Jr, D. G. (2014). Using a tactic unseen in a century, countries cordon off Ebola-racked areas. *The New York Times*, 18.

Onishi, N. (2014). As Ebola grips Liberia's capital, a quarantine sows social chaos. *The New York Times*, 28.

Qiu, Y., Chen, X., and Shi, W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, page 1.

Ravallion, M. (2020). Could pandemic lead to famine? *Project Syndicate*.

Covid Economics 26, 5 June 2020: 107-136

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Roy, R. and Agarwal, V. (2020). Millions of indians are fleeing cities, raising fears of a coronavirus 'land mine' in villages. *The Wall Street Journal*.

Shi, Y., Wang, Y., Shao, C., Huang, J., Gan, J., Huang, X., Bucci, E., Piacentini, M., Ippolito, G., and Melino, G. (2020). Covid-19 infection: the perspectives on immune responses.

The Lancet (2020). Covid-19: too little, too late? *Lancet (London, England)*, 395(10226):755.

Tognotti, E. (2013). Lessons from the history of quarantine, from plague to Influenza A. *Emerging Infectious Diseases*, 19(2):254.

Towers, S., Patterson-Lomba, O., and Castillo-Chavez, C. (2014). Temporal variations in the effective reproduction number of the 2014 West Africa Ebola outbreak. *PLoS Currents*, 6.

Villas-Boas, S. B., Sears, J., Villas-Boas, M., and Villas-Boas, V. (2020). Are we #stayinghome to flatten the curve?

Vogel, G. (2020). Antibody surveys suggesting vast undercount of coronavirus infections may be unreliable. *Science*, 4.

World Health Organization Writing Group (2006). Nonpharmaceutical interventions for pandemic influenza, international measures. *Emerging Infectious Diseases*, 12(1):81.

Yilmazkuday, H. (2020). Stay-at-home works to fight against COVID-19: International evidence from Google mobility data. *Available at SSRN 3571708*.

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Appendix

Table A1: List of Countries

#	Country	Stringency Index	Cases Growth Rate	#	Country	Stringency Index	Cases Growth Rate
1	Afghanistan	50.056	.153	60	Libya	88.541	.208
2	Angola	84.413	.075	61	Luxembourg	67.045	.172
3	Argentina	79.216	.172	62	Malaysia	53.761	.077
4	Aruba	69.340	.100	63	Mali	76.190	.192
5	Australia	49.116	.081	64	Mauritius	85.027	.139
6	Austria	63.530	.148	65	Mexico	56.029	.158
7	Bahrain	64.758	.229	66	Moldova	78.445	.171
8	Bangladesh	78.700	.158	67	Mongolia	65.153	.097
9	Barbados	80.394	.121	68	Mozambique	53.203	.153
10	Belarus	11.047	.181	69	Myanmar	76.925	.115
11	Belgium	57.854	.181	70	Namibia	64.296	.047
12	Belize	64.521	.086	71	Nepal	61.150	.068
13	Benin	53.961	.133	72	Netherlands	66.337	.193
14	Bolivia	89.296	.151	73	New Zealand	71.856	.123
15	Bosnia and Herzegovina	78.140	.172	74	Nicaragua	13.260	.069
16	Botswana	86.168	.066	75	Niger	60.327	.218
17	Brazil	55.017	.197	76	Nigeria	57.909	.141
18	Bulgaria	68.718	.143	77	Norway	62.489	.170
19	Burkina Faso	75.651	.172	78	Oman	68.540	.117
20	Cameroon	57.931	.158	79	Pakistan	75.192	.201
21	Canada	50.817	.119	80	Panama	73.834	.245
22	Cape Verde	75.741	.152	81	Papua New Guinea	74.159	.096
23	Chile	59.446	.190	82	Paraguay	85.995	.154
24	Colombia	76.634	.192	83	Peru	87.598	.261
25	Costa Rica	68.742	.155	84	Philippines	72.511	.124
26	Cote d'Ivoire	75.580	.179	85	Poland	70.174	.201
27	Croatia	72.261	.123	86	Portugal	71.590	.170
28	Czech Republic	64.538	.135	87	Puerto Rico	96.835	.093
29	Denmark	71.204	.167	88	Qatar	74.145	.282
30	Dominican Republic	73.720	.183	89	Romania	72.632	.165
31	Ecuador	76.866	.238	90	Rwanda	92.702	.158
32	Egypt	53.374	.158	91	Saudi Arabia	77.283	.212
33	El Salvador	92.936	.166	92	Senegal	52.949	.144
34	Estonia	58.387	.141	93	Serbia	85.981	.216
35	Finland	56.220	.129	94	Singapore	54.101	.073
36	France	67.215	.131	95	Slovakia	76.697	.147
37	Gabon	68.453	.149	96	Slovenia	75.849	.178
38	Georgia	79.713	.112	97	South Africa	73.410	.175
39	Germany	57.094	.132	98	South Korea	62.016	.089
40	Ghana	66.817	.171	99	Spain	63.260	.174
41	Greece	70.640	.147	100	Sri Lanka	63.661	.097
42	Guatemala	93.115	.190	101	Sweden	28.324	.156
43	Honduras	94.689	.138	102	Switzerland	64.134	.230
44	Hungary	68.523	.131	103	Taiwan	28.324	.042
45	India	65.155	.159	104	Tanzania	45.349	.158
46	Indonesia	56.511	.166	105	Thailand	50.180	.063
47	Iraq	82.571	.148	106	Trinidad and Tobago	76.006	.145
48	Ireland	69.106	.182	107	Turkey	72.869	.373
49	Israel	71.557	.154	108	Uganda	87.276	.243
50	Italy	80.108	.206	109	United Arab Emirates	58.885	.102
51	Jamaica	76.759	.123	110	United Kingdom	51.247	.135
52	Japan	47.249	.076	111	United States	49.452	.157
53	Jordan	78.330	.271	112	Uruguay	70.600	.119
54	Kazakhstan	79.759	.149	113	Venezuela	83.516	.086
55	Kenya	83.182	.147	114	Vietnam	66.303	.037
56	Kuwait	72.466	.124	115	Yemen	44.793	.241
57	Kyrgyzstan	84.603	.147	116	Zambia	52.778	.126
58	Laos	85.710	.073	117	Zimbabwe	82.384	.096
59	Lebanon	67.771	.118				

Note: Mean Stringency Index & Cases Growth Rate values from the date range 15 Feb - 09 May.

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Table A2: Data Sources

Variable	Data Source
Stringency Index	Oxford Government Response Tracker
Retail and Recreation (% change)	Google Community Mobility Report
Grocery and Pharmacy (% change)	Google Community Mobility Report
Parks (% change)	Google Community Mobility Report
Transit Stations (% change)	Google Community Mobility Report
Workplaces (% change)	Google Community Mobility Report
Residential (% change)	Google Community Mobility Report
Tests (Growth Rate)	Our World In Data (OWID)
Confirmed Cases (Growth Rate)	Johns Hopkins Center for Systems Science and Engineering (CSSE)
Deaths (Growth Rate)	Johns Hopkins Center for Systems Science and Engineering (CSSE)
Recoveries (Growth Rate)	Johns Hopkins Center for Systems Science and Engineering (CSSE)
Population Density	World Development Indicators (most recent year available)
Primary Education	World Development Indicators (most recent year available)
Poverty Headcount (2011 PPP)	World Development Indicators (most recent year available)
Gini Index	World Development Indicators (most recent year available)
Population Aged 65 or older	World Development Indicators (most recent year available)
PM2.5 (2010-2017 Average)	World Development Indicators
Hospital Beds per 100k Population	OECD, Eurostat, World Bank, National Government Records, and other sources (most recent year available since 2010)
Handwashing Facilities	United Nations Statistics Division (most recent year available)
CVD Death Rate	Global Burden of Disease Study 2017 Results
Democracy Score	Economist Intelligence Unit (EIU)
Governance Effectiveness	Worldwide Governance Indicators (WGI)
Corruption Perception Index	Transparency International (TI)

Table A3: Summary statistics by level of development

	N	Mean	SD	Median	Min	Max	N	Mean	SD	Median	Min	Max
	Developing Countries						Developed Countries					
Oxford Government Response Tracker												
Stringency Index	3244	51.280	34.632	53.830	0.000	100.000	6657	56.869	34.197	71.420	0.000	100 .000
Google Mobility Measures												
Retail and Recreation (% change)	3315	-27.056	28.057	-19.000	-94.000	28.000	6800	-37.630	31.774	-42.000	-97.000	37.000
Grocery and Pharmacy (% change)	3315	-16.636	23.152	-8.000	-95.000	34.000	6796	-17.222	24.251	-12.000	-97.000	76.000
Parks (% change)	3315	-17.276	20.814	-12.000	-90.000	65.000	6800	-17.599	38.020	-14.000	-95.000	226.000
Transit Stations (% change)	3315	-28.985	28.270	-23.000	-92.000	23.000	6800	-38.684	31.279	-46.000	-95.000	31.000
Workplaces (% change)	3315	-18.124	26.364	-10.000	-87.000	56.000	6800	-29.826	27.730	-33.000	-92.000	43.000
Residential (% change)	3290	10.948	11.167	9.000	-5.000	49.000	6773	13.959	12.011	14.000	-5.000	55.000
Outbreak Variables												
Tests (Growth Rate)	878	0.117	0.447	0.055	0.000	9.856	3461	0.111	0.731	0.047	-0.084	39.778
Confirmed Cases (Growth Rate)	2321	0.137	0.413	0.038	0.000	7.955	5462	0.152	0.470	0.050	-0.077	14.000
Deaths (Growth Rate)	1417	0.096	0.263	0.000	0.000	3.007	3999	0.121	0.277	0.037	0.000	4.598
Recoveries (Growth Rate)	1774	0.163	0.827	0.023	-0.912	14.500	4518	0.354	5.265	0.033	-1.000	17.086
Days since first case (by Country)	3315	17.385	28.002	17.000	-55.000	84.000	6715	26.911	26.997	27.000	-46.000	84.000
Heterogeneity Variables												
Population Density	3230	152.582	219.197	82.025	1.980	1265.036	6800	350.257	1171.510	94.592	3.078	7915.731
Primary Education	1785	52.196	22.313	51.424	13.870	99.442	4760	89.755	10.491	92.306	61.796	100.000
Poverty Headcount (2011 PPP)	3145	24.641	20.182	21.200	0.000	62.900	5780	2.110	3.909	0.500	0.000	18.900
Gini Index	3145	40.122	7.188	40.500	25.700	57.100	5695	37.178	8.508	34.900	24.200	63.000
Population Aged 65 or older	3230	4.199	1.841	3.597	2.168	10.864	6800	12.575	6.363	13.921	1.144	27.049
PM2.5 (2010-2017 Average)	3230	40.514	20.968	33.802	13.805	98.248	6630	22.738	16.224	17.919	6.455	87.022
Hospital Beds per 100k Population	2720	1.437	1.532	0.900	0.100	7.000	6460	3.762	2.524	2.965	0.600	13.050
Handwashing Facilities	2975	45.206	27.828	41.949	2.735	90.650	1615	80.458	17.033	87.847	43.993	99.000
CVD Death Rate	3315	296.950	115.538	268.024	103.957	597.029	6630	196.817	96.585	170.668	79.370	496.218
Democracy Score	3060	4.729	1.440	4.970	1.950	7.730	6460	6.662	2.036	7.090	1.930	9.870
Governance Effectiveness	3230	-0.533	0.575	-0.595	-2.244	1.362	6800	0.575	0.896	0.472	-1.847	2.231
Corruption Perception Index	3145	32.378	9.022	33.000	14.000	57.000	6375	54.547	19.224	52.000	17.000	88.000

Note: Here Low- and Lower Middle-Income Countries are categorized as developing countries while High- and Upper Middle-Income Countries are categorized as Developed countries. Low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of $1,025 or less in 2018; lower middle-income economies are those with a GNI per capita between $1,026 and $3,995; upper middle-income economies are those with a GNI per capita between $3,996 and $12,375; high-income economies are those with a GNI per capita of $12,376 or more.

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Table A4: Impact on mobility using alternative instruments

VARIABLES	(1) Retail Recreation	(2) Grocery Pharmacy	(3) Parks	(4) Transit Stations	(5) Workplaces	(6) Residential
			2SLS: World excluding Country IV			
Stringency Index (Lag 0)	-1.1056***	-0.6678***	-0.7514***	-1.0768***	-0.9559***	0.3814***
	(0.0451)	(0.0401)	(0.0790)	(0.0400)	(0.0363)	(0.0179)
Mean of DV	-43.567	-22.378	-23.332	-44.998	-33.861	16.376
F-Stat	346.324	346.294	346.324	346.324	346.324	345.179
Stringency Index (Lag 14)	-0.4175***	-0.4491***	-0.2396***	-0.4132***	-0.5116***	0.1856***
	(0.0498)	(0.0460)	(0.0521)	(0.0484)	(0.0460)	(0.0196)
Mean of DV	-45.797	-23.563	-24.851	-47.393	-35.588	17.185
F-Stat	365.482	365.317	365.482	365.482	365.482	362.968
			2SLS: Region excluding Country IV			
Stringency Index (Lag 0)	-1.1119***	-0.5778***	-0.5414***	-1.0520***	-0.9081***	0.3655***
	(0.0691)	(0.0610)	(0.1585)	(0.0546)	(0.0476)	(0.0237)
Mean of DV	-43.567	-22.378	-23.332	-44.998	-33.861	16.376
F-Stat	212.740	212.541	212.740	212.740	212.740	211.859
Stringency Index (Lag 14)	-0.2199*	-0.2350***	0.2507	-0.1751	-0.3093***	0.0932**
	(0.1311)	(0.0912)	(0.1779)	(0.1250)	(0.1066)	(0.0442)
Mean of DV	-45.797	-23.563	-24.851	-47.393	-35.588	17.185
F-Stat	74.426	74.408	74.426	74.426	74.426	74.218
			2SLS: World excluding Region IV			
Stringency Index (Lag 0)	-1.1043***	-0.6873***	-0.7970***	-1.0822***	-0.9663***	0.3849***
	(0.0459)	(0.0412)	(0.0699)	(0.0438)	(0.0399)	(0.0199)
Mean of DV	-43.567	-22.378	-23.332	-44.998	-33.861	16.376
F-Stat	226.656	226.615	226.656	226.656	226.656	225.722
Stringency Index (Lag 14)	-0.4723***	-0.5085***	-0.3756***	-0.4792***	-0.5677***	0.2112***
	(0.0666)	(0.0568)	(0.0621)	(0.0667)	(0.0617)	(0.0261)
Mean of DV	-45.797	-23.563	-24.851	-47.393	-35.588	17.185
F-Stat	168.185	168.109	168.185	168.185	168.185	166.147
			2SLS: Sub-region excluding Country IV			
Stringency Index (Lag 0)	-1.1274***	-0.7204***	-1.0329***	-1.0663***	-0.9064***	0.3956***
	(0.0722)	(0.0596)	(0.1039)	(0.0595)	(0.0537)	(0.0243)
Mean of DV	-43.567	-22.378	-23.332	-44.998	-33.861	16.376
F-Stat	168.375	168.403	168.375	168.375	168.375	167.566
Stringency Index (Lag 14)	-0.4851***	-0.5148***	-0.7307***	-0.4293***	-0.4462***	0.2155***
	(0.1101)	(0.0815)	(0.1349)	(0.1068)	(0.0942)	(0.0389)
Mean of DV	-45.797	-23.563	-24.851	-47.393	-35.588	17.185
F-Stat	92.105	92.037	92.105	92.105	92.105	92.110
Fixed Effects			Country; Days since first case			
Number of country	117	117	117	117	117	117
Observations (Lag 0)	7,701	7,697	7,701	7,701	7,701	7,655
Observations (Lag 14)	7,389	7,385	7,389	7,389	7,389	7,342

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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Table A5: Impact on growth rates using alternative instruments

VARIABLES	(1) Tests	(2) Cases	(3) Deaths	(4) Recoveries
	2SLS: World excluding Country IV			
Stringency Index (Lag 0)	-0.0047	-0.0010*	-0.0010	0.0166**
	(0.0030)	(0.0005)	(0.0013)	(0.0072)
Mean of DV	0.112	0.149	0.116	0.304
F-Stat	84.652	341.595	51.000	179.140
Stringency Index (Lag 14)	-0.0005	-0.0030***	-0.0033***	-0.0124
	(0.0006)	(0.0005)	(0.0005)	(0.0087)
Mean of DV	0.098	0.145	0.114	0.306
F-Stat	150.551	362.780	287.694	332.094
	2SLS: Region excluding Country IV			
Stringency Index (Lag 0)	-0.0087	-0.0023***	-0.0028*	0.0213*
	(0.0055)	(0.0008)	(0.0017)	(0.0110)
Mean of DV	0.112	0.149	0.116	0.304
F-Stat	85.755	212.513	66.274	167.360
Stringency Index (Lag 14)	-0.0024***	-0.0046***	-0.0039***	-0.0298
	(0.0008)	(0.0008)	(0.0008)	(0.0185)
Mean of DV	0.098	0.145	0.114	0.306
F-Stat	30.371	75.313	123.282	91.143
	2SLS: World excluding Region IV			
Stringency Index (Lag 0)	-0.0038	-0.0007	-0.0006	0.0157**
	(0.0025)	(0.0005)	(0.0013)	(0.0065)
Mean of DV	0.112	0.149	0.116	0.304
F-Stat	61.194	224.070	40.052	122.171
Stringency Index (Lag 14)	0.0001	-0.0025***	-0.0031***	-0.0079
	(0.0007)	(0.0005)	(0.0006)	(0.0065)
Mean of DV	0.098	0.145	0.114	0.306
F-Stat	73.003	168.636	140.128	167.248
	2SLS: Sub-region excluding Country IV			
Stringency Index (Lag 0)	-0.0042	-0.0019**	-0.0025	0.0138*
	(0.0030)	(0.0009)	(0.0016)	(0.0079)
Mean of DV	0.112	0.149	0.116	0.304
F-Stat	35.140	167.031	31.764	99.499
Stringency Index (Lag 14)	-0.0006	-0.0033***	-0.0036***	-0.0086
	(0.0009)	(0.0011)	(0.0008)	(0.0057)
Mean of DV	0.098	0.145	0.114	0.306
F-Stat	30.994	93.769	74.389	104.432
Fixed Effects	Country; Days since first case			
Number of country	72	117	108	113
Observations (Lag 0)	4,113	7,607	5,277	6,141
Observations (Lag 14)	4,008	7,319	5,300	5,939

Robust standard errors clustered at the country level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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Social capital and the spread of Covid-19: Insights from European countries

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We explore the role of social capital in the spread of the recent Covid-19 pandemic in independent analyses for Austria, Germany, Italy, the Netherlands, Sweden, Switzerland and the UK. We exploit within-country variation in social capital and Covid-19 cases to show that high-social-capital areas accumulated between 12% and 32% fewer Covid-19 cases per capita from mid-March until mid-May. Using Italy as a case study, we find that high-social-capital areas exhibit lower excess mortality and a decline in mobility. Our results have important implications for the design of local containment policies in future waves of the pandemic.

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1 Introduction

The current Covid-19 pandemic has triggered a tremendous amount of research contributing to a better understanding of the virus and its containment. In absence of medical answers like pharmaceuticals or vaccines, human behavior is the key margin to contain the spread of the pandemic (Van Bavel et al., 2020). Policymakers and health experts around the world summon the population to limit social contacts and follow strict hygiene and distance recommendations, appealing to the social responsibility of their citizens.[1] In other words, politicians ask their citizens to consider the social costs of their individual actions. We define this willingness to act collectively and pursue socially valuable activities as social capital (Putnam, 1993, 2000).[2]

While social capital plays a key role in official Covid-19 strategies around the globe, there is no systematic evidence on whether it is indeed an important factor in containing Covid-19. This paper adds empirical evidence to this timely question by studying the relationship between social capital and the early spread of the virus. We independently investigate the relationship in seven European countries – Austria, Germany, Italy, the Netherlands, Sweden, Switzerland and the UK. As countries differ in many macroeconomic and Covid-19-specific aspects, it is challenging to identify the systematic effect of any economic or cultural factor from the comparisons between countries. Our empirical strategy rather draws on several independent country analyses, exploiting within-country regional variation in the spread of Covid-19 and social capital. Following the literature, we operationalize social capital by area-specific electoral turnout in the 2019 European election, yielding a consistent and comparable measure across countries that has little measurement error and is likely to be largely unaffected by economic factors (Putnam, 1993, 2000).

From a theoretical perspective, social capital, the spread of Covid-19 and containment policies interact in various ways. First, high-social-capital areas are known to be more vibrant and better connected, economically and socially (see, e.g., Knack and Keefer, 1997; Tabellini, 2010). Hence, we expect the virus to spread more quickly in those areas in the beginning of the pandemic, when information about the virus and its severity were incomplete. Second, as soon as the importance of behavioral containment norms becomes more salient, we expect the relationship to change. Complying with containment norms yields a classical collective action problem (Ostrom, 1991): it is costly for the individual,

[1] Some prominent examples are: Angela Merkel (18.03.2020): "This is the greatest challenge for our country since WWII, in which taking action collectively as a society is key." Emmanuel Macron (16.03.2020): "But the best rule is the rule that you, as citizens, impose on yourselves. Once again, I am appealing to your sense of responsibility and solidarity." Giuseppe Conte (26.04.2020): "The responsible conduct of everyone of us will be fundamentally important. (...) If you love Italy, keep your distance."

[2] In this definition, sometimes also referred to as civic capital (Guiso et al., 2011; Lichter et al., 2020), we narrow down the broader concept of social capital to its positive facet of helping a group to overcome free rider problems, which fits best to the current Covid-19 crisis.

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while the single individuals' contribution to the collective goal is negligible. Social capital is assumed to overcome exactly such problems by increasing the willingness to contribute to the common good (Coleman, 1990; Ostrom, 1999; Putnam, 1993, 2000). Hence, we expect that informal rules of containment are more likely to be (voluntarily) adopted in areas with high social capital, leading to a relative decrease in infections. Third, there are interactions with the strictness of containment policies. During lockdowns, rules are formalized, violations are easier to detect and to be sanctioned, making non-compliance more costly for the individual. Hence, we would expect containment to depend less on social capital during stricter policy regimes.

We implement the same microeconometric within-country design in all seven countries. Our main empirical specification boils down to a two-way fixed effects model with area and day fixed effects. In each country, we regress the daily log cumulative Covid-19 cases on a measure of pre-determined social capital interacted with day fixed effects. The logarithmic model accounts for the exponential growth of the virus. We flexibly control for differences in regional outbreak patterns, e.g. due to regional policies, with region-by-day fixed effects. Furthermore, we account for the possibility that high-social-capital areas might be hit earlier and that the pattern of the spread might change over time, e.g., due to more accurate information about the virus, by including weeks-since-outbreak-by-day fixed effects.

We choose cases as our main outcome because it is available at a fine geographic level across many countries. To address well-known issues of measurement error and endogeneity related to the number of reported cases, such as (non-random) differences in testing, we use log cumulative excess mortality as an alternative outcome for Italy. Excess mortality is defined as the count of all deaths on a given day relative to the same day in 2019. In addition, we use mobility data from cell phone locations to test for the hypothesized underlying individual behavior. For both mortality and mobility, we observe outcomes prior to the outbreak, giving rise to a standard differences-in-differences design and enabling us to test for differential pre-treatment trends. Moreover, we validate that our results are not driven by obvious confounders like education level, income or population size, and that they are sustained when using well-established alternative measures of social capital such as blood donations and historical literacy rates (Guiso et al., 2004; Tabellini, 2010).

We derive the following main findings. First, the number of Covid-19 cases is initially higher in high-social-capital areas. Second, as information on the virus spreads, high-social-capital areas start to show a slower increase in Covid-19 cases in all seven countries. Third, high-social-capital areas also exhibit a slower growth in excess deaths in Italy. Fourth, individual mobility is reduced more strongly before the lockdown in Italian high-social-capital areas. Fifth, we provide suggestive evidence that the role of social capital is reduced when national lockdowns are enforced, as the differences in mobility between high- and low-social-capital areas vanish after the national lockdown is enacted.

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Our findings contribute to the current literature evolving around the Covid-19 pandemic, individual behavior and containment policies. Engle et al. (2020) and Painter and Qiu (2020) show that the impact of restriction orders in the US is stronger in democratic-leaning counties. On the macro level, Frey et al. (2020) show that countries with democratically accountable governments introduced less stringent lockdowns, but were more effective in reducing geographic mobility at the same level of policy stringency. Born et al. (2020) show that Sweden – the only European country without a lockdown – did not behave much differently from other European countries in terms of crisis dynamics. They conclude that "voluntary social restraint goes some way in resolving the lockdown puzzle". Our study complements these macro studies by providing within-country evidence and pointing to social capital as a key driving force behind this social restraint.

There are two projects looking at the role of social capital and mobility. Durante et al. (2020) investigate the relationship between social capital and mobility for Italy using similar data. We show that social capital only induces differential mobility responses *before* the lockdown when controlling for local economic conditions. This finding is in line with evidence by Borgonovi and Andrieu (2020), who show a positive correlation between social capital and early mobility reductions for US counties.

More generally, our findings contribute to the literature on the importance of social capital for society. Apart from well-established positive economic, social and political implications (see, e.g., Glaeser et al., 1996; Goldin and Katz, 1999; Guiso et al., 2004; Knack and Keefer, 1997; Nannicini et al., 2013; Tabellini, 2010), we add another dimension by showing social capital's important impact on health during medical crises. This is in line with the study by Klinenberg (1999), arguing that a lack of social capital was related to the high mortality rate during the 1995 Chicago heat wave.

In the light of possible future Covid-19 waves, our findings have important implications for policymakers when deciding on the relaxation of containment policies. As regional turnout is easily observable, local policy makers can take this proxy into account when determining the strictness of local containment policies, trading off the economic consequences of a lockdown against infection risk.

The remainder of the paper is structured as follows. Section 2 summarizes the data. In Section 3, we present within-country evidence on the spread of Covid-19 across seven European countries. In Section 4, we zoom in on the case of Italy, providing further supportive evidence on mortality and mobility and validate that our main results are robust to various endogeneity concerns. Section 5 concludes.

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2 Data

We use publicly available data on health and social capital from seven European countries that publish the daily number of total Covid-19 infections at fine-grained geographical levels. In the following, we briefly describe the variables used in the empirical analysis. More information and detailed data sources are documented in Appendix Table A.1. Appendix Table A.2 provides the corresponding descriptive statistics.

Geographical level. We compile measures of the spread of Covid-19 and social capital at the finest geographical level available for each country. We refer to this unit of observation as "area" throughout the paper. Areas have different names across countries, but mostly refer to the NUTS3 definition of the European Union (see Appendix Table A.3).[3] We refer to the higher NUTS1 geographical level as regions.

Outcomes. For all countries, we obtain the daily number of Covid-19 cases since the early phase of the outbreak. The respective country samples start when more than 90% of all NUTS3 areas in a country have registered at least one official case. Our main outcome variable is the log cumulative number of confirmed Covid-19 infections per 100,000 inhabitants within an area on a given day. Appendix Figure A.1 shows the evolution of cumulative Covid-19 cases per 100,000 inhabitants at the national level across countries.

For Italy, we additionally use data on the number of excess deaths at the municipality level, which is finer than the area (province) level. Excess mortality measures the number of deaths per day relative to the same day in the previous year. The evolution of daily excess mortality at the national level until mid-April 2020 is plotted in Appendix Figure A.2.

We also acquired proprietary data on daily individual movements in Italy from the technology firm Teralytics. The data contain the number of journeys within and across provinces based on changes in cell phone locations. Appendix Figure A.3 plots the number of weekly journeys per capita at the national level.

Social capital. We operationalize social capital by voter turnout in the 2019 European Parliament election. Political participation is a frequently-used and well-established measure of social capital, or civicness (Putnam, 1993, 2000). An extensive literature documents that political participation is a strong correlate of pro-social preferences and the willingness to contribute to public goods (see, e.g., Bolsen et al., 2014; Dawes et al., 2011;

[3] In the Netherlands (municipality level) and Austria (district level), we have data on even finer levels. The NUTS system is based on existing national administrative subdivisions. The average population size within a NUTS3 area in a country is typically between 150,000 and 800,000 inhabitants.

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Fowler, 2006; Fowler and Kam, 2007; Jankowski, 2007). Turnout is unlikely to be driven by other economic and legal factors and should have little to no measurement error (Guiso et al., 2004). In the context of our study, we can use data from the same election in most countries. For Switzerland, we use data on turnout at the last national elections in 2019. As a sensitivity check, we use two alternative measures of social capital proposed in the literature for the case of Italy: blood donations per capita (Guiso et al., 2004; Putnam, 1993) and historical literacy rates (Tabellini, 2010) (see Section 4.3).

Controls. We test the sensitivity of our results to potential confounders for the case of Italy by controlling for the share of white-collar workers, the share of the population older than 65 years, the share of college-educated individuals, the number of hospitals per capita, log population, log GDP per capita, and the population density. See Section 4.3 for results, and Tables A.1 and A.2 for more details on the variables.

Timing of events. The timing of the Covid-19 outbreak and policy responses differ across countries. Moreover, the adopted policy measures vary in strictness. While Italy enforced a strict and long lockdown, Sweden has not adopted a lockdown so far. We highlight the most important events in each country in Appendix Table A.4.

Lag of responses. Any change in behavior or policy will affect the number of Covid-19 cases with a lag. First, there is the incubation time, which is the time from the infection until the appearance of first symptoms. Second, there is the confirmation time, which is the time between the first symptoms and the confirmation of the case. Naturally, both periods differ across individuals, time and countries. For incubation time, we follow the WHO and assume a duration of 5 days (Lauer et al., 2020). There is much less evidence on confirmation time. We assume that the confirmation time is 7 days, using the reported median duration from a study by the official German health agency RKI (Heide and Hamouda, 2020). In total, we conclude that any behavioral change will affect Covid-19 cases after around 12 days.

3 Cross-country results on Covid-19 cases

3.1 Descriptive evidence

In a first step, we investigate the descriptive pattern of the spread of Covid-19 and its relation to social capital across countries. We dichotomize social capital into high- (above-regional-median turnout) and low-social-capital (below-regional-median turnout) areas for each country. We define the ratio of the number of cases per capita in high- relative to

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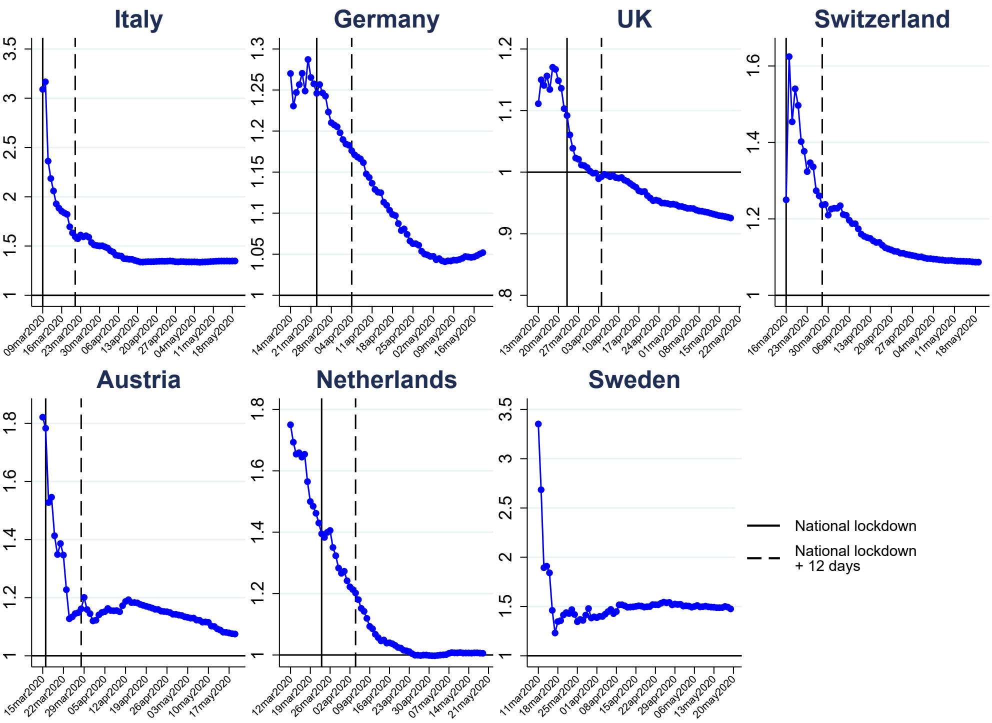
Figure 1: Cumulative Covid-19 cases in high relative to low-social-capital areas



Notes: This figure shows the ratio of cumulative Covid-19 cases per capita in high- vs. low-social-capital areas. The sample is divided at the median of turnout at the NUTS1 region level. Areas with a value above the median are defined as high-social-capital areas and those below as low-social-capital areas. The blue lines plot the population-weighted average of the regional ratios over time. The solid black line marks the date of the national lockdown, the dashed black line the date of the national lockdown plus an incubation period of 12 days.

low-social-capital areas within each region and calculate the population-weighted average ratio across regions to obtain the national ratio.

Figure 1 plots the cumulative per-capita Covid-19 cases in high-social-capital areas relative to low-social-capital areas over time. Across all countries, we see that the virus initially is more prevalent in high-social-capital areas. The initially high level is to be expected as people in areas with a high level of social capital have been shown to have closer social and economic connections, which should exacerbate the spread of the virus initially when information on the severity of the virus and appropriate behavior are incomplete. Starting from this high initial level, we then see a sharp decline in the ratio. In Italy, for instance, high-social-capital areas initially exhibit about three times more cases per capita relative to low-social-capital areas. Over time, the differential drops until high- and low-social-capital areas have almost equally many cases per inhabitant. Strikingly, the decline starts before national lockdown policies could have been effective due to the lagged response, which is a first indication that socially responsible behavior might play

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a role. The Swedish case without a lockdown is the prime example.

3.2 Empirical model

While Figure 1 presents simple correlations over time, we suggest the following more rigorous empirical model to systematically study the evolution of the relationship between social capital and the spread of the virus in each country:

$$\ln cumcases_{ard} = \sum_{d=2}^{d^{max}} \beta_d date_d \cdot SocCap_a + \gamma_a + \omega_{rd} + \varepsilon_{ard}. \quad (1)$$

Our main outcome variable $\ln cumcases_{ard}$ is the log cumulative number of cases per 100,000 inhabitants in area a within region r on day d. The logarithmic model accounts for the exponential growth of the virus. The variable $SocCap_a$ is our measure of social capital, defined as turnout in the European Parliament election of 2019, normalized by its country-specific standard deviation. Hence, a one-standard-deviation increase in turnout (social capital) affects the number of cumulative cases per 100,000 inhabitants measured on day d by approximately $100 \times \beta_d$%.

The indicator variable $date_d$ is set to one for the respective day, which runs from the first until the last day, day^{max}, for which we observe the number of Covid-19 cases. We start the sample when more than 90% of all NUTS3 areas have registered at least one official case. Indicator variable γ_a captures area fixed effects, which account for time-invariant, area-specific factors. Given area fixed effects γ_a, we normalize coefficients β_1 to zero in all countries, such that all other β_d coefficients measure the effect of social capital relative to this reference day. Loosely speaking, the empirical model (1) investigates the slope of the country-specific patterns shown in Figure 1. The set of dummy variables ω_{rd} captures NUTS1-region-specific day fixed effects and, hence, flexibly accounts for potential policy responses at the regional level and region-specific dynamics in the spread of the virus. We cluster standard errors at the area level.

The β coefficients compare the evolution of areas with a higher turnout to areas with a lower turnout over time and associate the differences in log cases with the level of social capital. Area A might have an earlier outbreak than area B and consequently be on a different point of the outbreak curve. We assess the sensitivity of our results to this potential bias by adding weeks-since-outbreak fixed effects to the baseline model. This set of fixed effects implicitly synchronizes the outbreak dates of the areas by accounting for the average pattern of an outbreak across areas. As information about Covid-19 spreads quickly, it is however possible that outbreak patterns change over time. To allow for these additional dynamics, we interact weeks-since-outbreak fixed effects with calendar-day fixed effects ($date_d \times weekssinceoutbreak_{ad}$) and assess whether our estimates are sensitive to the inclusion of this large set of fixed effects. Reassuringly, Appendix Figure

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B.2 shows that estimates barely change.

Our identifying assumption is that no other factor correlated with social capital systematically affects growth rates of Covid-19 cases. We conduct various sensitivity checks to assess whether the assumption is likely to be violated. First, we control directly for the most obvious confounders, for instance GDP per capita, education or population density (each interacted with day fixed effects). We also interact these covariates with weeks-since-outbreak fixed effects to test whether the potential confounder led to differential growth rates between the date of the outbreak and our sample start. Second, we use historical proxies for social capital that are less likely to be correlated with contemporaneous confounders. We conduct all these tests for the case of Italy in Section 4.3 of the paper. Last, we analyze excess deaths and mobility patterns for Italy. While the concept of Covid-19 cases is not defined before the outbreak, such that we cannot test for parallel pre-trends, the same is not true for excess mortality and mobility. Our results in in Sections 4.1 and 4.2 show that high- and low-social-capital areas did not differ systematically with respect to these outcomes before the outbreak.

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3.3 Estimation results

Figure 2 visualizes the β coefficients from equation (1). Across all countries, we see a similar pattern: high-social-capital areas exhibit a slower growth in cumulative cases than low-social-capital areas. This reduces the cases they accumulate over the considered periods by between 12% (Germany) and 32% (Italy). Results are significant at the 95% level for Italy, the UK, the Netherlands and Germany, and at the 90% level for Sweden. Countries with a loose (the Netherlands) or no lockdown (Sweden) show effects which are in the ballpark of Italy.

Below, we show that results are not driven by potentially confounding variables, such as GDP, educational attainment or population density. Neither are the results sensitive to the choice of our proxy for social capital (see Section 4.3 and Figure 5).

Overall, we interpret the consistent pattern obtained from independent analyses of seven countries as strong evidence in favor of the hypothesis that social capital plays an important role in slowing down the spread of the virus.

In terms of dynamics, Figure 2 shows that areas with high social capital exhibit a slower growth in Covid-19 cases in the early phase of the pandemic. Importantly, this occurs before the lockdown could have had an effect. It is exactly during this initial phase that we expect the impact of social capital to be strongest, as responsible individual behavior such as reducing mobility and practicing voluntary distancing is the only means to flatten the curve. The case of Sweden, which did not enact a lockdown, corroborates this claim. After national lockdowns take effect, the growth differential between low- and high-social

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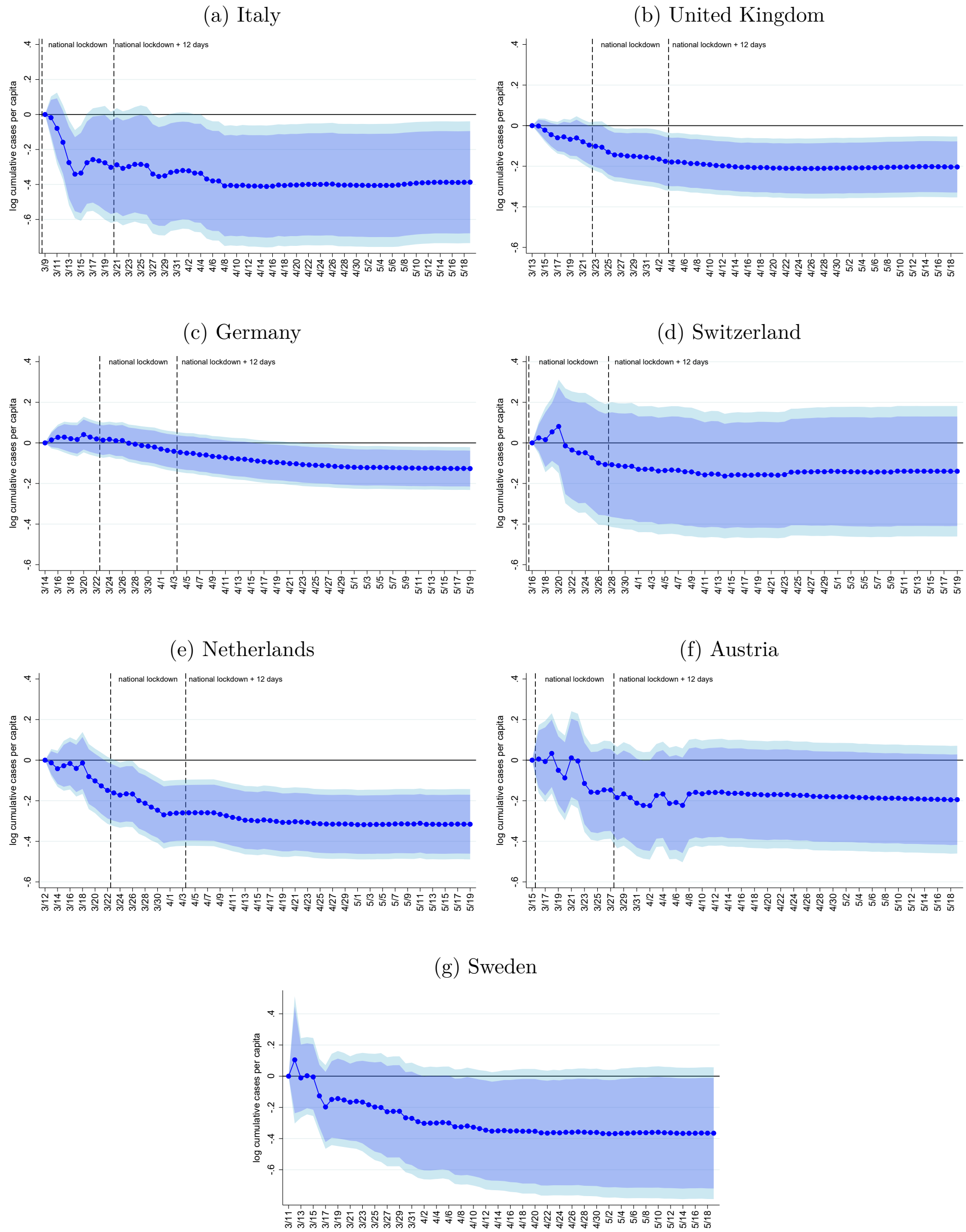
Figure 2: Effect of social capital on the spread of Covid-19 cases



Notes: The figure presents the differential evolution of the relationship between cumulative Covid-19 infections per 100,000 inhabitants and social capital across time. The estimates are based on on the model outlined in equation 1 (see Appendix table C.1 for the point estimates). All values are normalized at the date of the first observation. The first dashed line marks the date of the national lockdown, the second dashed line the date of the national lockdown plus 12 days to account for incubation plus confirmation time. Since there was no official lockdown in Sweden, no dashed lines are displayed in panel (g). The dark (light) blue area corresponds to the 90% (95%) confidence interval.

capital areas stabilizes and remains constant thereafter.[4] This suggests that there is no additional effect of social capital once lockdowns are in place. Below, we use mobility data to provide further evidence in support of the claim that socially responsible behavior in low- and high-social capital areas converges after a lockdown (see Section 4.2).

4 The Italian Case: Mortality, Mobility and Sensitivity

In this section, we zoom in on the Italian case. We use this example to show that our results are robust to various conceptual and econometric concerns. We present additional evidence on excess mortality and on the mobility patterns of individuals, supporting our hypothesis that social capital is an important factor driving the spread of the virus.

We singled out Italy for four reasons. First, it was the first country in Europe to be hit by the virus. Hence, government and citizens were more surprised by and unprepared for the severity of the epidemic than other European countries. The Italian case, in turn, influenced all other countries' populations and policymakers. Second, Italy is one of the few countries to report data on excess mortality at the municipality level, which is another important outcome, and has conceptual advantages over the number of cases. Third, we were able to collect mobility data at the province level for Italy. As a consequence, we can investigate how social capital directly affects individual behavior, which is key to validate the mechanism behind our hypotheses. Fourth, research on social capital has oftentimes focused on Italy, such that there are well-established historical measures of social capital which can be used to corroborate our findings.

4.1 Excess mortality

If higher social capital slows down the spread of Covid-19 cases, we would also expect to see an effect on the number of Covid-19-related deaths. Looking at mortality is clearly important in its own right. In the absence of effective medication, it is also insightful as the number of deaths should depend less on testing capacities, which might in turn be endogenous to social capital.[5] Our preferred measure of mortality is the number of local excess deaths, defined as the difference in mortality between 2020 and 2019. We prefer this measure over official Covid-19 deaths for three reasons. First, and in contrast to the number of Covid-19-cases, we observe excess mortality already before the start of the pandemic. This enables us to evaluate the common trend assumption as in a standard

[4]This convergence is also depicted in Appendix Figure B.1, which plots the daily social capital effect relative to the effect on the last sample day.

[5] Mortality is not completely immune to that concern, as more testing might imply more effective isolation of infected individuals.

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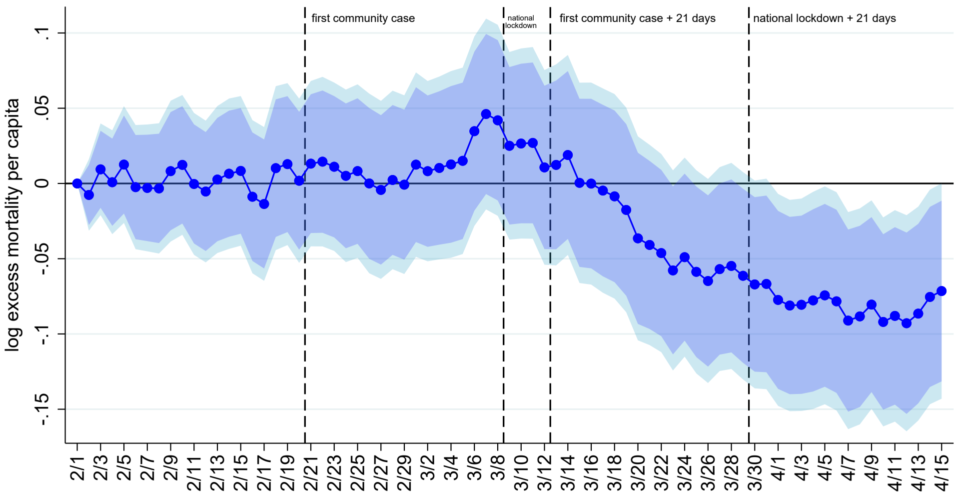
Figure 3: Effect of social capital on excess deaths in Italy



Notes: The outcome variable is the log number of excess deaths per 100,000 inhabitants (additional deaths in 2020 compared to 2019) from February 1^{st} to April 15^{th}. The estimates are based on the estimation model outlined in equation 2 (see Appendix table C.2 for the point estimates). The dark (light) blue area corresponds to the 90% (95%) confidence interval.

difference-in-difference model and test for pre-treatment differences between high- and low-social-capital municipalities. Second, official Covid-19 mortality is only published at the regional level in Italy, while excess mortality is available at the municipality level. Third, the official numbers are likely to underestimate the true increase in mortality, since a substantial number of people died without being tested (Ciminelli and Garcia-Mandicó, 2020).

In order to study the impact of social capital on mortality, we transform our baseline model (1) to the municipal level:

$$\ln excessmortality_{mpd} = \sum_{d=2}^{d^{max}} \beta_d date_d \cdot SocCap_m + \gamma_m + \omega_{pd} + \varepsilon_{cpd}. \tag{2}$$

Now, our outcome variable is the log cumulative excess deaths per 100,000 inhabitants in municipality m located in province p on day d. As we are able to exploit variation at the municipal level, we can also include more fine-grained province-by-day fixed effects, ω_{pd}.

Figure 3 shows that by mid-April, a one standard deviation increase in turnout is significantly associated with 7% fewer accumulated excess deaths. Reassuringly, mortality before the pandemic evolved in parallel between high- and low-social-capital municipalities, which lends support to our identifying assumption. Results are also robust to controlling for different potential confounders, see Section 4.3 and Figure B.3 in the Appendix.

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The observed dynamics corresponds well with the pattern observed in Figures 1 and 2. In early March, the number of excess deaths in high-social-capital areas increases slightly, which is in line with the hypothesis that areas with a higher social capital are more connected socially and economically, such that the virus can initially spread faster. We then see a sharp turning point around the day of the national lockdown. This trend break cannot be driven by the lockdown due to the incubation time and the duration of the disease before it leads to a fatality. Instead, we find that excess mortality drops in high-social-capital areas about two to three weeks after the first community case was discovered, which is in line with (preliminary) evidence that deaths tend to occur around three weeks (21 days) after the infection (Yang et al., 2020). The effect of social capital on excess deaths stabilized around 20 to 25 days after the lockdown.

4.2 Mobility effects

Next, we take a closer look at individual mobility, one of the main mechanisms through which social capital might affect the spread of the virus. Moreover, mobility, being a direct measure of individuals' behavior, is immune to the concern of endogenous testing. Hence, it can help us to check whether changes in individuals' behavior are likely to drive our effects. Using the number of weekly journeys per capita, as captured by data on cell phone locations, as an outcome, we re-estimate equation (1) to see whether individuals' mobility in high-social-capital areas evolves systematically differently over the course of the Covid-19 outbreak in Italy.

We aggregate the empirical model given in equation (1) from the daily to the weekly level to reduce noise and use the total number of journeys originating in area a and week w as our outcome measure. Similar to the number of excess deaths, we observe mobility before the outbreak, giving rise to a standard differences-in-differences design.

Figure 4 presents the mobility results. Up until the third week of February, we do not detect significant differences in the number of journeys between high- and low-social-capital areas. The flat pre-outbreak trends imply that our identifying assumptions holds. After Italy experiences its first Covid-19 community case, around the end of the third week of February, mobility in areas with higher social capital declines significantly over the following two weeks. This differential between high- and low-social-capital areas vanishes after the national lockdown is enforced. In terms of magnitude, we find that a one-standard-deviation increase in turnout decreases mobility by 0.16 journeys per capita in the first week of March. This translates to a 15% reduction relative to the average pre-Covid mobility.

The dynamic pattern shown in Figure 4 is different from the findings by Durante et al. (2020), who show that higher social capital leads to persistently lower levels of mobility

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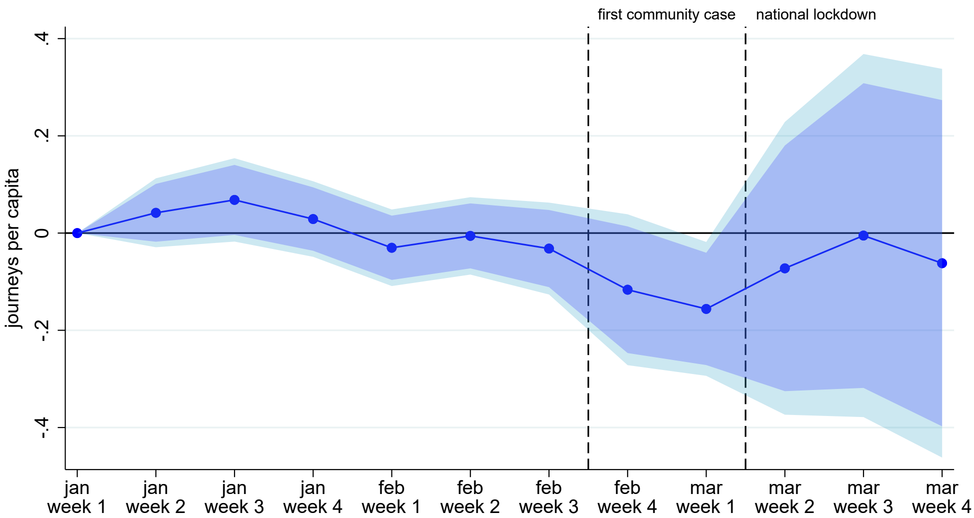
Figure 4: Effect of social capital on mobility in Italy



Notes: The figure shows the estimation results of the impact of social capital on individuals mobility. They are based on the estimation model outlined in equation 1 (see Appendix Table C.3 for point estimates). The outcome variable captures the weekly number of journeys per capita. The estimates control for the share of people above 65, the share of males, the share of white-collar workers, the share of college graduates, the number of hospitals per 100,000 inhabitants, population density, log population, altitude, the share of inhabitants living at the coast, an indicator for having an airport and log GDP per capita.

even after the lockdown. The reason for this difference is that our model controls for NUTS1-by-day fixed effects and GDP. Appendix Figure B.4 shows that the inclusion of both variables is important for the post-lockdown effect.[6] NUTS1-by-day fixed effects are important, since they account for regional policy responses and different regional outbreak patterns. GDP per capita is an important control because mobility in high-income areas is likely to be quite different from low-income areas after the lockdown, for example due to different possibilities to work from home. In line with this reasoning, Engle et al. (2020) show for the US that high-income counties reduce mobility more strongly following stay-at-home-orders.

Overall, our results corroborate the implied mechanism of social capital reducing the spread of Covid-19 through individual behavior. The used data, discussed in Section 2, are only able to capture the quantity of mobility (the number of journeys undertaken) and not the quality (what people travel for). It is, however, likely that social capital also affects the quality of mobility. People in high-social-capital areas might, for example, additionally reduce their contact to risk groups voluntarily and more quickly. As a consequence, the mobility estimates are likely a lower bound of the overall behavioral effects which drive the differential development of cases.

[6] Other small differences in the set of controls do not affect our results.

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4.3 Robustness

Confounders. Measures of social capital, like voter turnout, are likely to be correlated with other, non-Covid-19-related characteristics. Hence, we have to make sure that the observed relationship between Covid-19 cases and social capital is not driven by these factors. Obvious confounders at the area level are (i) education (more skilled people understand more quickly what is at stake); (ii) age (older people are more endangered by the virus); (iii) income (higher-income groups can afford to reduce their labor supply more); (iv) occupation type (white-collar workers can work from home more easily) (v) population density (facilitates the spread of the disease); (vi) hospital density (better medical infrastructure helps to fight the virus) and (vii) population size (economies of scale might imply better infrastructure).

A straightforward test whether these confounders drive the observed differences is to control for them in the empirical model. We do so by allowing for day-specific effects of each control variable. Moreover, areas might differ in their infection curve even before our sample start. For example, areas with a high GDP per capita might exhibit a sharper increase in the beginning. We test the sensitivity of our estimates to this potential bias by additionally interacting our control variables with the number of weeks since the local outbreak.

Panel (a) of Figure 5 shows the resulting estimates. Magnitudes, dynamics and statistical significance are very similar across specifications. The same is true when looking at excess deaths (see Appendix Figure B.3). These results corroborate the independent role of social capital in our main results.

Historical social capital measure. An alternative approach to address endogeneity concerns is to make use of a historically predetermined measure of social capital. The literature on social capital frequently studies the case of Italy, because there is large variation in social capital which can be attributed to historical origins (see, e.g., Nannicini et al., 2013; Putnam, 2000). It is well established that culture, and thus also cultural traits like social capital, are passed on from generation to generation and are thus quite persistent over time (Alesina et al., 2013; Bisin and Verdier, 2000; Tabellini, 2008). Consequently, historical institutions, which have shaped social capital in the past but have long disappeared, still predict the level of social capital today.

Tabellini (2010) shows that 19th-century literacy rates are good predictors of social capital across contemporaneous European regions. Following this rationale, we use the literacy rates from Italy in 1821 as a proxy for social capital. The province-level data are reported in Ciccarelli and Weisdorf (2018).[7] The literacy rate is measured prior to the strong

[7] As we operate at the NUTS3 level, we could not use the data in Tabellini (2010), which cover NUTS1 or NUTS2 regions across Europe.

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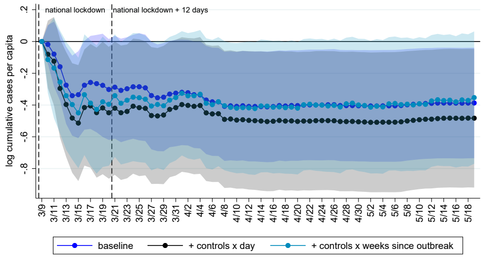
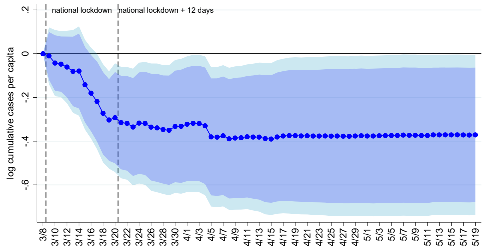
Figure 5: Sensitivity tests for Italy

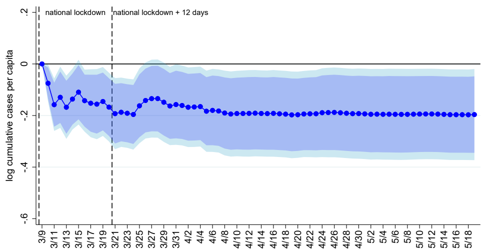
(a) Baseline model with controls



(b) Literacy rate in 1821 as social capital proxy



(c) Blood donations per capita as social capital proxy



Notes: The figure shows the estimation results of the impact of social capital on the evolution of Covid-19 infections. They are based on the estimation model outlined in equation 1 and the outcome variable is the log cumulative number of Covid-19 infections per 100,000 inhabitants. Estimates in Panel (a) control for the share of people above 65, the share of white-collar workers, the share of college graduates, the number of hospitals per 100,000 inhabitants, population density, log population, and log GDP per capita (see Appendix Table C.4 for point estimates). In Panel (b) we use literacy rates in 1821 as our proxy for social capital (see Appendix Table C.5 for point estimates). In Panel (c) we proxy for social capital with the number of blood donations per capita in 2017 (see Appendix Table C.6 for point estimates).

economic divide between Northern and Southern Italy that emerged in the years before the Italian unification in 1861 (Ciccarelli and Weisdorf, 2018). Panel (b) of Figure 5 shows that the result with this alternative measures of social capital is very similar to our baseline estimates.

Alternative contemporaneous social capital measure. As a final test, we show that our results are also robust to using a different contemporaneous social capital measure. Instead of turnout, we utilize another well-established measure of social capital, namely the number of blood donations per capita in an area (see, e.g., Guiso et al., 2004; Putnam, 1993). We obtain the number of whole blood and plasma donations per capita at the province level from AVIS, the Italian association of blood donors. Panel (c) of Figure 5 shows that the result is again similar when using this alternative measure of social capital.

5 Discussion

In this paper, we provide evidence from seven European countries that culture and social capital have a considerable impact on the containment of Covid-19 and the number of deaths. Social capital, long known to be related to favorable economic developments, can thus unfold additional potential in times of (health) crises which call for collective action and socially responsible behavior. The positive effects of social capital are likely to go beyond health outcomes. Experience from the Spanish Flu demonstrates that the success of virus containment directly relates to the size of the following economic downturn and its recovery speed (Barro, 2020; Barro et al., 2020). Hence, we expect that higher social capital also has an indirect positive effect on the economy during and after the crisis.

Our results have important implication for policymakers. During the current crisis, our findings suggest that low-social-capital areas might need to consider stricter formal policies to contain the virus. Since turnout rates are readily observable, they could be directly targeted when designing the local policy response to Covid-19. The recent policy shift in Germany that delegated more responsibility to the county level might be a good way to allow for this regional flexibility, especially with the looming threat of a second outbreak in the fall or winter.

In the longer run, investing in social capital formation is an important insurance against similar future pandemics. The insights from our study mandate policymakers to invest not only into the health system, but also into social capital formation to be well-prepared. Possible points of departure are local community programs to increase social interactions, which may carry over to increased cooperation and pro-social behavior (see, e.g., Fearon et al., 2009). However, investments should not be limited to low-social-capital areas. This is in particular true since pandemics might themselves erode social capital (Aassve et al., 2020).

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References

Aassve, Arnstein, Guido Alfani, Francesco Gandolfi, and Marco Le Moglie (2020). *Epidemics and Trust: The Case of the Spanish Flu*. Working Papers 661. IGIER (Innocenzo Gasparini Institute for Economic Research), Bocconi University. URL: https://ideas.repec.org/p/igi/igierp/661.html.

Alesina, Alberto, Paola Giuliano, and Nathan Nunn (2013). "On the origins of gender roles: Women and the plough". In: *The Quarterly Journal of Economics* 128.2, pp. 469–530.

Barro, Robert J. (2020). "Non-Pharmaceutical Interventions and Mortality in U.S. Cities during the Great Influenza Pandemic, 1918-1919". In: *NBER Working Paper Series* 27049, pp. 1–19.

Barro, Robert J., José F Ursúa, and Joanna Weng (2020). "The Coronavirus and the Great Influenza Pandemic: Lessons from the "Spanish Flu" for the Conoravirus's Potential Effects on Mortality and Economic Activity". In: *NBER Working Paper Series* 26866, pp. 1–27.

Bisin, Alberto and Alberto Verdier (2000). "Beyond the Melting Pot: Cultural Transmission, Marriage, and the Evolution of Ethnic and Religious Traits". In: *The Quarterly Journal of Economics* 115.3, pp. 955–988. URL: http://www.jstor.org/stable/2586900.

Bolsen, Toby, Paul J. Ferraro, and Juan Jose Miranda (2014). "Are Voters More Likely to Contribute to Other Public Goods? Evidence from a Large-scale Randomized Policy Experiment". In: *American Journal of Political Science* 58.1, pp. 17–30.

Borgonovi, Francesca and Elodie Andrieu (2020). "Bowling together by bowling alone: Social capital and Covid-19". In: *Covid Economics* 17, pp. 73–96.

Born, Benjamin, Alexander Dietrich, and Gernot J. Müller (2020). "Do Lockdowns Work? A Counterfactual for Sweden". In: *Covid Economics* 16, pp. 1–22.

Ciccarelli, Carlo and Jacob Weisdorf (2018). "Pioneering into the past: Regional literacy developments in Italy before Italy". In: *European Review of Economic History* 23.3, pp. 329–364. DOI: 10.1093/ereh/hey014. eprint: https://academic.oup.com/ereh/article-pdf/23/3/329/30622302/hey014.pdf. URL: https://doi.org/10.1093/ereh/hey014.

Ciminelli, Gabriele and Sílvia Garcia-Mandicó (2020). "COVID-19 in Italy: An Analysis of Death Registry Data". In: *Working Paper*.

Coleman, James S. (1990). *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.

Dawes, Christopher T., Peter John Loewen, and James H. Fowler (2011). "Social Preferences and Political Participation". In: *The Journal of Politics* 73.3, pp. 845–856.

Durante, Ruben, Luigi Guiso, and Giorgio Gulino (2020). *Civic Capital and Social Distancing: Evidence from Italians' Response to Covid-19*. VOXEU. URL: `https://voxeu.org/article/civic-capital-and-social-distancing`.

Engle, Samuel, John Stromme, and Anson Zhou (2020). "Staying at Home: Mobility Effects of COVID-19". In: *SSRN Working Paper*, pp. 1–16. URL: `"http://dx.doi.org/10.2139/ssrn.3565703"`.

Fearon, James D, Macartan Humphreys, and Jeremy M Weinstein (2009). "Can development aid contribute to social cohesion after civil war? Evidence from a field experiment in post-conflict Liberia". In: *American Economic Review* 99.2, pp. 287–91.

Fowler, James H. (2006). "Altruism and Turnout". In: *The Journal of Politics* 68.3, pp. 674–683.

Fowler, James H. and Cindy D. Kam (2007). "Beyond the Self: Social Identity, Altruism, and Political Participation". In: *The Journal of Politics* 69.3, pp. 813–827.

Frey, Carl Benedikt, Chinchih Chen, and Giorgio Presidente (2020). "Democracy, Culture, and Contagion: Political Regimes and Countries Responsiveness to Covid-19". In: *Covid Economics* 18, pp. 1–20.

Glaeser, Edward L., Bruce Sacerdote, and Jose A. Scheinkman (1996). "Crime and Social Interactions". In: *The Quarterly Journal of Economics* 111.2, pp. 507–548.

Goldin, Claudia and Lawrence F. Katz (1999). "Human Capital and Social Capital: The Rise of Secondary Schooling in America, 1910–1940". In: *Journal of Interdisciplinary History* 29.4, pp. 683–723.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2004). "The Role of Social Capital in Financial Development". In: *American Economic Review* 94.3, pp. 526–556.

— (2011). "Civic Capital As the Missing Link". In: *Handbook of Social Economics*. Vol. 1. Elsevier, pp. 417–480.

Heide, Matthias an der and Osamah Hamouda (2020). "Schätzung der aktuellen Entwicklung der SARS-Cov-2-Epidemie in Deutschland". In: *Epidemiologisches Bulletin* 17, pp. 10–16.

Covid Economics 26, 5 June 2020: 137-190

Jankowski, Richard (2007). “Altruism and the Decision to Vote: Explaining and Testing High Voter Turnout”. In: *Rationality and Society* 19.1, pp. 5–34.

Klinenberg, Eric (1999). “Denaturalizing Disaster: A Social Autopsy of the 1995 Chicago Heat Wave”. In: *Theory and Society* 28.2, pp. 239–295.

Knack, Stephen and Philip Keefer (1997). “Does Social Capital Have an Economic Payoff? A Cross-Country Investigation”. In: *Quarterly Journal of Economics* 112.4, pp. 1251–1288.

Lauer, Stephen A. et al. (2020). “The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application”. In: *Annals of Internal Medicine* 172.9, pp. 577–582. DOI: `10.7326/M20-0504`. eprint: `https://www.acpjournals.org/doi/pdf/10.7326/M20-0504`. URL: `https://www.acpjournals.org/doi/abs/10.7326/M20-0504`.

Lichter, Andreas, Max Löffler, and Sebastian Siegloch (2020). “The Long-Term Costs of Government Surveillance: Insights from Stasi Spying in East Germany”. In: *Journal of the European Economic Association*.

Nannicini, Tommaso, Andrea Stella, Guido Tabellini, and Ugo Troiano (2013). “Social Capital and Political Accountability”. In: *American Economic Journal: Economic Policy* 5.2, pp. 222–50.

Ostrom, Elinor (1991). *Managing the Commons: The Evolution of Institutions for Collective Action*. New York: Cambridge University Press.

— (1999). “Social Capital: A Multifaceted Perspective”. In: ed. by I. Serageldin P. Dasgupta. Washington, DC: World Bank. Chap. Social Capital: A Fad or a Fundamental Concept, pp. 172–214.

Painter, Marcus O. and Tian Qiu (2020). “Political Beliefs Affect Compliance with COVID-19 Social Distancing Orders”. In: *SSRN Working Paper*, pp. 1–21. URL: `"http://dx.doi.org/10.2139/ssrn.3569098"`.

Putnam, Robert D. (1993). *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton University Press, Princeton, NJ.

— (2000). *Bowling Alone: The Collapse and Revival of American Community*. Simon and Schuster.

Tabellini, Guido (2008). “The Scope of Cooperation: Norms and Incentives”. In: *Quarterly Journal of Economics* 123.3, pp. 905–950.

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Tabellini, Guido (2010). "Culture and Institutions: Economic Development in the Regions of Europe". In: *Journal of the European Economic Association* 8.4, pp. 677–716.

Van Bavel, Jay J. et al. (2020). "Using Social and Behavioural Science to Support Covid-19 Pandemic Response". In: *Nature Human Behaviour*, pp. 1–12.

Yang, Xiaobo et al. (2020). "Clinical Course and Outcomes of Critically Ill Patients with Sars-Cov-2 Pneumonia in Wuhan, China: A Single-centered, Retrospective, Observational Study". In: *The Lancet Respiratory Medicine* 8.5, pp. 475 –481. ISSN: 2213-2600. DOI: https://doi.org/10.1016/S2213-2600(20)30079-5. URL: http://www.sciencedirect.com/science/article/pii/S2213260020300795.

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A Online Appendix: Data

The countries included in our study are Austria, Germany, Italy, the Netherlands, Sweden, Switzerland, and the UK. We recover the total number of Covid-19 cases from the official institutions in each country. We augment the data sets with information on social capital and other regional characteristics. Appendix Table A.1 briefly describes the data for each country separately. As in the main text we refer to each geographical unit as "area". Appendix Table A.2 shows summary statistics for all variables. Appendix Table A.3 summarizes the different geographical units for each country.

Table A.1: Definition of variables and data sources

	year	description	source
Panel A – Outcomes			
Italy: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the province-day level. The numbers have been published daily starting February 24^{th}. We normalize this variable with population numbers from ISTAT.	Italian Department of Civil Protection
Italy: cumulative excess deaths per 100,000 inhabitants	2020	The number of additional deaths recorded from January 1^{st} to April 15^{th} 2020 compared to the same period in 2019 at the municipality-day level. We normalize this variable with population numbers from ISTAT. The data are available for 4,424 out of the roughly 8,000 municipalities covering about 57% of the total population.	ISTAT
Italy: journeys per capita	2020	The number of journeys made per capita based on mobile phone location at the day-province level from January 2020 to March 2020. A journey ends when the use remains in place for at least one hour. Short journeys with a distance of less 2 kilometres are not captured. We normalize this variable with population numbers from ISTAT.	Teralytics

continued

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Table A.1 continued

	year	description	source
Austria: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the district-day level. The numbers have been published daily since March 11^{th}, but historic values are only reported from March 22^{nd} onward. We drop the four districts in the state of Vorarlberg as they start reporting cases on March 16^{th} (results do not change when we include them). We impute occasionally missing daily observations by linear interpolation. We normalize this variable with population numbers from Statistics Austria.	Austrian Government Addendum (Austrian Newspaper) for values from March 11^{th} to 22^{nd}
Germany: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the county-day level. These numbers have been published daily since January 28^{th}. We normalize this variable with population numbers from the statistical offices of the German states.	Robert-Koch Institute
Netherlands: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the municipality-day level. These numbers have been published daily since February 27^{th}. We impute occasionally missing daily observations by linear interpolation. We normalize this variable with population numbers from Statistics Netherlands.	National Institute for Public Health and the Environment
Sweden: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the county-day level. These numbers have been published daily since February 4^{th}. We normalize this variable with population numbers from Statistics Sweden.	Public Health Agency of Sweden
Switzerland: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the canton-day level. These numbers have been published daily since February 25^{th}. We impute occasionally missing daily observations by linear interpolation. We normalize this variable with population numbers from the Swiss federal statistical office.	Health Offices of the Swiss Cantons

continued

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Table A.1 continued

	year	description	source
UK: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the Upper Tier Local Authority-day level. For England, the data has been reported daily since March 9^{th} alongside historical values at the Upper Tier Local Authority (UTLA) level. Scotland and Wales only publish daily updates at the NHS Health Board level, spanning several UTLAs, starting at March 1^{st} and March 5^{th} respectively. We normalize this variable with population numbers from the Office of National Statistics (ONS).	Public Health Board (England) Public Health Board Scotland and Wales, historic values collected by Tom White[8]
Panel B – Independent Variables			
Italy: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the province level.	Department of Internal Affairs
Italy: blood donations per capita	2017	Whole blood and plasma donations per capita as reported by AVIS, the Italian association of voluntary blood donors. This variable is only available for 103 of the 107 provinces (Belluno, Gorizia, Imperia and Lucca are missing).	AVIS
Italy: literacy rate	1821	The literacy rate for the total population (men and women combined) in 1821. The data are only available in the 1911 province boundaries. We drop the modern provinces of Bolzano, Trento, Gorizia and Trieste since they were not part of Italy in 1911. We also exclude the modern provinces of Varese, Frosinone, Rieti, Pescara, Latina, Nuoro and Enna because it is not straightforward to match the historical data to the new jurisdictions.	Ciccarelli and Weisdorf (2018)
Austria: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the district level.	Austrian State Governments
Germany: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the county level.	Statistical Offices of the German States
Netherlands: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the municipality level.	Dutch Electoral Council

continued

[8] https://github.com/tomwhite/Covid-19-uk-data/blob/master/data/Covid-19-cases-uk.csv

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Table A.1 continued

	year	description	source
Sweden: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the county level.	Swedish Election Authority
Switzerland: turnout	2019	Turnout to the 2019 national parliament election held in October 2019 at the canton level.	Swiss Federal Statistical Office
UK: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the ward level. We aggregate this number to the corresponding geographical unit at which the infections are reported.	House of Commons Library
Panel C – Additional Controls for Italy			
hospitals per 100,000 inhabitants	2019	The number of hospitals normalized with population numbers from ISTAT.	ISTAT
share of college-educated	2011	The share of the population that has completed at least some college education.	Census (ISTAT)
share of white-collar workers	2017	The share of working population that is employed in a white-collar sector.	OECD
GDP per capita	2017	Value added per inhabitant at current prices.	ISTAT
taxable income per capita	2018	The municipal tax base of the national income tax divided by the number of inhabitants.	Italian Fiscal Agency
share old	2011	The share of the population that is older than 65 years of age.	Census (ISTAT)
population density	2019	The number of inhabitants per square kilometre.	ISTAT
altitude	2019	The population-weighted mean of altitude.	ISTAT
share male	2011	The share of the male population.	Census (ISTAT)
share coastal	2019	The share of the population that lives at the coast.	ISTAT
airport dummy	2019	A dummy variable that takes the value 1 if the province has at least one airport.	ISTAT

Notes: This table provides details on the definition and sources for all variables used.

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Table A.2: Summary statistics

	mean	p25	p75	sd	min	max	N
Austria: district level							
turnout	0.59	0.52	0.66	0.08	0.43	0.71	94
population (in 100,000)	0.94	0.44	0.99	1.93	0.02	18.97	94
Germany: county level							
turnout	0.61	0.57	0.64	0.05	0.48	0.74	401
population (in 100,000)	2.07	1.04	2.42	2.48	0.34	37.54	401
Italy: province level							
turnout	0.56	0.50	0.65	0.11	0.34	0.70	107
blood donations per capita	0.04	0.02	0.05	0.02	0.00	0.12	103
literacy rate in 1821	0.25	0.16	0.35	0.11	0.09	0.54	69
population (in 100,000)	5.64	2.35	6.22	6.17	0.84	43.42	107
population density (in 1000/km^2)	0.27	0.11	0.28	0.38	0.04	2.63	107
GDP per capita (in 1,000€)	23.51	16.95	28.25	6.66	12.89	48.69	107
hospitals per 100,000 inhabitants	1.79	1.30	2.25	0.69	0.47	4.00	107
share white-collar	0.34	0.31	0.37	0.04	0.25	0.47	107
share old	0.24	0.22	0.25	0.02	0.18	0.29	107
share college-educated	0.10	0.09	0.11	0.02	0.06	0.16	107
share male	0.48	0.48	0.49	0.00	0.47	0.49	107
share coast	0.27	0.00	0.49	0.30	0.00	0.96	107
airport	0.32	0.00	1.00	0.47	0.00	1.00	107
altitude (in 100 meter)	2.16	0.85	3.11	1.71	0.05	7.10	107
Netherlands: municipality level							
turnout	0.42	0.38	0.47	0.07	0.26	0.80	355
population (in 100,000)	0.49	0.21	0.50	0.72	0.01	8.63	355
Sweden: county level							
turnout	0.54	0.52	0.55	0.03	0.50	0.59	21
population (in 100,000)	4.92	2.45	3.64	5.73	0.60	23.77	21
Switzerland: canton level							
turnout	0.41	0.38	0.43	0.06	0.32	0.63	26
population (in 100,000)	3.29	0.73	4.10	3.52	0.16	15.21	26
UK: upper tier local authority level							
turnout	0.36	0.33	0.40	0.05	0.23	0.54	171
population (in 100,000)	3.92	2.10	4.96	2.87	0.09	15.69	171
Italy: municipality level							
turnout	0.60	0.52	0.71	0.14	0.12	1.00	4424
population (in 100,000)	0.08	0.01	0.07	0.31	0.00	13.79	4424
population density (in 1000/km^2)	0.32	0.05	0.32	0.59	0.00	7.78	4424
taxable income per capita (in 1,000€)	13.26	10.93	15.30	3.11	4.53	35.45	4424
hospitals per 100,000 inhabitants	0.87	0.00	0.00	5.94	0.00	235.81	4424
share old	0.29	0.25	0.32	0.06	0.11	0.69	4424
share college-educated	0.07	0.06	0.09	0.03	0.00	0.27	4424

Notes: Blood donations per capita are missing for 4 (Belluno, Gorizia, Imperia and Lucca) out of 107 provinces. The literacy rate in 1821 refers to the province boundaries of 1911 when only 69 provinces existed.

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Table A.3: Geographical units across countries

country	area name	# areas	NUTS1 name	# NUTS1
Austria	District (*Bezirk*)	94	groups of States (*Bundesländer*)	3
Germany	County (*Kreis*)	401	States (*Bundesländer*)	16
Italy	Province (*Province*)	107	groups of Regions (*Regioni*)	5
Netherlands	Municipality (*Gemeente*)	355	Land (*Landsdeel*)	4
Sweden	County (*Län*)	21	Land (*Landsdelar*)	3
Switzerland	Canton (*Kanton*)	26	groups of Cantons (*Kanton*)	7
UK	Upper Tier Local Authority (NHS Health Boards for Wales & Scotland)	171	Wales, Scotland and Statistical Regions of England	11

Notes: This table provides an overview about the different geographical units within each country. With the exception of Austria and the Netherlands, all "areas" correspond to the NUTS3 regions. The column NUTS1 refers to the name of the NUTS1 region, except for Switzerland where the NUTS1 region corresponds to the whole country. Hence, we are using the the NUTS2 region for Switzerland.

Table A.4: Timing of pandemic-related events and policy responses

country	first Covid-19 case	ban of gatherings and events	closure of educational facilities	lockdown
Italy	Jan. 30^{th}	Feb. 23^{th}	Mar. 4^{th}	Mar. 9^{th}
Austria	Feb. 25^{th}	Mar. 10^{th}	Mar. 10^{th}	Mar. 16^{th}
Germany	Jan. 28^{th}	Mar. 8^{th}	Mar. 16^{th}	Mar. 23^{nd}
Netherlands	Feb. 27^{th}	Mar. 12^{th}	Mar. 15^{th}	Mar. 23^{rd}
Sweden	Jan. 31^{st}	Mar. 11^{th}	-	-
Switzerland	Feb. 25^{th}	Feb. 28^{th}	Mar.13^{th}	Mar. 16^{th}
UK	Jan. 29^{th}	Mar. 23^{rd}	Mar. 18^{th}	Mar. 23^{rd}

Notes: This table displays the timeline of the onset of Covid-19 in each country and the respective policy measures implemented to contain the spread.

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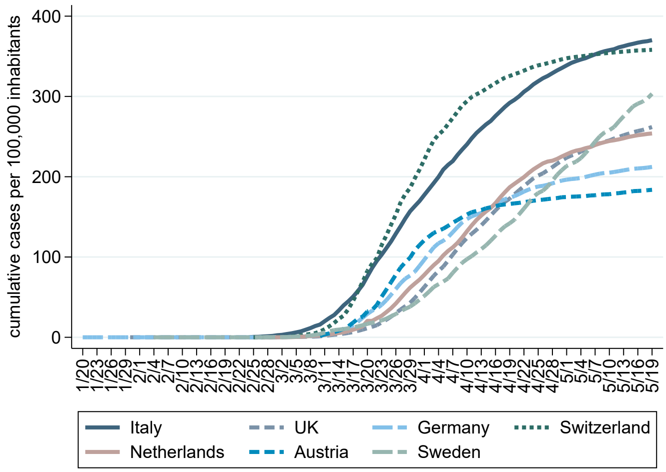
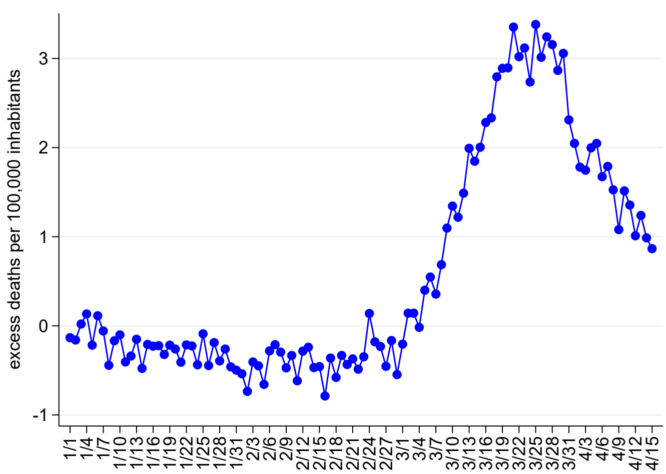
Figure A.1: Number of cases per 100,000 inhabitants at the national level over time



Notes: The graph shows the development of the pandemic for each country over time expressed as the infections per 100,000 inhabitants.

Figure A.2: Number of daily excess deaths at the national level in Italy over time



Notes: The graph shows the number of excess deaths in Italy between January 1^{st} and April 15^{th} per 100,000 inhabitants. Excess deaths are defined as the difference in reported deaths between 2020 and 2019. These numbers are published by ISTAT.

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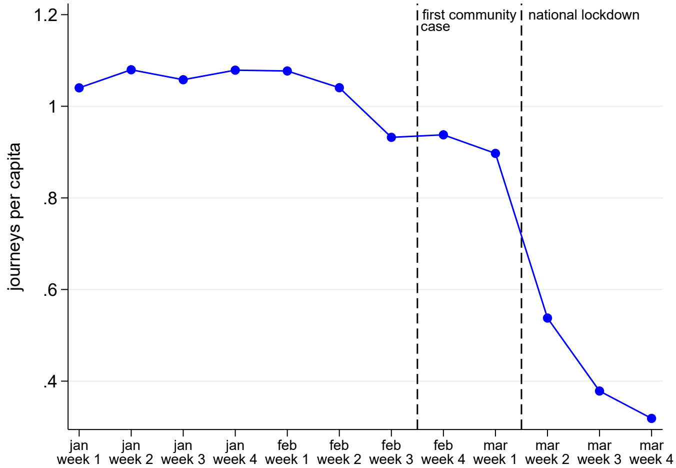
Figure A.3: Number of journeys per capita at the national level in Italy over time



Notes: The graph shows the journeys per capita in Italy between January and March 2020 based on mobile phone location data. The first dashed line corresponds to the discovery of the first Covid-19 community case in Italy. The second dashed line marks the date of the nationwide lockdown on March 9^{th}.

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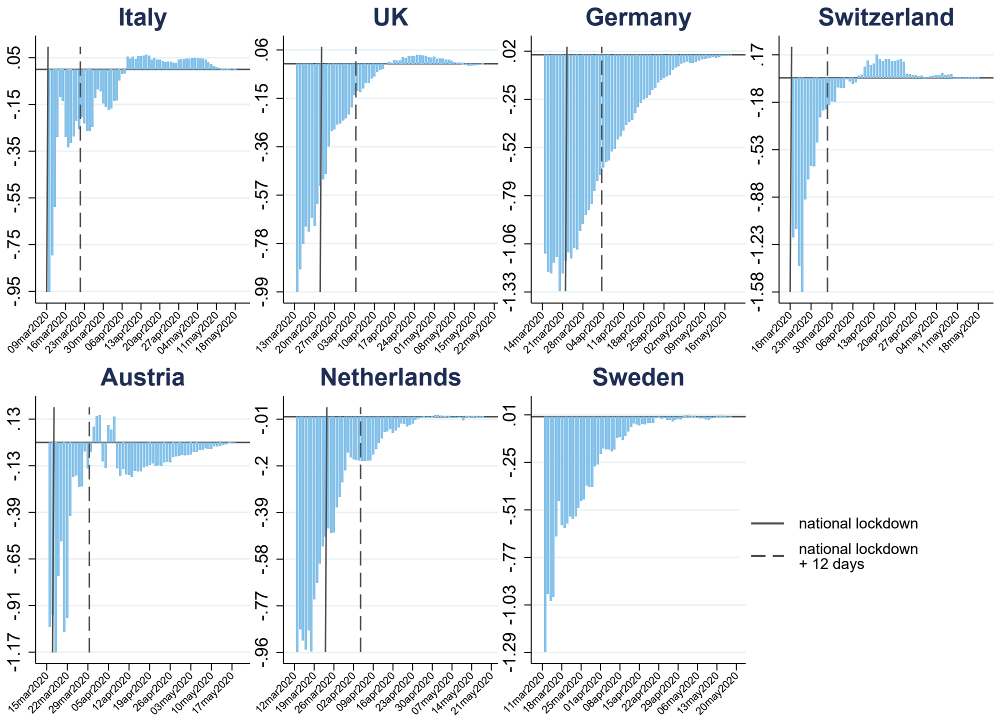
B Online Appendix: Additional Results

Figure B.1: Evolution of coefficient on social capital relative to the last day in the sample



Notes: This figure shows the percentage change in the coefficient on our measure of social capital relative to the coefficient we capture at the last day of our estimation window $((\beta_d/\beta_{d^{max}}) - 1)$. Negative values therefore indicate that the coefficient is smaller compared to the one on the last day of the window and positive ones that it is larger. The solid black line marks the date of the national lockdown, the dashed black line the date of the national lockdown plus an incubation + confirmation time of 12 days. These numbers are based on the estimates presented in Figure 2.

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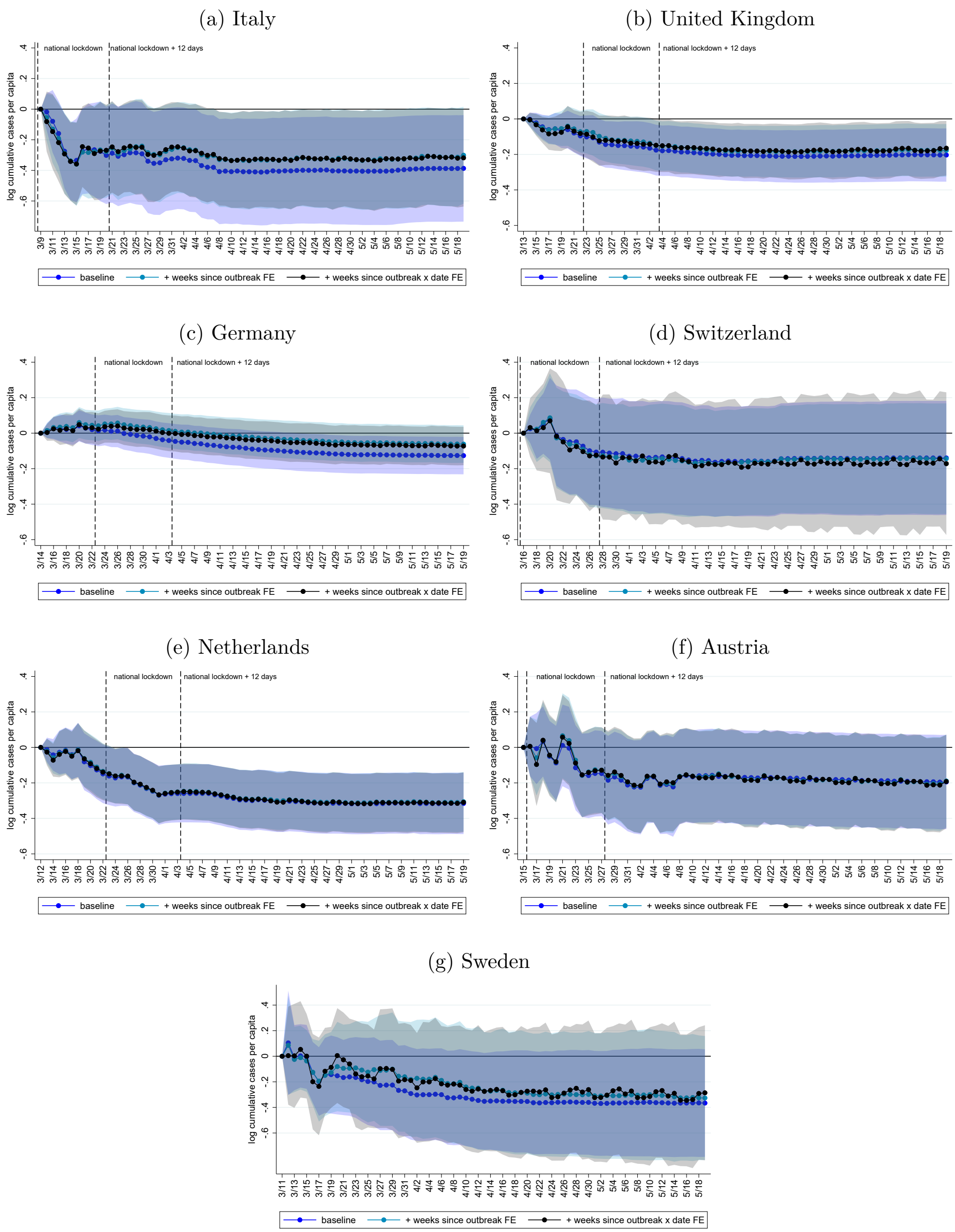
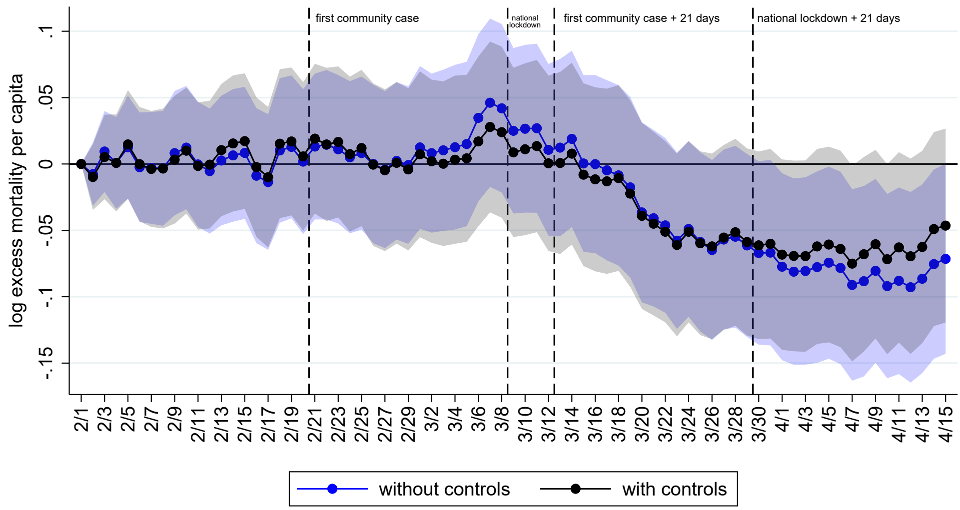
Figure B.2: Robustness: Effect of social capital on the spread of Covid-19 cases



Notes: This graph shows alternative specifications for the results reported in Figure 2 (see Appendix Table C.1 for the point estimates). The light-blue line reports the baseline results in Figure 2. The blue line includes additional weeks-since-outbreak fixed effects to control for potential differences arising from differential onset dates. The black line includes a set of weeks-since-outbreak - day fixed effect that additionally controls for differential trends not only due to the onset of the pandemic but also to the day we are observing these values. The first vertical dashed line marks the date of the national lockdown in each country. The second vertical dashed line corresponds to the date of the national lockdown plus 12 days, which accounts for incubation plus confirmation time. The shaded areas report the 95% confidence intervals.

Figure B.3: Effect of social capital on excess deaths with controls



Notes: The graph shows the the log number of excess deaths per 100,000 inhabitants (additional deaths in 2020 compared to 2019) from January 1^{st} to April 15^{th} based on specification 2 (see Appendix Table C.2 for point estimates). The controls include the share of people above 65, the share of college graduates, the number of hospitals per 100,000 inhabitants, population density, log population, and log income per capita. The shaded areas represent the 95% confidence intervals.

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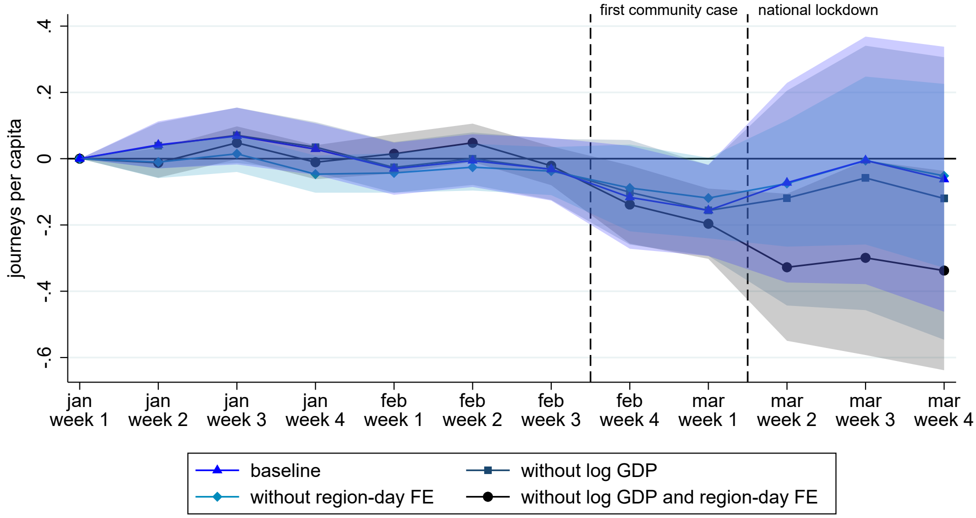
Figure B.4: Robustness: Effect of social capital on mobility



Notes: The graph shows the number of journeys per capita. The controls include the share of people above 65, the share of males, the share of white-collar workers, the share of college graduates, the number of hospitals per 100,000 inhabitants, population density, log population, altitude, the share of inhabitants living at the coast, a dummy for having an airport and log GDP per capita. The shaded areas represent the 95% confidence intervals. The point estimates are presented in Appendix Table C.3.

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C Online Appendix: Regression results

Table C.1: Effect of social capital on the spread of cumulative Covid-19 cases

	(1)		(2)		(3)	
Panel A – Italy						
turnout x 10mar2020	-0.018	(0.062)	-0.055	(0.079)	-0.081	(0.100)
turnout x 11mar2020	-0.079	(0.104)	-0.130	(0.113)	-0.146	(0.125)
turnout x 12mar2020	-0.159	(0.109)	-0.192	(0.121)	-0.218	(0.129)
turnout x 13mar2020	-0.275	(0.124)	-0.288	(0.134)	-0.293	(0.134)
turnout x 14mar2020	-0.341	(0.129)	-0.338	(0.132)	-0.342	(0.131)
turnout x 15mar2020	-0.335	(0.140)	-0.359	(0.139)	-0.358	(0.138)
turnout x 16mar2020	-0.275	(0.143)	-0.281	(0.144)	-0.245	(0.134)
turnout x 17mar2020	-0.258	(0.150)	-0.283	(0.154)	-0.254	(0.149)
turnout x 18mar2020	-0.265	(0.156)	-0.278	(0.154)	-0.290	(0.155)
turnout x 19mar2020	-0.276	(0.166)	-0.266	(0.163)	-0.273	(0.163)
turnout x 20mar2020	-0.302	(0.162)	-0.277	(0.154)	-0.269	(0.152)
turnout x 21mar2020	-0.288	(0.165)	-0.253	(0.154)	-0.247	(0.152)
turnout x 22mar2020	-0.308	(0.166)	-0.292	(0.154)	-0.278	(0.149)
turnout x 23mar2020	-0.297	(0.166)	-0.270	(0.154)	-0.253	(0.148)
turnout x 24mar2020	-0.285	(0.167)	-0.260	(0.156)	-0.242	(0.152)
turnout x 25mar2020	-0.285	(0.172)	-0.245	(0.158)	-0.250	(0.158)
turnout x 26mar2020	-0.292	(0.171)	-0.241	(0.157)	-0.249	(0.157)
turnout x 27mar2020	-0.340	(0.173)	-0.284	(0.158)	-0.296	(0.158)
turnout x 28mar2020	-0.354	(0.171)	-0.296	(0.155)	-0.302	(0.156)
turnout x 29mar2020	-0.351	(0.174)	-0.298	(0.158)	-0.289	(0.155)
turnout x 30mar2020	-0.331	(0.171)	-0.275	(0.155)	-0.265	(0.152)
turnout x 31mar2020	-0.325	(0.171)	-0.263	(0.153)	-0.248	(0.150)
turnout x 01apr2020	-0.320	(0.170)	-0.251	(0.151)	-0.246	(0.148)
turnout x 02apr2020	-0.322	(0.170)	-0.252	(0.152)	-0.255	(0.149)
turnout x 03apr2020	-0.335	(0.171)	-0.265	(0.154)	-0.272	(0.153)
turnout x 04apr2020	-0.336	(0.172)	-0.268	(0.155)	-0.272	(0.156)
turnout x 05apr2020	-0.368	(0.174)	-0.298	(0.159)	-0.288	(0.158)
turnout x 06apr2020	-0.380	(0.174)	-0.311	(0.159)	-0.302	(0.157)
turnout x 07apr2020	-0.380	(0.174)	-0.303	(0.156)	-0.296	(0.155)
turnout x 08apr2020	-0.408	(0.175)	-0.329	(0.158)	-0.323	(0.157)
turnout x 09apr2020	-0.405	(0.175)	-0.329	(0.158)	-0.326	(0.156)
turnout x 10apr2020	-0.408	(0.175)	-0.335	(0.159)	-0.336	(0.157)
turnout x 11apr2020	-0.404	(0.176)	-0.334	(0.160)	-0.334	(0.159)
turnout x 12apr2020	-0.409	(0.177)	-0.334	(0.163)	-0.327	(0.161)
turnout x 13apr2020	-0.409	(0.177)	-0.337	(0.162)	-0.335	(0.162)
turnout x 14apr2020	-0.410	(0.177)	-0.329	(0.161)	-0.327	(0.160)
turnout x 15apr2020	-0.412	(0.178)	-0.331	(0.161)	-0.325	(0.160)
turnout x 16apr2020	-0.410	(0.178)	-0.333	(0.162)	-0.328	(0.160)
turnout x 17apr2020	-0.403	(0.177)	-0.330	(0.162)	-0.328	(0.160)
turnout x 18apr2020	-0.406	(0.177)	-0.335	(0.163)	-0.334	(0.161)
turnout x 19apr2020	-0.403	(0.177)	-0.328	(0.164)	-0.326	(0.163)

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 20apr2020	-0.403	(0.177)	-0.332	(0.164)	-0.335	(0.163)
turnout x 21apr2020	-0.401	(0.177)	-0.319	(0.161)	-0.323	(0.160)
turnout x 22apr2020	-0.399	(0.178)	-0.318	(0.161)	-0.315	(0.160)
turnout x 23apr2020	-0.400	(0.178)	-0.322	(0.162)	-0.320	(0.160)
turnout x 24apr2020	-0.400	(0.178)	-0.325	(0.163)	-0.324	(0.162)
turnout x 25apr2020	-0.398	(0.178)	-0.327	(0.163)	-0.325	(0.162)
turnout x 26apr2020	-0.398	(0.178)	-0.321	(0.165)	-0.320	(0.164)
turnout x 27apr2020	-0.403	(0.178)	-0.330	(0.165)	-0.334	(0.165)
turnout x 28apr2020	-0.404	(0.178)	-0.321	(0.163)	-0.327	(0.162)
turnout x 29apr2020	-0.403	(0.179)	-0.322	(0.163)	-0.319	(0.161)
turnout x 30apr2020	-0.405	(0.179)	-0.328	(0.163)	-0.325	(0.162)
turnout x 01may2020	-0.404	(0.179)	-0.330	(0.164)	-0.330	(0.163)
turnout x 02may2020	-0.406	(0.179)	-0.335	(0.165)	-0.333	(0.163)
turnout x 03may2020	-0.406	(0.179)	-0.330	(0.166)	-0.330	(0.166)
turnout x 04may2020	-0.405	(0.179)	-0.333	(0.167)	-0.338	(0.166)
turnout x 05may2020	-0.405	(0.179)	-0.324	(0.165)	-0.333	(0.164)
turnout x 06may2020	-0.405	(0.180)	-0.325	(0.165)	-0.324	(0.163)
turnout x 07may2020	-0.403	(0.180)	-0.328	(0.165)	-0.325	(0.164)
turnout x 08may2020	-0.399	(0.179)	-0.326	(0.165)	-0.326	(0.164)
turnout x 09may2020	-0.396	(0.179)	-0.326	(0.165)	-0.324	(0.163)
turnout x 10may2020	-0.392	(0.178)	-0.318	(0.166)	-0.318	(0.165)
turnout x 11may2020	-0.390	(0.178)	-0.320	(0.165)	-0.324	(0.165)
turnout x 12may2020	-0.389	(0.178)	-0.308	(0.163)	-0.320	(0.163)
turnout x 13may2020	-0.388	(0.178)	-0.307	(0.162)	-0.308	(0.161)
turnout x 14may2020	-0.387	(0.178)	-0.310	(0.162)	-0.310	(0.161)
turnout x 15may2020	-0.387	(0.178)	-0.312	(0.163)	-0.314	(0.162)
turnout x 16may2020	-0.388	(0.178)	-0.315	(0.163)	-0.316	(0.162)
turnout x 17may2020	-0.388	(0.178)	-0.312	(0.164)	-0.313	(0.164)
turnout x 18may2020	-0.387	(0.177)	-0.314	(0.164)	-0.320	(0.164)
turnout x 19may2020	-0.387	(0.178)	-0.301	(0.161)	-0.318	(0.162)
province FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	4.645		4.645		4.652	
observations	7,681		7,681		7,627	
Panel B – The UK						
turnout x 14mar2020	-0.002	(0.019)	-0.007	(0.019)	-0.004	(0.021)
turnout x 15mar2020	-0.022	(0.029)	-0.029	(0.030)	-0.033	(0.031)
turnout x 16mar2020	-0.044	(0.035)	-0.050	(0.036)	-0.062	(0.038)
turnout x 17mar2020	-0.060	(0.040)	-0.062	(0.041)	-0.084	(0.046)
turnout x 18mar2020	-0.055	(0.045)	-0.056	(0.046)	-0.083	(0.049)
turnout x 19mar2020	-0.067	(0.049)	-0.054	(0.050)	-0.075	(0.054)
turnout x 20mar2020	-0.060	(0.054)	-0.040	(0.057)	-0.045	(0.060)
turnout x 21mar2020	-0.079	(0.056)	-0.056	(0.059)	-0.069	(0.060)

continued

Covid Economics 26, 5 June 2020: 137-190

Table C.1 continued

	(1)		(2)		(3)	
turnout x 22mar2020	-0.096	(0.057)	-0.072	(0.060)	-0.082	(0.062)
turnout x 23mar2020	-0.101	(0.062)	-0.071	(0.063)	-0.086	(0.068)
turnout x 24mar2020	-0.106	(0.065)	-0.076	(0.066)	-0.102	(0.071)
turnout x 25mar2020	-0.130	(0.066)	-0.098	(0.067)	-0.123	(0.072)
turnout x 26mar2020	-0.144	(0.067)	-0.109	(0.067)	-0.120	(0.071)
turnout x 27mar2020	-0.145	(0.067)	-0.118	(0.067)	-0.120	(0.071)
turnout x 28mar2020	-0.150	(0.068)	-0.120	(0.068)	-0.125	(0.072)
turnout x 29mar2020	-0.151	(0.070)	-0.121	(0.069)	-0.125	(0.074)
turnout x 30mar2020	-0.153	(0.071)	-0.124	(0.069)	-0.136	(0.075)
turnout x 31mar2020	-0.155	(0.072)	-0.126	(0.071)	-0.138	(0.076)
turnout x 01apr2020	-0.159	(0.073)	-0.130	(0.071)	-0.142	(0.077)
turnout x 02apr2020	-0.165	(0.073)	-0.137	(0.071)	-0.142	(0.076)
turnout x 03apr2020	-0.176	(0.073)	-0.149	(0.072)	-0.148	(0.077)
turnout x 04apr2020	-0.179	(0.073)	-0.153	(0.071)	-0.151	(0.076)
turnout x 05apr2020	-0.178	(0.073)	-0.152	(0.071)	-0.150	(0.076)
turnout x 06apr2020	-0.182	(0.073)	-0.156	(0.071)	-0.161	(0.077)
turnout x 07apr2020	-0.187	(0.073)	-0.161	(0.072)	-0.162	(0.076)
turnout x 08apr2020	-0.187	(0.073)	-0.161	(0.072)	-0.161	(0.076)
turnout x 09apr2020	-0.190	(0.073)	-0.166	(0.072)	-0.162	(0.076)
turnout x 10apr2020	-0.192	(0.073)	-0.168	(0.072)	-0.165	(0.077)
turnout x 11apr2020	-0.196	(0.073)	-0.174	(0.072)	-0.167	(0.077)
turnout x 12apr2020	-0.198	(0.074)	-0.175	(0.073)	-0.169	(0.077)
turnout x 13apr2020	-0.199	(0.073)	-0.177	(0.072)	-0.176	(0.077)
turnout x 14apr2020	-0.203	(0.073)	-0.180	(0.072)	-0.174	(0.076)
turnout x 15apr2020	-0.205	(0.073)	-0.182	(0.073)	-0.176	(0.076)
turnout x 16apr2020	-0.204	(0.074)	-0.181	(0.073)	-0.173	(0.077)
turnout x 17apr2020	-0.207	(0.074)	-0.183	(0.073)	-0.181	(0.078)
turnout x 18apr2020	-0.206	(0.074)	-0.181	(0.073)	-0.181	(0.078)
turnout x 19apr2020	-0.206	(0.074)	-0.181	(0.073)	-0.180	(0.078)
turnout x 20apr2020	-0.209	(0.074)	-0.183	(0.074)	-0.183	(0.078)
turnout x 21apr2020	-0.209	(0.074)	-0.183	(0.073)	-0.178	(0.077)
turnout x 22apr2020	-0.210	(0.075)	-0.184	(0.074)	-0.179	(0.078)
turnout x 23apr2020	-0.210	(0.075)	-0.184	(0.074)	-0.182	(0.078)
turnout x 24apr2020	-0.210	(0.075)	-0.184	(0.074)	-0.185	(0.079)
turnout x 25apr2020	-0.211	(0.075)	-0.184	(0.074)	-0.186	(0.079)
turnout x 26apr2020	-0.211	(0.075)	-0.184	(0.075)	-0.185	(0.079)
turnout x 27apr2020	-0.211	(0.076)	-0.183	(0.075)	-0.180	(0.079)
turnout x 28apr2020	-0.210	(0.076)	-0.183	(0.075)	-0.177	(0.078)
turnout x 29apr2020	-0.209	(0.076)	-0.182	(0.075)	-0.174	(0.079)
turnout x 30apr2020	-0.209	(0.076)	-0.182	(0.075)	-0.179	(0.079)
turnout x 01may2020	-0.210	(0.076)	-0.183	(0.075)	-0.184	(0.080)
turnout x 02may2020	-0.208	(0.076)	-0.181	(0.075)	-0.182	(0.079)
turnout x 03may2020	-0.208	(0.076)	-0.181	(0.075)	-0.182	(0.079)
turnout x 04may2020	-0.208	(0.076)	-0.180	(0.075)	-0.175	(0.079)
turnout x 05may2020	-0.207	(0.076)	-0.179	(0.075)	-0.171	(0.078)
turnout x 06may2020	-0.207	(0.076)	-0.179	(0.075)	-0.171	(0.079)

continued

Covid Economics 26, 5 June 2020: 137-190

Table C.1 continued

	(1)		(2)		(3)	
turnout x 07may2020	-0.206	(0.076)	-0.179	(0.075)	-0.179	(0.080)
turnout x 08may2020	-0.205	(0.076)	-0.179	(0.076)	-0.182	(0.080)
turnout x 09may2020	-0.205	(0.076)	-0.178	(0.076)	-0.180	(0.080)
turnout x 10may2020	-0.204	(0.076)	-0.177	(0.076)	-0.179	(0.080)
turnout x 11may2020	-0.204	(0.076)	-0.175	(0.076)	-0.169	(0.079)
turnout x 12may2020	-0.203	(0.076)	-0.174	(0.076)	-0.166	(0.079)
turnout x 13may2020	-0.202	(0.076)	-0.174	(0.076)	-0.165	(0.079)
turnout x 14may2020	-0.202	(0.076)	-0.177	(0.076)	-0.177	(0.080)
turnout x 15may2020	-0.202	(0.076)	-0.177	(0.076)	-0.181	(0.080)
turnout x 16may2020	-0.202	(0.076)	-0.177	(0.076)	-0.179	(0.080)
turnout x 17may2020	-0.203	(0.077)	-0.177	(0.076)	-0.178	(0.080)
turnout x 18may2020	-0.204	(0.077)	-0.177	(0.076)	-0.168	(0.079)
turnout x 19may2020	-0.203	(0.077)	-0.177	(0.076)	-0.165	(0.079)
upper tier local authority FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	4.387		4.387		4.390	
observations	11,527		11,527		11,484	
Panel C – Germany						
turnout x 15mar2020	0.015	(0.022)	0.015	(0.022)	0.004	(0.024)
turnout x 16mar2020	0.027	(0.032)	0.032	(0.032)	0.024	(0.034)
turnout x 17mar2020	0.028	(0.039)	0.034	(0.039)	0.016	(0.042)
turnout x 18mar2020	0.021	(0.041)	0.038	(0.041)	0.025	(0.044)
turnout x 19mar2020	0.017	(0.043)	0.031	(0.042)	0.014	(0.046)
turnout x 20mar2020	0.041	(0.045)	0.060	(0.044)	0.048	(0.046)
turnout x 21mar2020	0.029	(0.044)	0.048	(0.043)	0.030	(0.045)
turnout x 22mar2020	0.020	(0.044)	0.044	(0.043)	0.031	(0.045)
turnout x 23mar2020	0.014	(0.044)	0.042	(0.044)	0.023	(0.046)
turnout x 24mar2020	0.018	(0.044)	0.052	(0.044)	0.036	(0.046)
turnout x 25mar2020	0.011	(0.045)	0.052	(0.046)	0.039	(0.047)
turnout x 26mar2020	0.012	(0.047)	0.057	(0.047)	0.040	(0.048)
turnout x 27mar2020	-0.002	(0.047)	0.047	(0.047)	0.029	(0.049)
turnout x 28mar2020	-0.007	(0.048)	0.043	(0.048)	0.024	(0.049)
turnout x 29mar2020	-0.013	(0.048)	0.037	(0.048)	0.021	(0.050)
turnout x 30mar2020	-0.016	(0.048)	0.035	(0.048)	0.022	(0.050)
turnout x 31mar2020	-0.021	(0.049)	0.032	(0.049)	0.019	(0.051)
turnout x 01apr2020	-0.030	(0.049)	0.025	(0.049)	0.011	(0.051)
turnout x 02apr2020	-0.037	(0.049)	0.019	(0.050)	0.004	(0.051)
turnout x 03apr2020	-0.041	(0.050)	0.015	(0.050)	-0.001	(0.051)
turnout x 04apr2020	-0.046	(0.050)	0.010	(0.050)	-0.002	(0.052)
turnout x 05apr2020	-0.050	(0.050)	0.006	(0.051)	-0.007	(0.052)
turnout x 06apr2020	-0.052	(0.051)	0.006	(0.051)	-0.007	(0.052)
turnout x 07apr2020	-0.058	(0.051)	0.001	(0.051)	-0.014	(0.052)
turnout x 08apr2020	-0.060	(0.051)	0.001	(0.052)	-0.014	(0.053)

continued

Covid Economics 26, 5 June 2020: 137-190

Table C.1 continued

	(1)		(2)		(3)	
turnout x 09apr2020	-0.066	(0.051)	-0.004	(0.052)	-0.020	(0.052)
turnout x 10apr2020	-0.069	(0.051)	-0.006	(0.052)	-0.022	(0.053)
turnout x 11apr2020	-0.073	(0.052)	-0.010	(0.052)	-0.021	(0.053)
turnout x 12apr2020	-0.077	(0.052)	-0.015	(0.053)	-0.026	(0.054)
turnout x 13apr2020	-0.079	(0.052)	-0.016	(0.053)	-0.029	(0.054)
turnout x 14apr2020	-0.080	(0.053)	-0.016	(0.053)	-0.031	(0.054)
turnout x 15apr2020	-0.085	(0.053)	-0.020	(0.053)	-0.038	(0.054)
turnout x 16apr2020	-0.089	(0.053)	-0.023	(0.053)	-0.038	(0.054)
turnout x 17apr2020	-0.092	(0.053)	-0.027	(0.053)	-0.040	(0.055)
turnout x 18apr2020	-0.095	(0.053)	-0.029	(0.054)	-0.040	(0.055)
turnout x 19apr2020	-0.096	(0.053)	-0.031	(0.054)	-0.043	(0.055)
turnout x 20apr2020	-0.098	(0.053)	-0.032	(0.054)	-0.046	(0.055)
turnout x 21apr2020	-0.102	(0.054)	-0.035	(0.054)	-0.050	(0.055)
turnout x 22apr2020	-0.103	(0.054)	-0.036	(0.054)	-0.054	(0.055)
turnout x 23apr2020	-0.107	(0.054)	-0.038	(0.054)	-0.052	(0.055)
turnout x 24apr2020	-0.109	(0.054)	-0.041	(0.054)	-0.054	(0.055)
turnout x 25apr2020	-0.110	(0.054)	-0.043	(0.054)	-0.054	(0.056)
turnout x 26apr2020	-0.111	(0.054)	-0.045	(0.055)	-0.057	(0.056)
turnout x 27apr2020	-0.112	(0.054)	-0.045	(0.055)	-0.060	(0.056)
turnout x 28apr2020	-0.116	(0.054)	-0.048	(0.054)	-0.064	(0.055)
turnout x 29apr2020	-0.117	(0.054)	-0.050	(0.054)	-0.067	(0.056)
turnout x 30apr2020	-0.118	(0.054)	-0.050	(0.054)	-0.062	(0.055)
turnout x 01may2020	-0.120	(0.054)	-0.053	(0.054)	-0.065	(0.055)
turnout x 02may2020	-0.121	(0.054)	-0.054	(0.054)	-0.064	(0.056)
turnout x 03may2020	-0.122	(0.054)	-0.055	(0.054)	-0.067	(0.056)
turnout x 04may2020	-0.121	(0.054)	-0.054	(0.054)	-0.067	(0.056)
turnout x 05may2020	-0.121	(0.054)	-0.054	(0.054)	-0.067	(0.055)
turnout x 06may2020	-0.122	(0.054)	-0.055	(0.054)	-0.070	(0.055)
turnout x 07may2020	-0.122	(0.054)	-0.054	(0.054)	-0.064	(0.055)
turnout x 08may2020	-0.123	(0.054)	-0.057	(0.054)	-0.067	(0.055)
turnout x 09may2020	-0.123	(0.054)	-0.057	(0.054)	-0.067	(0.056)
turnout x 10may2020	-0.124	(0.054)	-0.058	(0.054)	-0.070	(0.055)
turnout x 11may2020	-0.124	(0.054)	-0.058	(0.054)	-0.071	(0.056)
turnout x 12may2020	-0.125	(0.054)	-0.059	(0.054)	-0.071	(0.055)
turnout x 13may2020	-0.124	(0.054)	-0.058	(0.054)	-0.072	(0.055)
turnout x 14may2020	-0.125	(0.054)	-0.058	(0.054)	-0.066	(0.055)
turnout x 15may2020	-0.126	(0.054)	-0.060	(0.054)	-0.069	(0.055)
turnout x 16may2020	-0.126	(0.054)	-0.061	(0.054)	-0.069	(0.056)
turnout x 17may2020	-0.126	(0.054)	-0.062	(0.054)	-0.072	(0.056)
turnout x 18may2020	-0.126	(0.054)	-0.061	(0.054)	-0.073	(0.056)
turnout x 19may2020	-0.126	(0.054)	-0.062	(0.054)	-0.073	(0.055)
county FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	4.439		4.439		4.438	

continued

Table C.1 continued

	(1)		(2)		(3)	
observations	26,635		26,635		26,587	
Panel D – Switzerland						
turnout x 17mar2020	0.025	(0.041)	0.030	(0.059)	0.032	(0.084)
turnout x 18mar2020	0.016	(0.082)	0.022	(0.094)	0.014	(0.114)
turnout x 19mar2020	0.054	(0.087)	0.061	(0.099)	0.031	(0.127)
turnout x 20mar2020	0.081	(0.118)	0.086	(0.128)	0.070	(0.151)
turnout x 21mar2020	-0.015	(0.144)	-0.027	(0.144)	-0.018	(0.184)
turnout x 22mar2020	-0.035	(0.147)	-0.048	(0.144)	-0.049	(0.174)
turnout x 23mar2020	-0.049	(0.151)	-0.062	(0.147)	-0.095	(0.155)
turnout x 24mar2020	-0.048	(0.150)	-0.067	(0.145)	-0.076	(0.139)
turnout x 25mar2020	-0.073	(0.153)	-0.091	(0.147)	-0.104	(0.147)
turnout x 26mar2020	-0.099	(0.155)	-0.120	(0.151)	-0.128	(0.159)
turnout x 27mar2020	-0.106	(0.152)	-0.127	(0.149)	-0.124	(0.144)
turnout x 28mar2020	-0.107	(0.157)	-0.126	(0.151)	-0.135	(0.180)
turnout x 29mar2020	-0.112	(0.157)	-0.132	(0.151)	-0.135	(0.180)
turnout x 30mar2020	-0.116	(0.158)	-0.136	(0.152)	-0.168	(0.167)
turnout x 31mar2020	-0.115	(0.159)	-0.137	(0.154)	-0.138	(0.165)
turnout x 01apr2020	-0.130	(0.158)	-0.152	(0.153)	-0.138	(0.162)
turnout x 02apr2020	-0.130	(0.158)	-0.153	(0.155)	-0.157	(0.171)
turnout x 03apr2020	-0.129	(0.159)	-0.152	(0.155)	-0.129	(0.166)
turnout x 04apr2020	-0.138	(0.160)	-0.148	(0.157)	-0.165	(0.178)
turnout x 05apr2020	-0.136	(0.160)	-0.145	(0.157)	-0.162	(0.179)
turnout x 06apr2020	-0.133	(0.160)	-0.143	(0.158)	-0.168	(0.177)
turnout x 07apr2020	-0.135	(0.161)	-0.147	(0.158)	-0.132	(0.181)
turnout x 08apr2020	-0.142	(0.162)	-0.154	(0.159)	-0.126	(0.185)
turnout x 09apr2020	-0.143	(0.162)	-0.156	(0.160)	-0.152	(0.186)
turnout x 10apr2020	-0.151	(0.160)	-0.164	(0.158)	-0.160	(0.179)
turnout x 11apr2020	-0.158	(0.158)	-0.169	(0.153)	-0.186	(0.177)
turnout x 12apr2020	-0.153	(0.159)	-0.164	(0.154)	-0.183	(0.177)
turnout x 13apr2020	-0.154	(0.159)	-0.166	(0.154)	-0.173	(0.182)
turnout x 14apr2020	-0.164	(0.157)	-0.174	(0.152)	-0.176	(0.178)
turnout x 15apr2020	-0.159	(0.157)	-0.170	(0.153)	-0.177	(0.180)
turnout x 16apr2020	-0.157	(0.157)	-0.167	(0.153)	-0.166	(0.181)
turnout x 17apr2020	-0.159	(0.158)	-0.169	(0.153)	-0.169	(0.184)
turnout x 18apr2020	-0.159	(0.158)	-0.163	(0.153)	-0.192	(0.174)
turnout x 19apr2020	-0.157	(0.158)	-0.161	(0.154)	-0.190	(0.175)
turnout x 20apr2020	-0.157	(0.158)	-0.161	(0.154)	-0.169	(0.184)
turnout x 21apr2020	-0.158	(0.158)	-0.160	(0.154)	-0.172	(0.189)
turnout x 22apr2020	-0.159	(0.158)	-0.162	(0.154)	-0.175	(0.190)
turnout x 23apr2020	-0.156	(0.159)	-0.158	(0.154)	-0.160	(0.186)
turnout x 24apr2020	-0.144	(0.159)	-0.146	(0.154)	-0.168	(0.193)
turnout x 25apr2020	-0.144	(0.159)	-0.148	(0.154)	-0.176	(0.177)
turnout x 26apr2020	-0.143	(0.160)	-0.147	(0.155)	-0.174	(0.178)
turnout x 27apr2020	-0.143	(0.161)	-0.147	(0.156)	-0.151	(0.190)
turnout x 28apr2020	-0.141	(0.162)	-0.144	(0.157)	-0.171	(0.196)

continued

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 29apr2020	-0.142	(0.162)	-0.145	(0.157)	-0.174	(0.196)
turnout x 30apr2020	-0.140	(0.162)	-0.143	(0.157)	-0.160	(0.191)
turnout x 01may2020	-0.141	(0.162)	-0.143	(0.157)	-0.169	(0.200)
turnout x 02may2020	-0.142	(0.163)	-0.146	(0.158)	-0.173	(0.181)
turnout x 03may2020	-0.142	(0.163)	-0.146	(0.158)	-0.173	(0.181)
turnout x 04may2020	-0.143	(0.164)	-0.147	(0.158)	-0.150	(0.193)
turnout x 05may2020	-0.143	(0.163)	-0.146	(0.159)	-0.174	(0.202)
turnout x 06may2020	-0.145	(0.163)	-0.148	(0.158)	-0.180	(0.200)
turnout x 07may2020	-0.143	(0.164)	-0.146	(0.159)	-0.164	(0.195)
turnout x 08may2020	-0.143	(0.164)	-0.146	(0.159)	-0.174	(0.204)
turnout x 09may2020	-0.143	(0.164)	-0.148	(0.159)	-0.174	(0.182)
turnout x 10may2020	-0.139	(0.164)	-0.144	(0.159)	-0.170	(0.182)
turnout x 11may2020	-0.140	(0.164)	-0.144	(0.159)	-0.146	(0.194)
turnout x 12may2020	-0.140	(0.164)	-0.143	(0.159)	-0.176	(0.203)
turnout x 13may2020	-0.139	(0.164)	-0.143	(0.159)	-0.177	(0.203)
turnout x 14may2020	-0.140	(0.164)	-0.142	(0.158)	-0.154	(0.196)
turnout x 15may2020	-0.140	(0.164)	-0.143	(0.159)	-0.166	(0.208)
turnout x 16may2020	-0.140	(0.164)	-0.144	(0.159)	-0.168	(0.183)
turnout x 17may2020	-0.140	(0.164)	-0.144	(0.159)	-0.169	(0.182)
turnout x 18may2020	-0.140	(0.164)	-0.144	(0.159)	-0.145	(0.194)
turnout x 19may2020	-0.140	(0.164)	-0.144	(0.159)	-0.172	(0.205)
canton FE	yes		yes		yes	
NUTS2 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	5.137		5.137		5.147	
observations	1,554		1,554		1,512	
Panel E – The Netherlands						
turnout x 13mar2020	-0.013	(0.035)	-0.021	(0.036)	-0.026	(0.038)
turnout x 14mar2020	-0.042	(0.045)	-0.059	(0.045)	-0.072	(0.047)
turnout x 15mar2020	-0.028	(0.063)	-0.034	(0.064)	-0.039	(0.066)
turnout x 16mar2020	-0.016	(0.066)	-0.019	(0.066)	-0.023	(0.067)
turnout x 17mar2020	-0.041	(0.071)	-0.044	(0.069)	-0.050	(0.071)
turnout x 18mar2020	-0.014	(0.078)	-0.014	(0.077)	-0.018	(0.079)
turnout x 19mar2020	-0.081	(0.082)	-0.063	(0.081)	-0.064	(0.082)
turnout x 20mar2020	-0.102	(0.081)	-0.084	(0.080)	-0.092	(0.082)
turnout x 21mar2020	-0.127	(0.084)	-0.111	(0.082)	-0.118	(0.083)
turnout x 22mar2020	-0.149	(0.084)	-0.135	(0.080)	-0.139	(0.081)
turnout x 23mar2020	-0.161	(0.084)	-0.147	(0.080)	-0.149	(0.080)
turnout x 24mar2020	-0.172	(0.082)	-0.161	(0.079)	-0.161	(0.079)
turnout x 25mar2020	-0.166	(0.083)	-0.157	(0.080)	-0.160	(0.081)
turnout x 26mar2020	-0.167	(0.084)	-0.163	(0.081)	-0.162	(0.081)
turnout x 27mar2020	-0.199	(0.084)	-0.197	(0.081)	-0.196	(0.081)
turnout x 28mar2020	-0.212	(0.084)	-0.208	(0.081)	-0.207	(0.081)
turnout x 29mar2020	-0.231	(0.084)	-0.228	(0.081)	-0.226	(0.081)

continued

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 30mar2020	-0.247	(0.083)	-0.244	(0.080)	-0.242	(0.080)
turnout x 31mar2020	-0.269	(0.085)	-0.268	(0.081)	-0.267	(0.082)
turnout x 01apr2020	-0.263	(0.084)	-0.257	(0.080)	-0.260	(0.081)
turnout x 02apr2020	-0.261	(0.083)	-0.254	(0.080)	-0.255	(0.080)
turnout x 03apr2020	-0.260	(0.083)	-0.251	(0.080)	-0.252	(0.080)
turnout x 04apr2020	-0.259	(0.083)	-0.247	(0.080)	-0.249	(0.080)
turnout x 05apr2020	-0.259	(0.083)	-0.248	(0.080)	-0.250	(0.080)
turnout x 06apr2020	-0.259	(0.084)	-0.248	(0.081)	-0.252	(0.081)
turnout x 07apr2020	-0.259	(0.084)	-0.253	(0.081)	-0.253	(0.081)
turnout x 08apr2020	-0.259	(0.084)	-0.253	(0.081)	-0.255	(0.081)
turnout x 09apr2020	-0.267	(0.085)	-0.261	(0.081)	-0.262	(0.081)
turnout x 10apr2020	-0.274	(0.085)	-0.267	(0.081)	-0.267	(0.082)
turnout x 11apr2020	-0.282	(0.085)	-0.273	(0.082)	-0.275	(0.082)
turnout x 12apr2020	-0.288	(0.085)	-0.280	(0.082)	-0.281	(0.083)
turnout x 13apr2020	-0.296	(0.086)	-0.289	(0.083)	-0.291	(0.083)
turnout x 14apr2020	-0.297	(0.086)	-0.289	(0.083)	-0.292	(0.084)
turnout x 15apr2020	-0.300	(0.086)	-0.293	(0.083)	-0.295	(0.083)
turnout x 16apr2020	-0.295	(0.087)	-0.289	(0.083)	-0.292	(0.084)
turnout x 17apr2020	-0.298	(0.087)	-0.292	(0.084)	-0.295	(0.084)
turnout x 18apr2020	-0.302	(0.087)	-0.295	(0.084)	-0.301	(0.084)
turnout x 19apr2020	-0.307	(0.087)	-0.300	(0.084)	-0.308	(0.084)
turnout x 20apr2020	-0.307	(0.087)	-0.301	(0.084)	-0.309	(0.084)
turnout x 21apr2020	-0.303	(0.086)	-0.295	(0.084)	-0.297	(0.084)
turnout x 22apr2020	-0.305	(0.086)	-0.298	(0.083)	-0.300	(0.084)
turnout x 23apr2020	-0.307	(0.087)	-0.301	(0.083)	-0.304	(0.084)
turnout x 24apr2020	-0.312	(0.087)	-0.306	(0.083)	-0.308	(0.084)
turnout x 25apr2020	-0.313	(0.087)	-0.307	(0.084)	-0.312	(0.084)
turnout x 26apr2020	-0.315	(0.087)	-0.309	(0.084)	-0.314	(0.085)
turnout x 27apr2020	-0.315	(0.087)	-0.310	(0.084)	-0.315	(0.085)
turnout x 28apr2020	-0.315	(0.087)	-0.305	(0.085)	-0.307	(0.085)
turnout x 29apr2020	-0.315	(0.088)	-0.307	(0.084)	-0.309	(0.085)
turnout x 30apr2020	-0.316	(0.088)	-0.311	(0.084)	-0.314	(0.085)
turnout x 01may2020	-0.318	(0.087)	-0.313	(0.084)	-0.315	(0.084)
turnout x 02may2020	-0.318	(0.087)	-0.312	(0.084)	-0.316	(0.085)
turnout x 03may2020	-0.317	(0.087)	-0.312	(0.085)	-0.317	(0.085)
turnout x 04may2020	-0.317	(0.087)	-0.312	(0.085)	-0.317	(0.085)
turnout x 05may2020	-0.317	(0.088)	-0.308	(0.085)	-0.310	(0.085)
turnout x 06may2020	-0.316	(0.088)	-0.309	(0.085)	-0.311	(0.085)
turnout x 07may2020	-0.314	(0.088)	-0.309	(0.084)	-0.312	(0.085)
turnout x 08may2020	-0.314	(0.088)	-0.309	(0.084)	-0.311	(0.085)
turnout x 09may2020	-0.314	(0.088)	-0.308	(0.085)	-0.313	(0.085)
turnout x 10may2020	-0.315	(0.088)	-0.309	(0.085)	-0.314	(0.085)
turnout x 11may2020	-0.311	(0.088)	-0.306	(0.085)	-0.311	(0.085)
turnout x 12may2020	-0.316	(0.088)	-0.307	(0.085)	-0.310	(0.086)
turnout x 13may2020	-0.316	(0.088)	-0.309	(0.085)	-0.310	(0.086)
turnout x 14may2020	-0.316	(0.088)	-0.311	(0.085)	-0.314	(0.085)

continued

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 15may2020	-0.317	(0.088)	-0.311	(0.085)	-0.313	(0.085)
turnout x 16may2020	-0.316	(0.088)	-0.310	(0.085)	-0.314	(0.086)
turnout x 17may2020	-0.315	(0.088)	-0.310	(0.085)	-0.314	(0.086)
turnout x 18may2020	-0.315	(0.088)	-0.310	(0.085)	-0.315	(0.086)
turnout x 19may2020	-0.316	(0.088)	-0.306	(0.086)	-0.310	(0.086)
municipality FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	4.531		4.531		4.531	
observations	23,171		23,171		23,140	
Panel F – Austria						
turnout x 16mar2020	0.005	(0.086)	0.006	(0.085)	0.006	(0.085)
turnout x 17mar2020	-0.007	(0.102)	-0.059	(0.109)	-0.096	(0.120)
turnout x 18mar2020	0.033	(0.101)	0.039	(0.111)	0.040	(0.116)
turnout x 19mar2020	-0.050	(0.102)	-0.045	(0.112)	-0.044	(0.117)
turnout x 20mar2020	-0.087	(0.107)	-0.082	(0.115)	-0.081	(0.117)
turnout x 21mar2020	0.011	(0.117)	0.066	(0.122)	0.058	(0.121)
turnout x 22mar2020	-0.004	(0.119)	0.038	(0.123)	0.022	(0.121)
turnout x 23mar2020	-0.115	(0.122)	-0.072	(0.125)	-0.088	(0.122)
turnout x 24mar2020	-0.157	(0.120)	-0.157	(0.120)	-0.154	(0.122)
turnout x 25mar2020	-0.159	(0.122)	-0.138	(0.122)	-0.141	(0.124)
turnout x 26mar2020	-0.147	(0.124)	-0.126	(0.124)	-0.131	(0.125)
turnout x 27mar2020	-0.147	(0.123)	-0.128	(0.123)	-0.129	(0.123)
turnout x 28mar2020	-0.185	(0.128)	-0.163	(0.127)	-0.158	(0.128)
turnout x 29mar2020	-0.166	(0.130)	-0.147	(0.129)	-0.138	(0.130)
turnout x 30mar2020	-0.184	(0.133)	-0.165	(0.132)	-0.158	(0.132)
turnout x 31mar2020	-0.212	(0.133)	-0.196	(0.134)	-0.194	(0.135)
turnout x 01apr2020	-0.223	(0.134)	-0.216	(0.133)	-0.213	(0.135)
turnout x 02apr2020	-0.224	(0.136)	-0.217	(0.135)	-0.216	(0.137)
turnout x 03apr2020	-0.174	(0.129)	-0.168	(0.130)	-0.162	(0.130)
turnout x 04apr2020	-0.167	(0.132)	-0.162	(0.132)	-0.162	(0.133)
turnout x 05apr2020	-0.213	(0.140)	-0.207	(0.139)	-0.207	(0.140)
turnout x 06apr2020	-0.209	(0.142)	-0.203	(0.141)	-0.194	(0.141)
turnout x 07apr2020	-0.223	(0.143)	-0.206	(0.141)	-0.199	(0.140)
turnout x 08apr2020	-0.167	(0.136)	-0.163	(0.135)	-0.165	(0.137)
turnout x 09apr2020	-0.158	(0.135)	-0.155	(0.134)	-0.154	(0.135)
turnout x 10apr2020	-0.166	(0.134)	-0.162	(0.133)	-0.162	(0.134)
turnout x 11apr2020	-0.160	(0.133)	-0.167	(0.133)	-0.172	(0.134)
turnout x 12apr2020	-0.159	(0.134)	-0.164	(0.134)	-0.171	(0.135)
turnout x 13apr2020	-0.157	(0.134)	-0.162	(0.134)	-0.171	(0.135)
turnout x 14apr2020	-0.164	(0.134)	-0.149	(0.132)	-0.154	(0.133)
turnout x 15apr2020	-0.163	(0.134)	-0.167	(0.132)	-0.166	(0.134)
turnout x 16apr2020	-0.163	(0.135)	-0.163	(0.133)	-0.157	(0.135)
turnout x 17apr2020	-0.168	(0.135)	-0.167	(0.133)	-0.167	(0.134)

continued

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 18apr2020	-0.169	(0.135)	-0.183	(0.134)	-0.186	(0.135)
turnout x 19apr2020	-0.170	(0.135)	-0.181	(0.134)	-0.185	(0.135)
turnout x 20apr2020	-0.172	(0.135)	-0.183	(0.135)	-0.187	(0.136)
turnout x 21apr2020	-0.169	(0.135)	-0.159	(0.132)	-0.160	(0.134)
turnout x 22apr2020	-0.170	(0.135)	-0.176	(0.133)	-0.175	(0.134)
turnout x 23apr2020	-0.169	(0.135)	-0.171	(0.134)	-0.169	(0.135)
turnout x 24apr2020	-0.173	(0.135)	-0.174	(0.134)	-0.174	(0.135)
turnout x 25apr2020	-0.174	(0.135)	-0.189	(0.134)	-0.190	(0.135)
turnout x 26apr2020	-0.173	(0.135)	-0.184	(0.134)	-0.187	(0.136)
turnout x 27apr2020	-0.179	(0.135)	-0.190	(0.135)	-0.195	(0.136)
turnout x 28apr2020	-0.179	(0.135)	-0.170	(0.133)	-0.170	(0.134)
turnout x 29apr2020	-0.180	(0.135)	-0.186	(0.133)	-0.184	(0.134)
turnout x 30apr2020	-0.181	(0.135)	-0.182	(0.134)	-0.180	(0.135)
turnout x 01may2020	-0.181	(0.135)	-0.181	(0.134)	-0.181	(0.135)
turnout x 02may2020	-0.181	(0.135)	-0.196	(0.134)	-0.198	(0.135)
turnout x 03may2020	-0.181	(0.135)	-0.193	(0.135)	-0.196	(0.135)
turnout x 04may2020	-0.184	(0.135)	-0.196	(0.135)	-0.199	(0.136)
turnout x 05may2020	-0.184	(0.135)	-0.174	(0.133)	-0.175	(0.134)
turnout x 06may2020	-0.187	(0.135)	-0.193	(0.133)	-0.190	(0.134)
turnout x 07may2020	-0.187	(0.135)	-0.188	(0.133)	-0.185	(0.134)
turnout x 08may2020	-0.188	(0.135)	-0.189	(0.133)	-0.188	(0.135)
turnout x 09may2020	-0.188	(0.135)	-0.203	(0.134)	-0.205	(0.135)
turnout x 10may2020	-0.188	(0.135)	-0.199	(0.134)	-0.203	(0.135)
turnout x 11may2020	-0.190	(0.135)	-0.202	(0.135)	-0.206	(0.136)
turnout x 12may2020	-0.190	(0.135)	-0.182	(0.133)	-0.184	(0.134)
turnout x 13may2020	-0.191	(0.135)	-0.197	(0.133)	-0.195	(0.134)
turnout x 14may2020	-0.192	(0.135)	-0.194	(0.133)	-0.191	(0.135)
turnout x 15may2020	-0.193	(0.135)	-0.194	(0.134)	-0.193	(0.135)
turnout x 16may2020	-0.193	(0.135)	-0.208	(0.134)	-0.213	(0.135)
turnout x 17may2020	-0.194	(0.135)	-0.204	(0.134)	-0.211	(0.135)
turnout x 18may2020	-0.196	(0.136)	-0.207	(0.135)	-0.212	(0.136)
turnout x 19may2020	-0.195	(0.135)	-0.189	(0.133)	-0.192	(0.135)
district FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	4.500		4.500		4.499	
observations	5,794		5,794		5,762	
Panel G – Sweden						
turnout x 12mar2020	0.105	(0.208)	0.086	(0.197)	0.005	(0.196)
turnout x 13mar2020	-0.011	(0.130)	-0.025	(0.130)	0.003	(0.207)
turnout x 14mar2020	0.003	(0.126)	-0.011	(0.127)	0.054	(0.192)
turnout x 15mar2020	-0.005	(0.128)	-0.037	(0.123)	0.000	(0.169)
turnout x 16mar2020	-0.126	(0.121)	-0.125	(0.132)	-0.199	(0.190)
turnout x 17mar2020	-0.197	(0.137)	-0.194	(0.161)	-0.236	(0.195)

continued

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 18mar2020	-0.149	(0.149)	-0.148	(0.163)	-0.117	(0.173)
turnout x 19mar2020	-0.143	(0.156)	-0.127	(0.161)	-0.087	(0.162)
turnout x 20mar2020	-0.153	(0.154)	-0.081	(0.178)	0.005	(0.189)
turnout x 21mar2020	-0.166	(0.150)	-0.094	(0.174)	-0.027	(0.189)
turnout x 22mar2020	-0.161	(0.155)	-0.094	(0.176)	-0.060	(0.181)
turnout x 23mar2020	-0.166	(0.161)	-0.091	(0.186)	-0.138	(0.213)
turnout x 24mar2020	-0.183	(0.168)	-0.108	(0.195)	-0.160	(0.213)
turnout x 25mar2020	-0.197	(0.174)	-0.124	(0.200)	-0.154	(0.205)
turnout x 26mar2020	-0.201	(0.178)	-0.105	(0.205)	-0.177	(0.197)
turnout x 27mar2020	-0.228	(0.178)	-0.111	(0.221)	-0.097	(0.237)
turnout x 28mar2020	-0.225	(0.180)	-0.108	(0.223)	-0.095	(0.237)
turnout x 29mar2020	-0.225	(0.180)	-0.101	(0.226)	-0.103	(0.244)
turnout x 30mar2020	-0.267	(0.178)	-0.156	(0.221)	-0.194	(0.229)
turnout x 31mar2020	-0.270	(0.182)	-0.160	(0.220)	-0.183	(0.226)
turnout x 01apr2020	-0.291	(0.184)	-0.181	(0.229)	-0.189	(0.221)
turnout x 02apr2020	-0.302	(0.183)	-0.172	(0.233)	-0.247	(0.219)
turnout x 03apr2020	-0.301	(0.185)	-0.179	(0.238)	-0.201	(0.239)
turnout x 04apr2020	-0.300	(0.183)	-0.179	(0.236)	-0.200	(0.237)
turnout x 05apr2020	-0.297	(0.183)	-0.165	(0.239)	-0.175	(0.243)
turnout x 06apr2020	-0.300	(0.185)	-0.189	(0.234)	-0.215	(0.230)
turnout x 07apr2020	-0.324	(0.187)	-0.213	(0.231)	-0.226	(0.231)
turnout x 08apr2020	-0.325	(0.189)	-0.215	(0.239)	-0.217	(0.232)
turnout x 09apr2020	-0.319	(0.191)	-0.204	(0.244)	-0.226	(0.237)
turnout x 10apr2020	-0.327	(0.191)	-0.240	(0.236)	-0.260	(0.241)
turnout x 11apr2020	-0.336	(0.191)	-0.249	(0.237)	-0.273	(0.242)
turnout x 12apr2020	-0.346	(0.194)	-0.249	(0.246)	-0.256	(0.255)
turnout x 13apr2020	-0.352	(0.193)	-0.274	(0.236)	-0.275	(0.237)
turnout x 14apr2020	-0.351	(0.194)	-0.272	(0.233)	-0.267	(0.242)
turnout x 15apr2020	-0.348	(0.197)	-0.267	(0.241)	-0.259	(0.247)
turnout x 16apr2020	-0.352	(0.199)	-0.266	(0.246)	-0.269	(0.255)
turnout x 17apr2020	-0.351	(0.201)	-0.284	(0.242)	-0.303	(0.247)
turnout x 18apr2020	-0.353	(0.204)	-0.286	(0.245)	-0.301	(0.251)
turnout x 19apr2020	-0.353	(0.204)	-0.283	(0.247)	-0.283	(0.264)
turnout x 20apr2020	-0.353	(0.204)	-0.288	(0.243)	-0.273	(0.247)
turnout x 21apr2020	-0.363	(0.205)	-0.299	(0.243)	-0.273	(0.255)
turnout x 22apr2020	-0.365	(0.204)	-0.301	(0.244)	-0.279	(0.260)
turnout x 23apr2020	-0.362	(0.205)	-0.295	(0.248)	-0.263	(0.268)
turnout x 24apr2020	-0.363	(0.205)	-0.302	(0.246)	-0.323	(0.252)
turnout x 25apr2020	-0.360	(0.207)	-0.298	(0.248)	-0.317	(0.255)
turnout x 26apr2020	-0.360	(0.207)	-0.296	(0.250)	-0.288	(0.269)
turnout x 27apr2020	-0.357	(0.207)	-0.298	(0.246)	-0.264	(0.251)
turnout x 28apr2020	-0.359	(0.209)	-0.300	(0.247)	-0.251	(0.257)
turnout x 29apr2020	-0.361	(0.208)	-0.301	(0.248)	-0.280	(0.269)
turnout x 30apr2020	-0.361	(0.209)	-0.298	(0.252)	-0.261	(0.275)
turnout x 01may2020	-0.368	(0.209)	-0.309	(0.250)	-0.323	(0.256)
turnout x 02may2020	-0.369	(0.209)	-0.311	(0.251)	-0.322	(0.256)

continued

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Table C.1 continued

	(1)		(2)		(3)	
turnout x 03may2020	-0.368	(0.209)	-0.308	(0.253)	-0.304	(0.268)
turnout x 04may2020	-0.366	(0.212)	-0.308	(0.252)	-0.270	(0.258)
turnout x 05may2020	-0.366	(0.213)	-0.308	(0.252)	-0.256	(0.262)
turnout x 06may2020	-0.363	(0.214)	-0.305	(0.254)	-0.295	(0.277)
turnout x 07may2020	-0.362	(0.214)	-0.302	(0.259)	-0.272	(0.285)
turnout x 08may2020	-0.363	(0.214)	-0.304	(0.259)	-0.323	(0.264)
turnout x 09may2020	-0.361	(0.215)	-0.302	(0.260)	-0.324	(0.265)
turnout x 10may2020	-0.359	(0.216)	-0.300	(0.263)	-0.314	(0.276)
turnout x 11may2020	-0.363	(0.216)	-0.306	(0.258)	-0.277	(0.263)
turnout x 12may2020	-0.363	(0.215)	-0.306	(0.258)	-0.268	(0.268)
turnout x 13may2020	-0.366	(0.215)	-0.310	(0.257)	-0.311	(0.280)
turnout x 14may2020	-0.367	(0.215)	-0.317	(0.259)	-0.289	(0.286)
turnout x 15may2020	-0.366	(0.214)	-0.325	(0.250)	-0.344	(0.263)
turnout x 16may2020	-0.366	(0.215)	-0.325	(0.250)	-0.345	(0.263)
turnout x 17may2020	-0.364	(0.215)	-0.323	(0.253)	-0.338	(0.274)
turnout x 18may2020	-0.365	(0.216)	-0.325	(0.249)	-0.291	(0.264)
turnout x 19may2020	-0.366	(0.214)	-0.326	(0.247)	-0.286	(0.269)
county FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
weeks-since-outbreak FE	no		yes		no	
weeks-since-outbreak x day FE	no		no		yes	
mean	4.058		4.057		4.040	
observations	1,467		1,466		1,378	

Notes: This table presents the regression results from our baseline model in equation (1). Standard errors clustered at the area level in parenthesis. Columns (2) and (3) add weeks-since-outbreak and weeks-since-outbreak x day FE.

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Table C.2: Effect of social capital on excess deaths

	(1)		(2)	
turnout x 02feb2020	-0.008	(0.012)	-0.010	(0.013)
turnout x 03feb2020	0.009	(0.016)	0.005	(0.016)
turnout x 04feb2020	0.001	(0.018)	0.001	(0.019)
turnout x 05feb2020	0.013	(0.020)	0.015	(0.021)
turnout x 06feb2020	-0.002	(0.021)	-0.000	(0.022)
turnout x 07feb2020	-0.003	(0.021)	-0.004	(0.022)
turnout x 08feb2020	-0.003	(0.022)	-0.003	(0.023)
turnout x 09feb2020	0.008	(0.024)	0.003	(0.025)
turnout x 10feb2020	0.012	(0.024)	0.010	(0.024)
turnout x 11feb2020	-0.000	(0.024)	-0.001	(0.024)
turnout x 12feb2020	-0.005	(0.024)	-0.000	(0.025)
turnout x 13feb2020	0.003	(0.025)	0.010	(0.025)
turnout x 14feb2020	0.007	(0.025)	0.015	(0.026)
turnout x 15feb2020	0.008	(0.025)	0.017	(0.026)
turnout x 16feb2020	-0.009	(0.026)	-0.002	(0.027)
turnout x 17feb2020	-0.014	(0.026)	-0.010	(0.027)
turnout x 18feb2020	0.010	(0.028)	0.015	(0.029)
turnout x 19feb2020	0.013	(0.027)	0.017	(0.028)
turnout x 20feb2020	0.002	(0.028)	0.006	(0.029)
turnout x 21feb2020	0.013	(0.028)	0.019	(0.029)
turnout x 22feb2020	0.015	(0.029)	0.015	(0.029)
turnout x 23feb2020	0.011	(0.029)	0.017	(0.029)
turnout x 24feb2020	0.005	(0.029)	0.007	(0.030)
turnout x 25feb2020	0.008	(0.029)	0.012	(0.030)
turnout x 26feb2020	0.000	(0.030)	-0.000	(0.031)
turnout x 27feb2020	-0.004	(0.030)	-0.005	(0.031)
turnout x 28feb2020	0.002	(0.030)	0.001	(0.031)
turnout x 29feb2020	-0.001	(0.030)	-0.004	(0.031)
turnout x 01mar2020	0.013	(0.031)	0.007	(0.032)
turnout x 02mar2020	0.008	(0.031)	0.002	(0.031)
turnout x 03mar2020	0.010	(0.031)	0.000	(0.032)
turnout x 04mar2020	0.013	(0.032)	0.003	(0.032)
turnout x 05mar2020	0.015	(0.032)	0.004	(0.032)
turnout x 06mar2020	0.035	(0.032)	0.017	(0.033)
turnout x 07mar2020	0.046	(0.032)	0.028	(0.033)
turnout x 08mar2020	0.042	(0.032)	0.024	(0.033)
turnout x 09mar2020	0.025	(0.032)	0.009	(0.033)
turnout x 10mar2020	0.027	(0.032)	0.011	(0.033)
turnout x 11mar2020	0.027	(0.032)	0.014	(0.033)
turnout x 12mar2020	0.011	(0.033)	0.001	(0.034)
turnout x 13mar2020	0.012	(0.034)	0.001	(0.035)
turnout x 14mar2020	0.019	(0.034)	0.008	(0.035)

continued

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Table C.2 continued

	(1)		(2)	
turnout x 15mar2020	0.000	(0.034)	-0.008	(0.035)
turnout x 16mar2020	-0.000	(0.034)	-0.012	(0.035)
turnout x 17mar2020	-0.005	(0.035)	-0.013	(0.036)
turnout x 18mar2020	-0.009	(0.035)	-0.011	(0.036)
turnout x 19mar2020	-0.018	(0.035)	-0.022	(0.036)
turnout x 20mar2020	-0.036	(0.035)	-0.039	(0.036)
turnout x 21mar2020	-0.041	(0.034)	-0.045	(0.035)
turnout x 22mar2020	-0.046	(0.034)	-0.051	(0.035)
turnout x 23mar2020	-0.058	(0.034)	-0.061	(0.035)
turnout x 24mar2020	-0.049	(0.034)	-0.051	(0.035)
turnout x 25mar2020	-0.059	(0.034)	-0.060	(0.035)
turnout x 26mar2020	-0.065	(0.035)	-0.062	(0.036)
turnout x 27mar2020	-0.057	(0.035)	-0.055	(0.036)
turnout x 28mar2020	-0.055	(0.035)	-0.051	(0.036)
turnout x 29mar2020	-0.061	(0.035)	-0.059	(0.036)
turnout x 30mar2020	-0.067	(0.035)	-0.061	(0.036)
turnout x 31mar2020	-0.067	(0.036)	-0.060	(0.036)
turnout x 01apr2020	-0.077	(0.036)	-0.068	(0.037)
turnout x 02apr2020	-0.081	(0.036)	-0.069	(0.037)
turnout x 03apr2020	-0.081	(0.036)	-0.069	(0.037)
turnout x 04apr2020	-0.078	(0.037)	-0.062	(0.037)
turnout x 05apr2020	-0.074	(0.037)	-0.061	(0.038)
turnout x 06apr2020	-0.078	(0.037)	-0.064	(0.038)
turnout x 07apr2020	-0.091	(0.037)	-0.075	(0.038)
turnout x 08apr2020	-0.088	(0.037)	-0.068	(0.037)
turnout x 09apr2020	-0.080	(0.035)	-0.060	(0.036)
turnout x 10apr2020	-0.092	(0.035)	-0.072	(0.037)
turnout x 11apr2020	-0.088	(0.036)	-0.063	(0.037)
turnout x 12apr2020	-0.093	(0.037)	-0.070	(0.038)
turnout x 13apr2020	-0.086	(0.036)	-0.063	(0.037)
turnout x 14apr2020	-0.075	(0.036)	-0.049	(0.037)
turnout x 15apr2020	-0.071	(0.036)	-0.046	(0.037)
controls x day FE	no		yes	
municipality FE	yes		yes	
province x day FE	yes		yes	
mean	4.645		4.645	
observations	140,362		140,362	

Notes: This table presents the regression results from our excess mortality regression for Italy in equation (2). Standard errors clustered at the municipality level in parenthesis. Column (2) adds control variables interacted with day FE.

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Table C.3: Effect of social capital on mobility

	(1)		(2)		(3)		(4)	
turnout x jan week 2	0.042	(0.036)	0.040	(0.035)	-0.010	(0.025)	-0.012	(0.023)
turnout x jan week 3	0.068	(0.044)	0.071	(0.043)	0.015	(0.028)	0.048	(0.025)
turnout x jan week 4	0.029	(0.040)	0.035	(0.039)	-0.047	(0.029)	-0.011	(0.026)
turnout x feb week 1	-0.030	(0.040)	-0.026	(0.039)	-0.043	(0.030)	0.015	(0.030)
turnout x feb week 2	-0.006	(0.041)	0.000	(0.040)	-0.026	(0.036)	0.048	(0.030)
turnout x feb week 3	-0.032	(0.048)	-0.032	(0.047)	-0.037	(0.037)	-0.021	(0.030)
turnout x feb week 4	-0.117	(0.079)	-0.101	(0.081)	-0.088	(0.067)	-0.138	(0.060)
turnout x mar week 1	-0.156	(0.070)	-0.156	(0.070)	-0.119	(0.062)	-0.196	(0.054)
turnout x mar week 2	-0.072	(0.154)	-0.119	(0.165)	-0.075	(0.097)	-0.328	(0.113)
turnout x mar week 3	-0.005	(0.191)	-0.058	(0.204)	-0.006	(0.129)	-0.299	(0.150)
turnout x mar week 4	-0.062	(0.204)	-0.120	(0.217)	-0.052	(0.142)	-0.338	(0.153)
controls x week FE	yes		yes		yes		yes	
log GDP per capita x week FE	yes		no		yes		no	
province FE	yes		yes		yes		yes	
week FE	no		no		yes		yes	
NUTS1 x week FE	yes		yes		no		no	
mean	5.927		5.927		5.927		5.927	
observations	1,248		1,248		1,248		1,248	

Notes: This table presents the regression results from our baseline model in equation (1). Standard errors clustered at the province level in parenthesis

Table C.4: Effect of social capital on the spread of Covid-19 cases with controls

	(1)		(2)		(3)	
turnout x 10mar2020	-0.018	(0.062)	-0.081	(0.108)	-0.114	(0.108)
turnout x 11mar2020	-0.079	(0.104)	-0.124	(0.142)	-0.167	(0.161)
turnout x 12mar2020	-0.159	(0.109)	-0.295	(0.159)	-0.255	(0.165)
turnout x 13mar2020	-0.275	(0.124)	-0.397	(0.169)	-0.341	(0.174)
turnout x 14mar2020	-0.341	(0.129)	-0.482	(0.176)	-0.397	(0.176)
turnout x 15mar2020	-0.335	(0.140)	-0.513	(0.186)	-0.449	(0.177)
turnout x 16mar2020	-0.275	(0.143)	-0.416	(0.187)	-0.335	(0.194)
turnout x 17mar2020	-0.258	(0.150)	-0.405	(0.199)	-0.388	(0.202)
turnout x 18mar2020	-0.265	(0.156)	-0.448	(0.209)	-0.428	(0.206)
turnout x 19mar2020	-0.276	(0.166)	-0.418	(0.213)	-0.380	(0.209)
turnout x 20mar2020	-0.302	(0.162)	-0.449	(0.212)	-0.395	(0.197)
turnout x 21mar2020	-0.288	(0.165)	-0.420	(0.214)	-0.341	(0.197)
turnout x 22mar2020	-0.308	(0.166)	-0.448	(0.216)	-0.389	(0.197)
turnout x 23mar2020	-0.297	(0.166)	-0.440	(0.215)	-0.370	(0.202)
turnout x 24mar2020	-0.285	(0.167)	-0.407	(0.217)	-0.350	(0.206)
turnout x 25mar2020	-0.285	(0.172)	-0.416	(0.220)	-0.354	(0.207)
turnout x 26mar2020	-0.292	(0.171)	-0.421	(0.215)	-0.363	(0.204)
turnout x 27mar2020	-0.340	(0.173)	-0.466	(0.220)	-0.406	(0.207)
turnout x 28mar2020	-0.354	(0.171)	-0.469	(0.218)	-0.396	(0.204)
turnout x 29mar2020	-0.351	(0.174)	-0.463	(0.222)	-0.405	(0.207)

continued

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Table C.4 continued

	(1)		(2)		(3)	
turnout x 30mar2020	-0.331	(0.171)	-0.428	(0.218)	-0.369	(0.203)
turnout x 31mar2020	-0.325	(0.171)	-0.416	(0.218)	-0.353	(0.202)
turnout x 01apr2020	-0.320	(0.170)	-0.397	(0.216)	-0.326	(0.200)
turnout x 02apr2020	-0.322	(0.170)	-0.402	(0.216)	-0.342	(0.201)
turnout x 03apr2020	-0.335	(0.171)	-0.408	(0.218)	-0.342	(0.205)
turnout x 04apr2020	-0.336	(0.172)	-0.403	(0.220)	-0.332	(0.206)
turnout x 05apr2020	-0.368	(0.174)	-0.449	(0.219)	-0.389	(0.209)
turnout x 06apr2020	-0.380	(0.174)	-0.456	(0.219)	-0.397	(0.208)
turnout x 07apr2020	-0.380	(0.174)	-0.454	(0.219)	-0.379	(0.207)
turnout x 08apr2020	-0.408	(0.175)	-0.490	(0.220)	-0.404	(0.207)
turnout x 09apr2020	-0.405	(0.175)	-0.488	(0.221)	-0.414	(0.208)
turnout x 10apr2020	-0.408	(0.175)	-0.495	(0.220)	-0.420	(0.209)
turnout x 11apr2020	-0.404	(0.176)	-0.493	(0.221)	-0.416	(0.210)
turnout x 12apr2020	-0.409	(0.177)	-0.496	(0.222)	-0.418	(0.214)
turnout x 13apr2020	-0.409	(0.177)	-0.499	(0.222)	-0.422	(0.213)
turnout x 14apr2020	-0.410	(0.177)	-0.501	(0.224)	-0.406	(0.213)
turnout x 15apr2020	-0.412	(0.178)	-0.504	(0.224)	-0.407	(0.212)
turnout x 16apr2020	-0.410	(0.178)	-0.502	(0.224)	-0.414	(0.213)
turnout x 17apr2020	-0.403	(0.177)	-0.497	(0.223)	-0.412	(0.213)
turnout x 18apr2020	-0.406	(0.177)	-0.501	(0.223)	-0.417	(0.212)
turnout x 19apr2020	-0.403	(0.177)	-0.500	(0.223)	-0.413	(0.214)
turnout x 20apr2020	-0.403	(0.177)	-0.503	(0.223)	-0.420	(0.213)
turnout x 21apr2020	-0.401	(0.177)	-0.501	(0.223)	-0.398	(0.211)
turnout x 22apr2020	-0.399	(0.178)	-0.501	(0.223)	-0.395	(0.211)
turnout x 23apr2020	-0.400	(0.178)	-0.498	(0.224)	-0.400	(0.211)
turnout x 24apr2020	-0.400	(0.178)	-0.498	(0.223)	-0.400	(0.213)
turnout x 25apr2020	-0.398	(0.178)	-0.498	(0.223)	-0.406	(0.211)
turnout x 26apr2020	-0.398	(0.178)	-0.499	(0.224)	-0.402	(0.214)
turnout x 27apr2020	-0.403	(0.178)	-0.504	(0.224)	-0.412	(0.213)
turnout x 28apr2020	-0.404	(0.178)	-0.504	(0.224)	-0.392	(0.213)
turnout x 29apr2020	-0.403	(0.179)	-0.503	(0.224)	-0.388	(0.213)
turnout x 30apr2020	-0.405	(0.179)	-0.506	(0.224)	-0.400	(0.213)
turnout x 01may2020	-0.404	(0.179)	-0.507	(0.224)	-0.403	(0.214)
turnout x 02may2020	-0.406	(0.179)	-0.509	(0.224)	-0.413	(0.213)
turnout x 03may2020	-0.406	(0.179)	-0.509	(0.225)	-0.407	(0.216)
turnout x 04may2020	-0.405	(0.179)	-0.508	(0.225)	-0.412	(0.215)
turnout x 05may2020	-0.405	(0.179)	-0.508	(0.225)	-0.393	(0.214)
turnout x 06may2020	-0.405	(0.180)	-0.508	(0.225)	-0.390	(0.215)
turnout x 07may2020	-0.403	(0.180)	-0.506	(0.225)	-0.397	(0.214)
turnout x 08may2020	-0.399	(0.179)	-0.500	(0.224)	-0.394	(0.214)
turnout x 09may2020	-0.396	(0.179)	-0.496	(0.224)	-0.399	(0.212)
turnout x 10may2020	-0.392	(0.178)	-0.492	(0.223)	-0.392	(0.214)
turnout x 11may2020	-0.390	(0.178)	-0.490	(0.223)	-0.396	(0.212)
turnout x 12may2020	-0.389	(0.178)	-0.489	(0.223)	-0.374	(0.212)

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Table C.4 continued

	(1)		(2)		(3)	
turnout x 13may2020	-0.388	(0.178)	-0.485	(0.222)	-0.367	(0.212)
turnout x 14may2020	-0.387	(0.178)	-0.483	(0.223)	-0.372	(0.211)
turnout x 15may2020	-0.387	(0.178)	-0.482	(0.223)	-0.369	(0.212)
turnout x 16may2020	-0.388	(0.178)	-0.483	(0.223)	-0.380	(0.211)
turnout x 17may2020	-0.388	(0.178)	-0.484	(0.223)	-0.368	(0.214)
turnout x 18may2020	-0.387	(0.177)	-0.482	(0.223)	-0.371	(0.212)
turnout x 19may2020	-0.387	(0.178)	-0.483	(0.223)	-0.353	(0.213)
province FE	yes		yes		yes	
NUTS1 x day FE	yes		yes		yes	
controls x day FE	no		yes		yes	
controls x weeks-since-outbreak FE	no		no		yes	
Mean	4.645		4.645		4.645	
Observations	7,681		7,681		7,681	

Notes: This table presents the regression results from our baseline model including controls for Italy in equation (1). Standard errors clustered at the province level in parenthesis. Columns (2) and (3) add control variables interacted with day FE and weeks-since-outbreak FE.

Table C.5: Effect of social capital on the spread of Covid-19 cases: literacy rates in 1821

	(1)	
literacy rate 1821 x 09mar2020	-0.010	(0.066)
literacy rate 1821 x 10mar2020	-0.043	(0.077)
literacy rate 1821 x 11mar2020	-0.048	(0.077)
literacy rate 1821 x 12mar2020	-0.061	(0.085)
literacy rate 1821 x 13mar2020	-0.081	(0.097)
literacy rate 1821 x 14mar2020	-0.079	(0.104)
literacy rate 1821 x 15mar2020	-0.142	(0.105)
literacy rate 1821 x 16mar2020	-0.180	(0.106)
literacy rate 1821 x 17mar2020	-0.219	(0.111)
literacy rate 1821 x 18mar2020	-0.272	(0.115)
literacy rate 1821 x 19mar2020	-0.303	(0.114)
literacy rate 1821 x 20mar2020	-0.293	(0.127)
literacy rate 1821 x 21mar2020	-0.315	(0.130)
literacy rate 1821 x 22mar2020	-0.319	(0.132)
literacy rate 1821 x 23mar2020	-0.335	(0.136)
literacy rate 1821 x 24mar2020	-0.317	(0.141)
literacy rate 1821 x 25mar2020	-0.319	(0.143)
literacy rate 1821 x 26mar2020	-0.336	(0.148)
literacy rate 1821 x 27mar2020	-0.339	(0.150)
literacy rate 1821 x 28mar2020	-0.347	(0.150)
literacy rate 1821 x 29mar2020	-0.350	(0.152)
literacy rate 1821 x 30mar2020	-0.333	(0.155)
literacy rate 1821 x 31mar2020	-0.332	(0.157)
literacy rate 1821 x 01apr2020	-0.322	(0.158)
literacy rate 1821 x 02apr2020	-0.318	(0.160)
literacy rate 1821 x 03apr2020	-0.319	(0.160)
literacy rate 1821 x 04apr2020	-0.330	(0.162)
literacy rate 1821 x 05apr2020	-0.380	(0.163)
literacy rate 1821 x 06apr2020	-0.382	(0.163)
literacy rate 1821 x 07apr2020	-0.375	(0.165)
literacy rate 1821 x 08apr2020	-0.389	(0.166)
literacy rate 1821 x 09apr2020	-0.386	(0.167)
literacy rate 1821 x 10apr2020	-0.384	(0.168)
literacy rate 1821 x 11apr2020	-0.380	(0.169)
literacy rate 1821 x 12apr2020	-0.381	(0.171)
literacy rate 1821 x 13apr2020	-0.381	(0.174)
literacy rate 1821 x 14apr2020	-0.388	(0.177)
literacy rate 1821 x 15apr2020	-0.390	(0.177)
literacy rate 1821 x 16apr2020	-0.381	(0.179)
literacy rate 1821 x 17apr2020	-0.376	(0.180)
literacy rate 1821 x 18apr2020	-0.375	(0.182)
literacy rate 1821 x 19apr2020	-0.375	(0.183)

continued

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Table C.5 continued

	(1)	
literacy rate 1821 x 20apr2020	-0.376	(0.183)
literacy rate 1821 x 21apr2020	-0.375	(0.183)
literacy rate 1821 x 22apr2020	-0.377	(0.184)
literacy rate 1821 x 23apr2020	-0.377	(0.184)
literacy rate 1821 x 24apr2020	-0.376	(0.185)
literacy rate 1821 x 25apr2020	-0.377	(0.187)
literacy rate 1821 x 26apr2020	-0.376	(0.187)
literacy rate 1821 x 27apr2020	-0.377	(0.187)
literacy rate 1821 x 28apr2020	-0.377	(0.186)
literacy rate 1821 x 29apr2020	-0.376	(0.187)
literacy rate 1821 x 30apr2020	-0.375	(0.187)
literacy rate 1821 x 01may2020	-0.376	(0.187)
literacy rate 1821 x 02may2020	-0.376	(0.187)
literacy rate 1821 x 03may2020	-0.375	(0.187)
literacy rate 1821 x 04may2020	-0.375	(0.187)
literacy rate 1821 x 05may2020	-0.374	(0.188)
literacy rate 1821 x 06may2020	-0.374	(0.188)
literacy rate 1821 x 07may2020	-0.372	(0.188)
literacy rate 1821 x 08may2020	-0.373	(0.188)
literacy rate 1821 x 09may2020	-0.373	(0.188)
literacy rate 1821 x 10may2020	-0.374	(0.188)
literacy rate 1821 x 11may2020	-0.374	(0.188)
literacy rate 1821 x 12may2020	-0.371	(0.187)
literacy rate 1821 x 13may2020	-0.371	(0.187)
literacy rate 1821 x 14may2020	-0.371	(0.187)
literacy rate 1821 x 15may2020	-0.371	(0.187)
literacy rate 1821 x 16may2020	-0.371	(0.187)
literacy rate 1821 x 17may2020	-0.372	(0.187)
literacy rate 1821 x 18may2020	-0.372	(0.187)
literacy rate 1821 x 19may2020	-0.371	(0.187)
province FE	yes	
NUTS1 x day FE	yes	
mean	4.647	
observations	5,029	

Notes: This table presents the regression results from our baseline model in equation (1). Standard errors clustered at the province level in parenthesis

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Table C.6: Effect of social capital on the spread of Covid-19 cases: blood donations per capita

	(1)	
blood donations per capita x 10mar2020	-0.075	(0.037)
blood donations per capita x 11mar2020	-0.158	(0.052)
blood donations per capita x 12mar2020	-0.129	(0.061)
blood donations per capita x 13mar2020	-0.168	(0.063)
blood donations per capita x 14mar2020	-0.136	(0.060)
blood donations per capita x 15mar2020	-0.109	(0.064)
blood donations per capita x 16mar2020	-0.142	(0.061)
blood donations per capita x 17mar2020	-0.152	(0.067)
blood donations per capita x 18mar2020	-0.156	(0.069)
blood donations per capita x 19mar2020	-0.146	(0.068)
blood donations per capita x 20mar2020	-0.167	(0.068)
blood donations per capita x 21mar2020	-0.193	(0.070)
blood donations per capita x 22mar2020	-0.187	(0.069)
blood donations per capita x 23mar2020	-0.191	(0.068)
blood donations per capita x 24mar2020	-0.196	(0.069)
blood donations per capita x 25mar2020	-0.162	(0.074)
blood donations per capita x 26mar2020	-0.142	(0.075)
blood donations per capita x 27mar2020	-0.135	(0.077)
blood donations per capita x 28mar2020	-0.134	(0.077)
blood donations per capita x 29mar2020	-0.148	(0.078)
blood donations per capita x 30mar2020	-0.163	(0.077)
blood donations per capita x 31mar2020	-0.157	(0.080)
blood donations per capita x 01apr2020	-0.161	(0.079)
blood donations per capita x 02apr2020	-0.168	(0.079)
blood donations per capita x 03apr2020	-0.167	(0.079)
blood donations per capita x 04apr2020	-0.165	(0.079)
blood donations per capita x 05apr2020	-0.183	(0.080)
blood donations per capita x 06apr2020	-0.180	(0.082)
blood donations per capita x 07apr2020	-0.182	(0.082)
blood donations per capita x 08apr2020	-0.190	(0.084)
blood donations per capita x 09apr2020	-0.194	(0.084)
blood donations per capita x 10apr2020	-0.192	(0.085)
blood donations per capita x 11apr2020	-0.192	(0.085)
blood donations per capita x 12apr2020	-0.192	(0.086)
blood donations per capita x 13apr2020	-0.191	(0.085)
blood donations per capita x 14apr2020	-0.192	(0.085)
blood donations per capita x 15apr2020	-0.193	(0.085)
blood donations per capita x 16apr2020	-0.192	(0.086)
blood donations per capita x 17apr2020	-0.193	(0.086)
blood donations per capita x 18apr2020	-0.195	(0.086)
blood donations per capita x 19apr2020	-0.197	(0.086)

continued

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Table C.6 continued

	(1)	
blood donations per capita x 20apr2020	-0.197	(0.085)
blood donations per capita x 21apr2020	-0.194	(0.085)
blood donations per capita x 22apr2020	-0.193	(0.086)
blood donations per capita x 23apr2020	-0.193	(0.086)
blood donations per capita x 24apr2020	-0.189	(0.088)
blood donations per capita x 25apr2020	-0.188	(0.089)
blood donations per capita x 26apr2020	-0.188	(0.089)
blood donations per capita x 27apr2020	-0.189	(0.089)
blood donations per capita x 28apr2020	-0.191	(0.089)
blood donations per capita x 29apr2020	-0.193	(0.089)
blood donations per capita x 30apr2020	-0.193	(0.089)
blood donations per capita x 01may2020	-0.194	(0.089)
blood donations per capita x 02may2020	-0.195	(0.090)
blood donations per capita x 03may2020	-0.195	(0.090)
blood donations per capita x 04may2020	-0.195	(0.090)
blood donations per capita x 05may2020	-0.195	(0.090)
blood donations per capita x 06may2020	-0.195	(0.090)
blood donations per capita x 07may2020	-0.196	(0.090)
blood donations per capita x 08may2020	-0.195	(0.090)
blood donations per capita x 09may2020	-0.195	(0.090)
blood donations per capita x 10may2020	-0.194	(0.090)
blood donations per capita x 11may2020	-0.194	(0.089)
blood donations per capita x 12may2020	-0.194	(0.090)
blood donations per capita x 13may2020	-0.195	(0.089)
blood donations per capita x 14may2020	-0.196	(0.090)
blood donations per capita x 15may2020	-0.197	(0.090)
blood donations per capita x 16may2020	-0.197	(0.090)
blood donations per capita x 17may2020	-0.197	(0.090)
blood donations per capita x 18may2020	-0.197	(0.090)
blood donations per capita x 19may2020	-0.196	(0.090)
province FE	yes	
NUTS1 x day FE	yes	
mean	4.628	
observations	7,393	

Notes: This table presents the regression results from our baseline model in equation (1). Standard errors clustered at the province level in parenthesis

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