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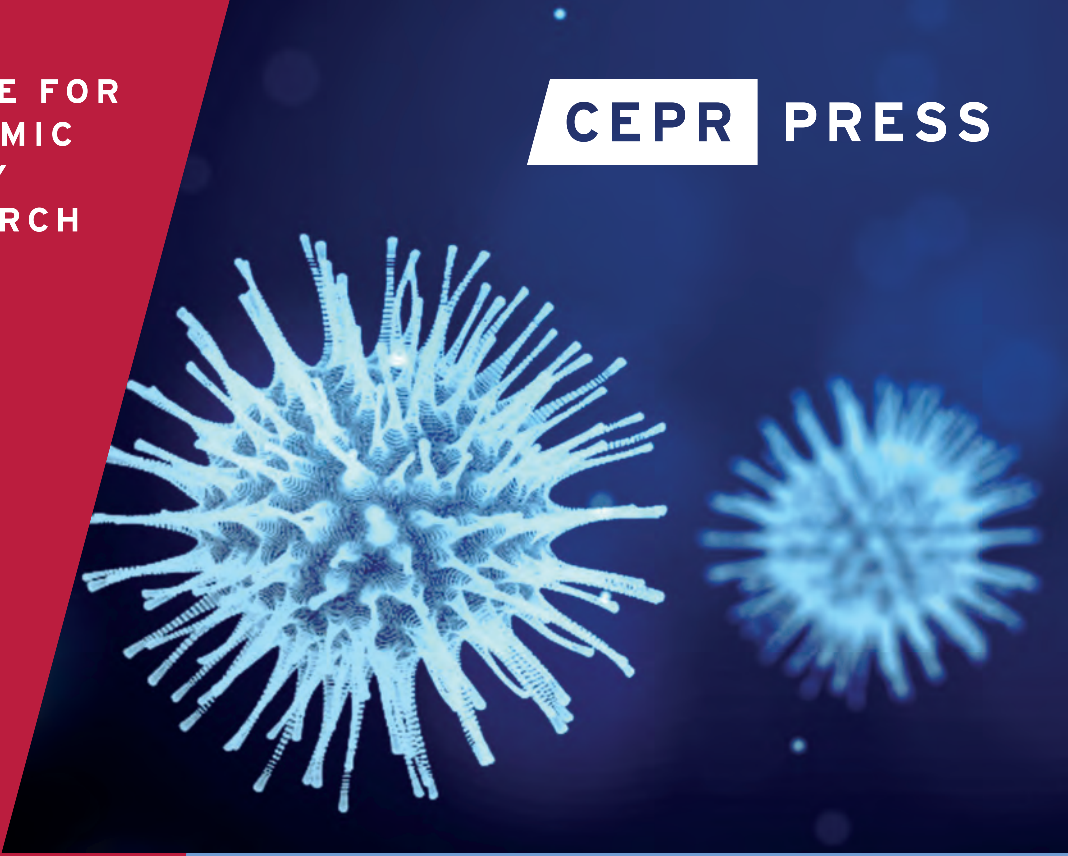

COVID ECONOMICS

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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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

*Econometrica**

Economic Journal

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*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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Covid Economics Issue 39, 23 July 2020

Global macroeconomic scenarios of the COVID-19 pandemic[1]

Warwick McKibbin[2] and Roshen Fernando[3]

Date submitted: 13 July 2020; Date accepted: 14 July 2020

The COVID-19 global pandemic has caused significant global economic and social disruption. In McKibbin and Fernando (2020), we used data from historical pandemics to explore seven plausible scenarios of the economic consequences if COVID-19 were to become a global pandemic. In this paper, we use currently observed epidemiological outcomes across countries and recent data on sectoral shutdowns and economic shocks to estimate the likely global economic impacts of the pandemic under six new scenarios. The first scenario explores the outcomes if the current course of COVID-19 is successfully controlled, and there is only a mild recurrence in 2021. We then explore scenarios where the opening of economies results in recurrent outbreaks of various magnitudes and countries respond with and without economic shutdowns. We also explore the impact if no vaccine becomes available and the world must adapt to living with COVID-19 in coming decades. The final scenario is the case where a given country is in the most optimistic scenario (Scenario 1), but the rest of the world is in the most pessimistic scenario. The scenarios demonstrate that even a contained outbreak will significantly impact the global economy in the coming years. The economic consequences of the pandemic under plausible scenarios are substantial and the ongoing economic adjustment is far from over.

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1 We gratefully acknowledge financial support from the Australia Research Council Centre of Excellence in Population Ageing Research (CE170100005). We thank Renee Fry-McKibbin, Jeff Oughton, Louise Sheiner and David Wessel and participants at a CAMA webinar for helpful comments. We thank Ausgrid for providing electricity use data that assisted in the calibration of shocks and Peter Wilcoxen and Larry Weifeng Liu for their research collaboration on the G-Cubed model. We also acknowledge the contributions to earlier research on modelling of pandemics with Jong-Wha Lee and Alexandra Sidorenko.

2 Australian National University; the Brookings Institution; and Centre of Excellence in Population Ageing Research (CEPAR).

3 Australian National University and Centre of Excellence in Population Ageing Research (CEPAR).

1 Introduction

In late 2019, a novel coronavirus was causing infections in China. The virus had close virological characteristics to the coronavirus that caused SARS (SARS-CoV) and was named SARS-CoV-2. Even though the SARS-CoV-2 has been less fatal than SARS-CoV, SARS-CoV-2 has been much more infectious. Shortly after the Chinese outbreak, other countries also began reporting cases. The evolving epidemic was officially declared a pandemic by the World Health Organization (WHO) on 11 March 2020.

In early February 2020, we undertook a study that applied data from historical pandemics, information on the evolving epidemic in China and our experience from modelling SARS and Bird Flu to explore the potential global economic implications of COVID-19 under seven plausible scenarios in a global economic model. "The global macroeconomic impacts of COVID-19: seven scenarios" was released on 2 March 2020. Early results were made available to policymakers in major economies and international institutions. At the time the paper was written, it was still uncertain whether the outbreak would translate into a pandemic. Thus, to estimate what could be the likely costs of a pandemic, three of the seven scenarios explored the economic costs to the world if the outbreak only occurred in China and four of the scenarios explored the global economic costs if a global pandemic occurred but at varying degrees of attack rates and case fatality rates.

The evolution of the pandemic and the economic implications continue to be highly uncertain. However, as new information emerges, notably greater understanding through scientifically based interventions in some countries and outright failure in others, the nature of the uncertainty has changed. Initially, uncertainty was about how close COVID-19 would be to the historical experience of pandemics. After six months, the concern is now about how frequently the pandemic might recur and how high the economic costs of responding or not responding in some countries might be. Policy in many countries initially was designed to contain the virus and to minimise economic disruption, particularly in the labour market. The focus now is how to open economies hit with a massive economic shock and how economies will adapt to the post-COVID-19 world. It is uncertain whether a vaccine will be available in time to prevent more pandemic waves and, if not, what would be the least costly option of managing them. It is an open question of whether lockdowns are the right option for managing recurring waves or if it will be possible for people to adapt to long-term social distancing and improved hygiene practices.

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In this paper, we attempt to guide policymakers determine how different responses might change possible economic futures. In addition to our previous experience in modelling pandemics and particularly COVID-19, we capitalise on the novel, yet imperfect, information on cases and responses to the pandemic worldwide.

The paper is structured as follows. The next section places the current study in the context of our previous study and other recent studies conducted by the International Monetary Fund (IMF), the Organization for Economic Cooperation and Development (OECD) and the World Bank on economic repercussions of COVID-19. Section 3 summarises the G-Cubed model used in the study. Section 4 explains in depth how and why different scenarios and shocks were constructed. The results from the simulations are presented in Section 5 before we conclude and present possible policy implications arising from the study in the final section.

2 Studies on Global Macroeconomics of COVID-19

When we conducted our first study, it was still uncertain whether the outbreak in China would spread to the rest of the world. Thus, our study included three scenarios where the outbreak was contained in China, still varying the proportion of people getting infected (the attack rate). We also varied the mortality rates using the case-fatality rate for SARS as a benchmark. The remaining four scenarios explored the economic implications if the outbreak were to translate into a global pandemic. Similar to the first three scenarios, we had three attack rates with varying degrees of mortality, resembling those of SARS and flu. The seventh scenario was a recurring pandemic at a moderate attack rate and case-fatality rate. Table 1 summarises these scenarios.

A handful of countries from East Asia and the Middle East had some previous experience with coronavirus outbreaks. However, the vast majority of the countries had limited experience. Thus, when formulating the shocks in the original study, including the mortality and morbidity, impact on productivity and consumption as well as changes in sector risk premia and government expenditure, the formulation of shocks for other countries used China as a benchmark. In the study, the susceptibility to a coronavirus outbreak for other countries relative to China was modelled using an Index of Vulnerability. This index considered population density within a given country, openness to tourism and health and sanitation standards of the country.

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Table 1 - Scenario assumptions in *The Global Macroeconomic Impacts of COVID-19: Seven Scenarios*

Scenario	Countries Affected	Severity	Attack Rate for China	Case Fatality Rate China	Nature of Shocks	Shocks Activated	Shocks Activated
						China	Other countries
1	China	Low	1.0%	2.0%	Temporary	All	Risk
2	China	Mid	10.0%	2.5%	Temporary	All	Risk
3	China	High	30.0%	3.0%	Temporary	All	Risk
4	Global	Low	10.0%	2.0%	Temporary	All	All
5	Global	Mid	20.0%	2.5%	Temporary	All	All
6	Global	High	30.0%	3.0%	Temporary	All	All
7	Global	Low	10.0%	2.0%	Permanent	All	All

Source: McKibbin and Fernando (2020a)

With the gradual evolution of the outbreak, more information has become available specifically regarding the cases, deaths and policy responses by governments to manage the pandemic. Nevertheless, as observed in the World Bank's *Global Economic Prospects* report (2020b), released on 8 June 2020, there have been very few studies exploring global economic consequences of the COVID-19 pandemic to date. The studies by the World Trade Organization (2020), Maliszewska et al. (2020) and the World Bank (2020a) utilise Computable General Equilibrium (CGE) models and mainly focus on the impact of mortality, morbidity and increased production costs on the economies. A study by the International Monetary Fund [IMF] (2020c), which utilises a semi-structural Dynamic Stochastic General Equilibrium (DSGE) model, also includes disruptions to financial markets.

The OECD (2020) released *Global Economic Outlook* on 10 June 2020, in which it explores two scenarios focusing on the recurrence of COVID-19 and presents its expectations about global economic repercussions. Table 2 summarises the current expectations about the global economic consequences of the pandemic set out in the recent reports by the IMF (2020a), World Bank (2020b) and OECD (2020), segregated by the countries and the regions that we focus on in this study.

The range of estimates across countries and studies are diverse. Still, all studies show a substantial negative shock to the global economy in 2020 with an expected rebound in 2021 but not back to the levels of GDP in most countries experienced in 2019. These are consistent with the analysis in this paper.

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Table 2 - GDP forecasts by the international financial institutions

Source	OECD (June 2020)				IMF (April 2020)		World Bank (June 2020)	
Country/Region	Single-hit Scenario 2020	Single-hit Scenario 2021	Double-hit Scenario 2020	Double-hit Scenario 2021	2020	2021	2020	2021
Unit	Average of Quarterly GDP Deviations from November 2019 Projections				Difference from January 2020 GDP Projections		Real GDP Growth	
Argentina	N/A	N/A	N/A	N/A	-6.30%	2.40%	-7.30%	2.10%
Australia	-0.78%	3.58%	-6.35%	5.35%	-7.70%	2.90%	-7.00%	3.90%
Brazil	N/A	N/A	N/A	N/A	-7.50%	0.60%	-8.00%	2.20%
Canada	-5.38%	4.63%	-11.80%	8.18%	-8.00%	2.40%	-7.00%	3.90%
China	N/A	N/A	N/A	N/A	-4.80%	3.40%	1.00%	6.90%
France	4.40%	3.18%	-7.38%	12.75%	-8.50%	3.20%	-7.00%	3.90%
Germany	2.83%	2.30%	-6.25%	6.65%	-8.10%	3.80%	-7.00%	3.90%
India	N/A	N/A	N/A	N/A	-3.90%	0..9%	-3.20%	3.10%
Indonesia	N/A	N/A	N/A	N/A	-5.40%	2.70%	0.00%	4.80%
Italy	2.25%	3.73%	-9.50%	13.68%	-9.60%	4.10%	-7.00%	3.90%
Japan	-0.60%	0.58%	-5.88%	2.10%	-5.90%	2.50%	-6.10%	2.50%
Mexico	N/A	N/A	N/A	N/A	-7.60%	1.40%	-7.50%	3.00%
Other Asia	N/A	N/A	N/A	N/A	-5.40%	2.70%	0.50%	6.60%
Other oil producing countries	N/A	N/A	N/A	N/A	-5.60%	0.80%	-4.20%	30.00%
Republic of Korea	-0.48%	2.28%	-5.45%	4.73%	-7.70%	2.90%	-7.00%	3.90%
Rest of Euro Zone	1.88%	3.20%	-8.38%	10.25%	-8.70%	3.10%	-9.10%	4.50%
Rest of OECD	-1.78%	3.73%	-9.35%	8.50%	-7.70%	2.90%	-7.00%	3.90%
Rest of the World	N/A	N/A	N/A	N/A	-6.30%	2.40%	-5.20%	4.20%
Russia	N/A	N/A	N/A	N/A	-7.40%	1.50%	-6.00%	2.70%
Saudi Arabia	N/A	N/A	N/A	N/A	-4.20%	0.70%	-3.80%	2.50%
South Africa	N/A	N/A	N/A	N/A	-6.60%	3.00%	-7.10%	2.90%
Turkey	N/A	N/A	N/A	N/A	-8.70%	3.10%	-3.80%	5.00%
United Kingdom	-1.45%	7.73%	-13.03%	16.10%	-7.90%	2.50%	-7.00%	3.90%
United States of America	-4.05%	4.60%	-9.48%	7.53%	-7.90%	3.00%	-6.10%	4.00%

3 The Hybrid DSGE/CGE Global Model

In this paper, we apply a global intertemporal general equilibrium model with heterogeneous agents called the G-Cubed Multi-Country Model. This model is a hybrid of Dynamic Stochastic General Equilibrium (DSGE) Models and Computable General Equilibrium (CGE) Models developed by McKibbin and Wilcoxen (1999, 2013).

The G-Cubed Model

The version of the G-Cubed (G20) model used in this paper can be found in McKibbin and Triggs (2018) who extended the original model documented in McKibbin and Wilcoxen (1999, 2013). The model has six sectors and 24 countries and regions. Table 3 presents all the regions and sectors in the model. Some of the data inputs include the I/O tables found in the Global Trade Analysis Project (GTAP) database (Aguiar et al. 2019), which enables us to differentiate sectors by country of production within a DSGE framework. Firms in each sector in each country produce output using the primary factor inputs of capital (K) and labour (L) as well as the intermediate or production chains of inputs in energy (E) and materials (M). These linkages are both within a country and across countries.

McKibbin and Wilcoxen (1999, 2013) document the approach embodied in the G-Cubed model. Several key features of the standard G-Cubed model are worth highlighting here.

First, the model completely accounts for stocks and flows of physical and financial assets. For example, budget deficits accumulate into government debt, and current account deficits accumulate into foreign debt. The model imposes an intertemporal budget constraint on all households, firms, governments, and countries. Thus, a long-run stock equilibrium obtains through the adjustment of asset prices, such as the interest rate for government fiscal positions or real exchange rates for the balance of payments. However, the adjustment towards the long-run equilibrium of each economy can be slow, occurring over much of a century.

Second, firms and households in G-Cubed must use money issued by central banks for all transactions. Thus, central banks in the model set short term nominal interest rates to target macroeconomic outcomes (such as inflation, unemployment, exchange rates, etc.) based on Henderson-McKibbin-Taylor monetary rules. These rules are designed to approximate actual monetary regimes in each country or region in the model. These monetary rules tie down the long-run inflation rates in each country as well as allowing short term adjustment of policy to smooth fluctuations in the real economy.

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Table 3 - Overview of the G-Cubed (G20) model

Countries (20)	Regions (4)
Argentina	Rest of the OECD
Australia	Rest of Asia
Brazil	Other oil-producing countries
Canada	Rest of the world
China	
Rest of Eurozone	**Sectors (6)**
France	Energy
Germany	Mining
Indonesia	Agriculture (including fishing and hunting)
India	Durable manufacturing
Italy	Non-durable manufacturing
Japan	Services
Korea	
Mexico	**Economic Agents in each Country (3)**
Russia	A representative household
Saudi Arabia	A representative firm (in each of the 6 production sectors)
South Africa	Government
Turkey	
United Kingdom	
United States	

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Third, nominal wages are sticky and adjust over time based on country-specific labour contracting assumptions. Firms hire labour in each sector up to the points that the marginal product of labour equals the real wage defined in terms of the output price level of that sector. Any excess labour enters the unemployed pool of workers. Unemployment or the presence of excess demand for labour causes the nominal wage to adjust to clear the labour market in the long run. In the short-run, unemployment can arise due to structural supply shocks or changes in aggregate demand in the economy.

Fourth, rigidities prevent the economy from moving quickly from one equilibrium to another. These rigidities include nominal stickiness caused by wage rigidities, costs of adjustment in investment by firms with physical capital being sector-specific in the short-run. The adjustment path is also affected by a lack of complete foresight in the formation of expectations and by monetary and fiscal authorities following particular monetary and fiscal rules. Short-term adjustment to economic shocks can be very different from the long-run equilibrium outcomes. The focus on short-run rigidities is essential for assessing the impact over the first decades of a major shock.

Fifth, we incorporate heterogeneous households and firms. Firms are modelled separately within each sector. We assume two types of consumers and two types of firms within each sector, within each country. One group of consumers and firms base their decisions on forward-looking expectations. The other group follow simple rules of thumb which are optimal in the long-run.

4 Modelling Economic Impacts of COVID-19

4.1 Modelling Scenarios

A pandemic directly affects an economy via its impacts on humans due to infections which lead to morbidity (unable to work temporarily) and mortality (death). There are also likely to be significant changes in the behaviour of households and firms to avoid contracting or transmitting the disease. Also, due to the substantial transmissibility of the SARS-CoV-2, governments across the world have responded with direct policy changes, to varying degrees, to reduce transmission. These responses include restricting movements across as well as within borders, banning public gatherings, closing educational institutions and non-essential businesses. While some countries adopted these measures at very early stages of the outbreak, some countries were late to respond. In general, early responders have witnessed lower levels of transmission, resulting in lower levels of infections and deaths. While controlling the transmission will significantly help the countries to return to the normality sooner and mitigate the long-term economic impacts emanating from the loss of human resources, the change in human behaviour and the industrial shutdowns are causing significant short- and medium-term economic consequences.

At the same time, it is currently uncertain whether the SARS-CoV-2 could be eliminated after the current wave. According to a wide range of medical opinion, the virus may join the other existing coronaviruses and is unlikely to disappear in the immediate future. Thus, until a vaccine for the disease is produced and is widely available for distribution, the COVID-19 pandemic could recur in the future.

In the case of continuous waves, it is unlikely that people and firms would continue to respond to the future potential outbreaks the same way most have responded to the current pandemic, i.e. by changing personal behaviour and by adopting economic shutdowns. In these cases, households and firms would need to select more permanent behavioural changes, including

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adopting better hygiene practices (see Levine & McKibbin (2020)) and implementing social distancing measures.

Given the uncertainty outlined above, we develop six alternative scenarios. Table 4 summarises these scenarios focussing on the number of pandemic waves in each year and whether or not countries respond with lockdowns. The extent of lockdown response is not the same across countries but reflects policies in place as of May 2020.

Table 4 - Modelling Scenarios

Scenario	Number of Waves & Government-imposed Lockdowns in 2020		Number of Waves & Government-imposed Lockdowns in 2021		Recurrence after 2021
	Number of Waves	Existence of Lockdowns	Number of Waves	Existence of Lockdowns	
1	1	Yes	1	Yes	No
2	1	Yes	1	Yes	Yes
3	2	Yes	1	Yes	No
4	2	Yes	2	Yes	No
5	1	Yes	1	No	Yes
	1	No			
6	Country of Interest - 1	Yes	Country of Interest – 0	-	No
	Rest of the World – 2	Yes	Rest of the World – 2	Yes	No

The first scenario assumes all countries experience only a single wave in early 2020 consistent with their experience as of 20 May. For countries that have not peaked by 20 May, we project the epidemiological outcome given the experience of other countries with similar characteristics. Countries are assumed to implement the lockdown measures announced up to 20 May, although the countries differ in the duration of the lockdowns depending on when the outbreak reached the respective country and the management of the severity of the pandemic. After the first wave, as a vaccine is yet to be developed, we assume that a milder outbreak occurs again in early 2021. We assume that infections in the second wave are limited to half of the infections that have emerged during the current wave. We assume that the shocks to households and firms are half of that experienced in 2020 and countries adopt half of the current lockdown durations. This scenario is an optimistic assessment that the current pandemic is at its worst today and will eventually improve, and a vaccine will eliminate future waves after 2021.

The second scenario allows for more persistence in the re-emergence of COVID-19. The first year of the second scenario is as same as the first year of the first scenario. However, the second scenario assumes that the pandemic will recur annually with an exponential decay in the number of infections. The countries are assumed to adopt lockdowns to manage the pandemic at the same rate as the pandemic emerges over time.

The third scenario assumes that countries, who have managed the pandemic with lockdowns, begin to relax the movement restrictions. The third scenario explores the possibility of a second wave emerging again in 2020 because the timing of easing restrictions turns out to be too early. However, the countries manage the second wave better with only half of the infections and lockdown durations compared to the first wave. A third wave, similar to the second wave, also emerges in 2021.

The fourth scenario is the same as the third scenario but with a fourth wave in the second half of 2021. This fourth wave is half of the size of the first wave in 2021 compared to the number of infections and the length of the lockdowns.

The fifth scenario assumes after the first wave, there is no vaccine developed, and the pandemic continues to emerge in subsequent years. The countries that followed lockdown discard that policy in future outbreaks after the first wave. In all countries, the pandemic eventually dies out due to herd immunity. In this case, we assume the increase in equity risk premia do not return to baseline so that there is a permanent change in global risk.

The sixth scenario consists of twenty-four simulations. We assume each country alone experiences scenario 01 while all other countries experience scenario 04. Comparing the first scenario with the sixth scenario shows how much economic impact there is on each country because of worsening global pandemic outcomes even if that country has the pandemic under control.

The shocks and how their magnitudes vary according to the scenarios are discussed next in section 4.2.

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4.2 Shock Formulation

One of the issues that we need to accommodate is the fact that the waves of infections are assumed to be waves over four months rather than over a year. Since the G-Cubed model is an annual model, we adjust the shocks to fit the periodicity of the model.

A flowchart outlining how we calculate each shock is contained in Appendix A. Further details can also be found on the results dashboard available via *https://cama.crawford.anu.edu.au/covid-19-macroeconomic-modelling-results-dashboard* and the discussion that follows.

4.2.1 Shocks to Labour Supply

There are three shocks to labour supply. Economic agents die due to the infection (mortality shock). Workers are also not able to work during their recovery if they catch the disease. People caring for infected children also cannot work and we assume the carers are female workers.

In formulating the mortality component of the labour supply shock, first, we use the number of COVID-19 cases reported across the world from Our World in Data [OWID] (2020) up to 20 May 2020. After 20 May, as the pandemic is continuing in many countries, we model how the pandemic would likely develop given the interventions governments have already implemented and behavioural changes experienced by 20 May 2020. In modelling the case numbers, we utilise a logistic regression model, which is more effective in demonstrating the short-term behaviour of the pandemic compared to compartmental models, and less data demanding compared to agent-based models (Almeshal et al 2020; Batista 2020). The modelling assumes that the momentum the pandemic has demonstrated by 20 May 2020 would continue until the pandemic is controlled within that country. The actual number of reported cases for a given country could change from our extrapolations depending on the responses by the country to the pandemic after 20 May 2020.

After obtaining the number of cases for each country, we distribute the total cases across three main age groups: 0-19 years, 20-59 years and 60+ years, based on data available from various national and international resources including the European Centre for Disease Prevention and Control [ECDC] (2020). For those countries and regions where the cases are broken down by age group could not be found, we approximate this distribution using data for a country with a similar general infection rate and for which the data is available. We then use the case-fatality rates for respective countries as at 20 May 2020 to obtain the overall mortality rates.

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While for the first year of the first scenario we use the epidemiological projections based on the current data, the second wave in the first scenario and the waves in following scenarios have either the same number of infections or a proportion of the infections as in the first year of the first scenario. Table 5 summarises the total number of infections under each scenario for 2020 and 2021, and Table 6 presents the estimated number of deaths under each scenario.

We do not list Scenario 6 in these tables because Scenario 6 is different for each country. Scenario 6 is constructed individually for each country, using Scenario 1 for a focus country and Scenario 4 for all other countries. Thus, twenty-four individual simulations are generated, rotating a new focus country for each simulation. For example, in the case of Argentina, the deaths for Scenario 6 are those from Scenario 1, while the deaths for all other countries are from Scenario 4.

The second component of the labour supply shock utilised the number of infections arising among the working-age population, the 20-59 years old population group, to obtain the number of working days lost due to the incubation after getting infected. We assume the incubation period is 14 days. Table 7 presents the magnitude of the morbidity shock emanating from the working-age population catching the infection for the first two years under each scenario.

The loss of productive work time among the female workers due to caregiving for children is the third component of the shock to labour supply. When estimating this, we utilise the number of cases among the children, i.e. the age group below 20 years, and the average female labour force participation. We also assume only 70 per cent of the female labour force would spend time on caregiving for dependent children. Table 8 presents the magnitude of the morbidity shock for the first two years feeding into simulations arising from the caregiving time spent by the female workers with infected children. This shock is small because few children are infected.

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Table 5 - Number of Infections under each Scenario

Country/Region	Scenario 01		Scenario 02		Scenario 03		Scenario 04		Scenario 05	
	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02
Argentina	12,969	6,485	12,969	6,485	19,454	6,485	19,454	9,727	45,392	64,845
Australia	7,397	3,699	7,397	3,699	11,096	3,699	11,096	5,548	25,890	36,985
Brazil	612,254	306,127	612,254	306,127	918,380	306,127	918,380	459,190	2,142,888	3,061,268
Canada	85,010	42,505	85,010	42,505	127,514	42,505	127,514	63,757	297,533	425,048
China	84,062	42,031	84,062	42,031	126,094	42,031	126,094	63,047	294,218	420,312
France	143,530	71,765	143,530	71,765	215,294	71,765	215,294	107,647	502,354	717,648
Germany	175,747	87,873	175,747	87,873	263,620	87,873	263,620	131,810	615,114	878,734
India	190,089	95,044	190,089	95,044	285,133	95,044	285,133	142,567	665,311	950,444
Indonesia	22,012	11,006	22,012	11,006	33,018	11,006	33,018	16,509	77,041	110,059
Italy	227,777	113,888	227,777	113,888	341,665	113,888	341,665	170,833	797,218	1,138,884
Japan	16,567	8,283	16,567	8,283	24,850	8,283	24,850	12,425	57,983	82,833
Mexico	85,105	42,552	85,105	42,552	127,657	42,552	127,657	63,829	297,866	425,523
Other Asia	60,596	30,298	60,596	30,298	90,893	30,298	90,893	45,447	212,084	302,978
Other oil producing countries	334,765	167,382	334,765	167,382	502,147	167,382	502,147	251,074	1,171,676	1,673,823
Republic of Korea	11,079	5,540	11,079	5,540	16,619	5,540	16,619	8,309	38,777	55,396
Rest of Euro Zone	521,439	260,719	521,439	260,719	782,158	260,719	782,158	391,079	1,825,036	2,607,194
Rest of OECD	108,994	54,497	108,994	54,497	163,490	54,497	163,490	81,745	381,477	544,968
Rest of the World	588,833	294,416	588,833	294,416	883,249	294,416	883,249	441,624	2,060,914	2,944,163
Russia	380,110	190,055	380,110	190,055	570,165	190,055	570,165	285,082	1,330,384	1,900,549
Saudi Arabia	84,628	42,314	84,628	42,314	126,942	42,314	126,942	63,471	296,197	423,138
South Africa	697,561	348,780	697,561	348,780	1,046,341	348,780	1,046,341	523,170	2,441,462	3,487,803
Turkey	152,857	76,428	152,857	76,428	229,285	76,428	229,285	114,643	534,998	764,283
United Kingdom	260,776	130,388	260,776	130,388	391,163	130,388	391,163	195,582	912,715	1,303,878
United States of America	1,601,664	800,832	1,601,664	800,832	2,402,495	800,832	2,402,495	1,201,248	5,605,823	8,008,318

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Table 6 – Number of Deaths Under Each Scenario

Country/Region	Scenario 01		Scenario 02		Scenario 03		Scenario 04		Scenario 05	
	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02
Argentina	593	296	593	296	889	296	889	445	2,075	2,964
Australia	104	52	104	52	156	52	156	78	363	519
Brazil	40,441	20,221	40,441	20,221	60,662	20,221	60,662	30,331	141,544	202,206
Canada	6,362	3,181	6,362	3,181	9,543	3,181	9,543	4,772	22,267	31,810
China	4,638	2,319	4,638	2,319	6,957	2,319	6,957	3,478	16,233	23,190
France	28,363	14,181	28,363	14,181	42,544	14,181	42,544	21,272	99,270	141,814
Germany	8,032	4,016	8,032	4,016	12,047	4,016	12,047	6,024	28,110	40,158
India	5,945	2,972	5,945	2,972	8,917	2,972	8,917	4,459	20,807	29,724
Indonesia	1,456	728	1,456	728	2,183	728	2,183	1,092	5,095	7,278
Italy	32,275	16,137	32,275	16,137	48,412	16,137	48,412	24,206	112,962	161,375
Japan	772	386	772	386	1,159	386	1,159	579	2,703	3,862
Mexico	8,789	4,394	8,789	4,394	13,183	4,394	13,183	6,591	30,760	43,943
Other Asia	1,204	602	1,204	602	1,806	602	1,806	903	4,213	6,019
Other oil producing countries	14,283	7,142	14,283	7,142	21,425	7,142	21,425	10,712	49,992	71,416
Republic of Korea	263	132	263	132	395	132	395	197	921	1,315
Rest of Euro Zone	54,511	27,256	54,511	27,256	81,767	27,256	81,767	40,884	190,790	272,557
Rest of OECD	2,730	1,365	2,730	1,365	4,095	1,365	4,095	2,048	9,555	13,650
Rest of the World	15,163	7,582	15,163	7,582	22,745	7,582	22,745	11,372	53,071	75,815
Russia	3,559	1,780	3,559	1,780	5,339	1,780	5,339	2,670	12,458	17,797
Saudi Arabia	472	236	472	236	708	236	708	354	1,653	2,361
South Africa	12,140	6,070	12,140	6,070	18,211	6,070	18,211	9,105	42,491	60,702
Turkey	4,234	2,117	4,234	2,117	6,351	2,117	6,351	3,175	14,818	21,168
United Kingdom	36,825	18,413	36,825	18,413	55,238	18,413	55,238	27,619	128,888	184,126
United States of America	95,927	47,963	95,927	47,963	143,890	47,963	143,890	71,945	335,744	479,634

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Table 7 - Morbidity Shock due to Workers Catching the Infection for each Scenario

(Proportion of lost days compared to the total workforce working days)

Country/Region	Scenario 01		Scenario 02		Scenario 03		Scenario 04		Scenario 05	
	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02
Argentina	0.0027	0.0013	0.0027	0.0013	0.0040	0.0013	0.0040	0.0020	0.0093	0.0133
Australia	0.0020	0.0010	0.0020	0.0010	0.0030	0.0010	0.0030	0.0015	0.0071	0.0102
Brazil	0.0241	0.0121	0.0241	0.0121	0.0362	0.0121	0.0362	0.0181	0.0844	0.1205
Canada	0.0135	0.0067	0.0135	0.0067	0.0202	0.0067	0.0202	0.0101	0.0472	0.0674
China	0.0004	0.0002	0.0004	0.0002	0.0006	0.0002	0.0006	0.0003	0.0014	0.0020
France	0.0100	0.0050	0.0100	0.0050	0.0150	0.0050	0.0150	0.0075	0.0351	0.0501
Germany	0.0086	0.0043	0.0086	0.0043	0.0129	0.0043	0.0129	0.0065	0.0301	0.0430
India	0.0015	0.0008	0.0015	0.0008	0.0023	0.0008	0.0023	0.0011	0.0054	0.0077
Indonesia	0.0007	0.0003	0.0007	0.0003	0.0010	0.0003	0.0010	0.0005	0.0024	0.0034
Italy	0.0304	0.0152	0.0304	0.0152	0.0456	0.0152	0.0456	0.0228	0.1064	0.1520
Japan	0.0009	0.0005	0.0009	0.0005	0.0014	0.0005	0.0014	0.0007	0.0033	0.0047
Mexico	0.0062	0.0031	0.0062	0.0031	0.0093	0.0031	0.0093	0.0046	0.0217	0.0309
Other Asia	0.0014	0.0007	0.0014	0.0007	0.0021	0.0007	0.0021	0.0011	0.0050	0.0071
Other oil producing countries	0.0038	0.0019	0.0038	0.0019	0.0057	0.0019	0.0057	0.0029	0.0134	0.0191
Republic of Korea	0.0015	0.0008	0.0015	0.0008	0.0023	0.0008	0.0023	0.0011	0.0053	0.0076
Rest of Euro Zone	0.0095	0.0048	0.0095	0.0048	0.0143	0.0048	0.0143	0.0072	0.0334	0.0477
Rest of OECD	0.0094	0.0047	0.0094	0.0047	0.0141	0.0047	0.0141	0.0071	0.0330	0.0471
Rest of the World	0.0031	0.0016	0.0031	0.0016	0.0047	0.0016	0.0047	0.0023	0.0109	0.0156
Russia	0.0111	0.0055	0.0111	0.0055	0.0166	0.0055	0.0166	0.0083	0.0387	0.0553
Saudi Arabia	0.0122	0.0061	0.0122	0.0061	0.0184	0.0061	0.0184	0.0092	0.0429	0.0612
South Africa	0.1338	0.0669	0.1338	0.0669	0.2007	0.0669	0.2007	0.1004	0.4684	0.6691
Turkey	0.0098	0.0049	0.0098	0.0049	0.0147	0.0049	0.0147	0.0073	0.0342	0.0488
United Kingdom	0.0196	0.0098	0.0196	0.0098	0.0294	0.0098	0.0294	0.0147	0.0686	0.0980
United States of America	0.0402	0.0201	0.0402	0.0201	0.0603	0.0201	0.0603	0.0302	0.1407	0.2010

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Table 8 - Morbidity due to Female Workers Losing Productive Time due to caregiving

(Proportion of lost days compared to the total workforce working days)

Country/Region	Scenario 01		Scenario 02		Scenario 03		Scenario 04		Scenario 05	
	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02	Year 01	Year 02
Argentina	0.0014	0.0007	0.0014	0.0007	0.0021	0.0007	0.0021	0.0011	0.0050	0.0072
Australia	0.0004	0.0002	0.0004	0.0002	0.0006	0.0002	0.0006	0.0003	0.0014	0.0019
Brazil	0.0126	0.0063	0.0126	0.0063	0.0188	0.0063	0.0188	0.0094	0.0440	0.0628
Canada	0.0034	0.0017	0.0034	0.0017	0.0051	0.0017	0.0051	0.0025	0.0119	0.0170
China	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0001	0.0002
France	0.0201	0.0101	0.0201	0.0101	0.0302	0.0101	0.0302	0.0151	0.0705	0.1007
Germany	0.0178	0.0089	0.0178	0.0089	0.0266	0.0089	0.0266	0.0133	0.0622	0.0888
India	0.0016	0.0008	0.0016	0.0008	0.0024	0.0008	0.0024	0.0012	0.0056	0.0079
Indonesia	0.0004	0.0002	0.0004	0.0002	0.0006	0.0002	0.0006	0.0003	0.0014	0.0020
Italy	0.0317	0.0159	0.0317	0.0159	0.0476	0.0159	0.0476	0.0238	0.1110	0.1586
Japan	0.0002	0.0001	0.0002	0.0001	0.0003	0.0001	0.0003	0.0001	0.0006	0.0009
Mexico	0.0038	0.0019	0.0038	0.0019	0.0056	0.0019	0.0056	0.0028	0.0132	0.0188
Other Asia	0.0004	0.0002	0.0004	0.0002	0.0007	0.0002	0.0007	0.0003	0.0016	0.0022
Other oil producing countries	0.0146	0.0073	0.0146	0.0073	0.0219	0.0073	0.0219	0.0109	0.0510	0.0729
Republic of Korea	0.0005	0.0002	0.0005	0.0002	0.0007	0.0002	0.0007	0.0004	0.0017	0.0025
Rest of Euro Zone	0.0199	0.0100	0.0199	0.0100	0.0299	0.0100	0.0299	0.0149	0.0697	0.0995
Rest of OECD	0.0196	0.0098	0.0196	0.0098	0.0294	0.0098	0.0294	0.0147	0.0686	0.0979
Rest of the World	0.0017	0.0008	0.0017	0.0008	0.0025	0.0008	0.0025	0.0012	0.0058	0.0083
Russia	0.0219	0.0110	0.0219	0.0110	0.0329	0.0110	0.0329	0.0164	0.0767	0.1095
Saudi Arabia	0.0712	0.0356	0.0712	0.0356	0.1069	0.0356	0.1069	0.0534	0.2493	0.3562
South Africa	0.0372	0.0186	0.0372	0.0186	0.0559	0.0186	0.0559	0.0279	0.1304	0.1862
Turkey	0.0287	0.0143	0.0287	0.0143	0.0430	0.0143	0.0430	0.0215	0.1004	0.1435
United Kingdom	0.0020	0.0010	0.0020	0.0010	0.0030	0.0010	0.0030	0.0015	0.0071	0.0101
United States of America	0.0034	0.0017	0.0034	0.0017	0.0050	0.0017	0.0050	0.0025	0.0118	0.0168

4.2.2 Shock to Total Factor Productivity in each Sector

The predominant sources of economic impacts with the COVID-19 pandemic have been the change in behaviour of households and firms in responding to the virus and the closure of non-essential economic sectors as means to manage the spread of the pandemic. Some firms in some sectors have been able to utilise technology to implement remote working arrangements. However, firms requiring the physical presence of workers to execute their operations, notably the durable manufacturing and service sectors, have suffered due to the economic shutdowns across the world. To assess the impact of the change in costs of doing business, which is equivalent to a decline in total factor productivity, we apply the estimates from the Australian Bureau of Statistics (2020), data from AUSGRID on electricity use by sector (2020) and estimates from del Rio-Chanona et al (2020). Given this data, we estimate the effective proportions of sub-sectors operational during the economic shutdowns. For each country, we estimate what proportion of the broad-sectors could be operational, based on the contribution from sub-sectors to the broad-sectors. We scale these estimates across countries and scenarios depending on the length of economic shutdowns. Table 9 presents the assumptions on the lengths of shutdowns (in months) in different countries under each scenario. Figure 1 shows the magnitude of the Total Factor Productivity Shock for each sector for all countries for the first year under the first scenario.

4.2.3 Shock to Consumption

The changes in the consumption preferences of households have been another significant source of economic impacts during the pandemic. We also attempt to capture the increase in risk, which affects households' discounting of future income.

The change in household behaviour is mainly due to the households getting infected as well as the inability to undertake particular economic activities due to social distancing or concern about the infection. These shifts in consumer preferences are assumed to be exogenous to the model. Other impacts on consumers such as a change in income, employment and wealth as well as shifts in relative prices of different sectors and changes in interest rate etc. are determined by the model. Households partially foresee the long-term impacts on their wealth with the broader economic implications of the pandemic and adjust their current consumption patterns to maximise the expected life-long utility.

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Table 9 - Length of Economic Shutdowns (in months) under each Scenario

Country/Region	Scenario 01 1 Year 01	Scenario 01 1 Year 02	Scenario 02 2 Year 01	Scenario 02 2 Year 02	Scenario 03 3 Year 01	Scenario 03 3 Year 02	Scenario 04 4 Year 01	Scenario 04 4 Year 02	Scenario 05 5 Year 01	Scenario 05 5 Year 02
Argentina	6.07	3.04	6.07	3.03	9.10	3.03	9.10	4.55	6.07	-
Australia	5.60	2.80	5.60	2.80	8.40	2.80	8.40	4.20	5.60	-
Brazil	7.50	3.75	7.50	3.75	11.25	3.75	11.25	5.63	7.50	-
Canada	6.37	3.19	6.37	3.18	9.55	3.18	9.55	4.78	6.37	-
China	4.70	2.35	4.70	2.35	7.05	2.35	7.05	3.53	4.70	-
France	5.13	2.57	5.13	2.57	7.70	2.57	7.70	3.85	5.13	-
Germany	4.97	2.49	4.97	2.48	7.45	2.48	7.45	3.73	4.97	-
India	7.60	3.80	7.60	3.80	11.40	3.80	11.40	5.70	7.60	-
Indonesia	5.27	2.64	5.27	2.63	7.90	2.63	7.90	3.95	5.27	-
Italy	5.63	2.82	5.63	2.82	8.45	2.82	8.45	4.23	5.63	-
Japan	5.13	2.57	5.13	2.57	7.70	2.57	7.70	3.85	5.13	-
Mexico	6.00	3.00	6.00	3.00	9.00	3.00	9.00	4.50	6.00	-
Other Asia	7.30	3.65	7.30	3.65	10.95	3.65	10.95	5.48	7.30	-
Other oil producing countries	8.60	4.30	8.60	4.30	12.00	4.30	12.00	6.45	8.60	-
Republic of Korea	4.07	2.04	4.07	2.03	6.10	2.03	6.10	3.05	4.07	-
Rest of Euro Zone	5.73	2.87	5.73	2.87	8.60	2.87	8.60	4.30	5.73	-
Rest of OECD	5.43	2.72	5.43	2.72	8.15	2.72	8.15	4.08	5.43	-
Rest of the World	8.33	4.17	8.33	4.17	12.00	4.17	12.00	6.25	8.33	-
Russia	6.60	3.30	6.60	3.30	9.90	3.30	9.90	4.95	6.60	-
Saudi Arabia	5.67	2.84	5.67	2.83	8.50	2.83	8.50	4.25	5.67	-
South Africa	10.93	5.47	10.93	5.47	12.00	5.47	12.00	8.20	10.93	-
Turkey	3.87	1.94	3.87	1.93	5.80	1.93	5.80	2.90	3.87	-
United Kingdom	6.37	3.19	6.37	3.18	9.55	3.18	9.55	4.78	6.37	-
United States of America	7.30	3.65	7.30	3.65	10.95	3.65	10.95	5.48	7.30	-

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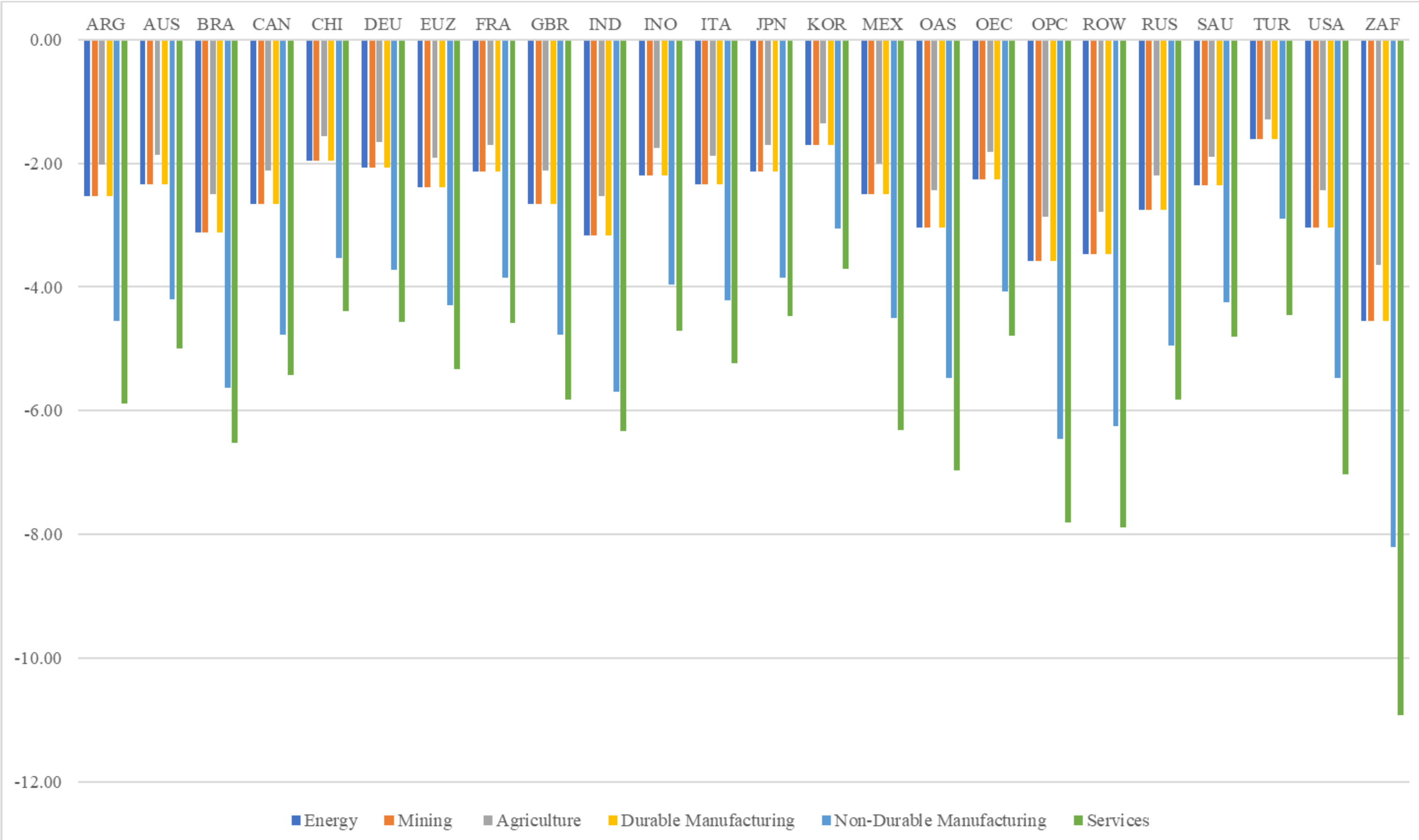
Figure 1 - Productivity Shock for the First Year under Scenario 01



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As the model endogenously generates some of the above effects due to the other shocks, we only introduce a shift in consumer preferences and a rise in the risk premium in the discount rate households use to discount future labour income in calculating human wealth. We first change consumer preferences over a large number of subsectors. We start with the proportions of the sub-sectors still operating and aggregate this data to calculate the broad sector change as well as the country-wide amount of consumption that is discontinued during the pandemic. The shock is scaled across the scenarios depending on the length of economic shutdowns in the countries. Figure 2 presents the magnitude of the shock to consumption for the first year under different scenarios.

The change in the risk premium for calculating human wealth is computed using the variation in the Volatility Index (VIX), which is an indicator of changes in market sentiment. We use the movement of the VIX in the US for four months after the outbreak reached the US and calibrate the shock for the US considering its standard deviation and excess variations from the healthy threshold level of 30. We then apply the Risk Aversion Index, compiled by Gandelman and Hernández-Murillo (2014), to scale the shock across the different regions in the model. For four countries for which the Risk Aversion Index is not available, we use those of their closest peers. The shocks are then scaled across scenarios using scaling factors reflecting the length of shutdowns. Figure 3 presents the Index of Risk Aversion relative to the US for the regions in the model and Figure 4 shows the magnitude of the risk on human wealth for the first year under the different scenarios.

4.2.4 Shock to the Country & Sector Risk Premia

While no country has been immune to the pandemic, the relative attractiveness of economies and economic sectors have changed. This is evident in the changes in financial markets after the outbreak. We attempt to capture this rebalancing in risk via a shock on the country risk premium and equity risk premia of sectors across all countries.

Following the approach in McKibbin and Sidorenko (2006), Lee and McKibbin (2004) and further improved in McKibbin and Fernando (2020a), we first construct a country risk index with three main components: the indexes of Health, Governance and Financial risks.

The Index of Health Risk is the average of the Index of Health Expenditure per capita and the Index of Health Security. The Health Expenditure per capita data are from the World Health Organization (2019) and the Global Health Security Index, constructed by the Johns Hopkins

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Figure 2 - Consumption Shock for the First Year (% GDP of Consumption Discontinued)

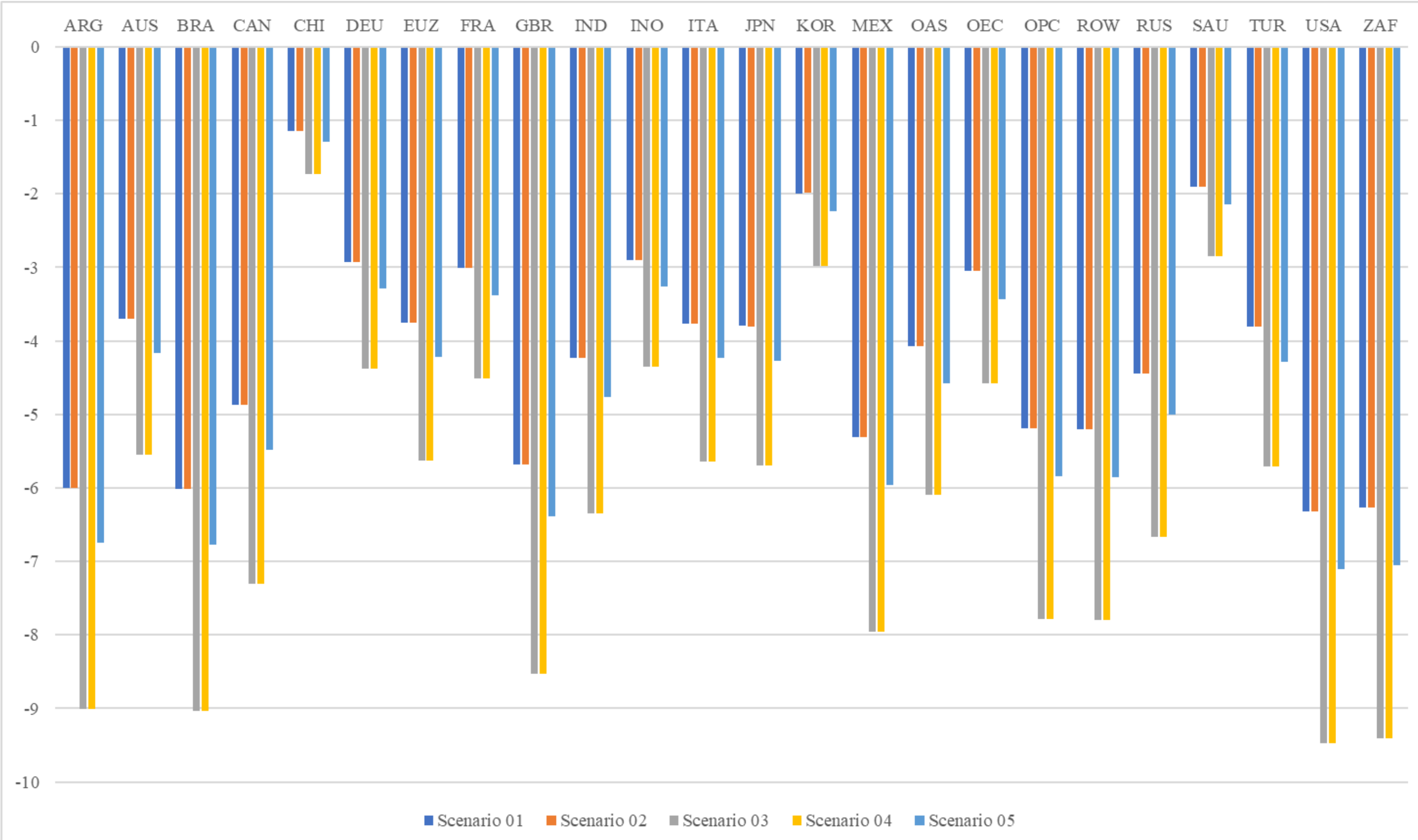


Figure 3 - Index of Risk Aversion

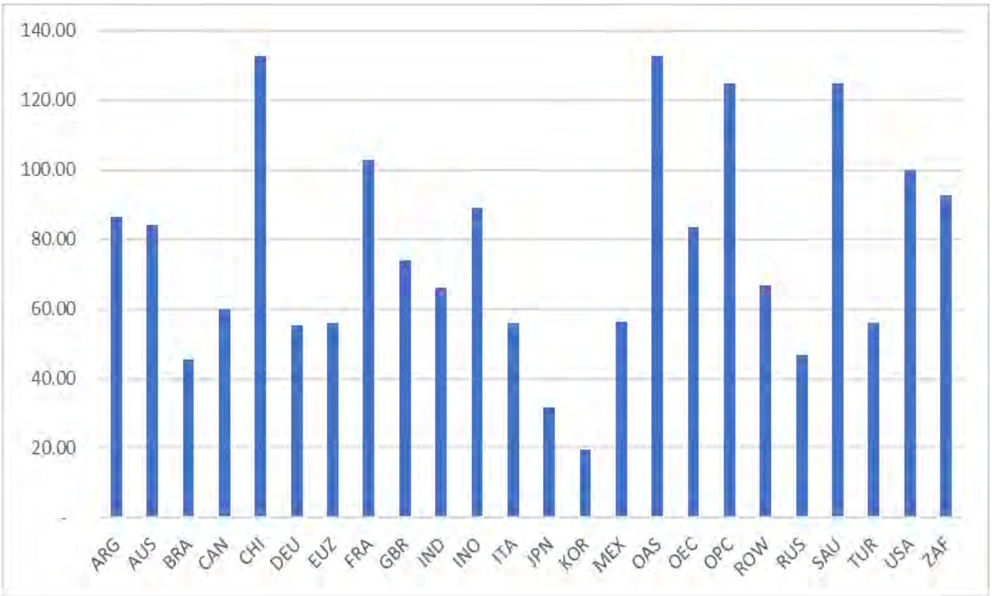
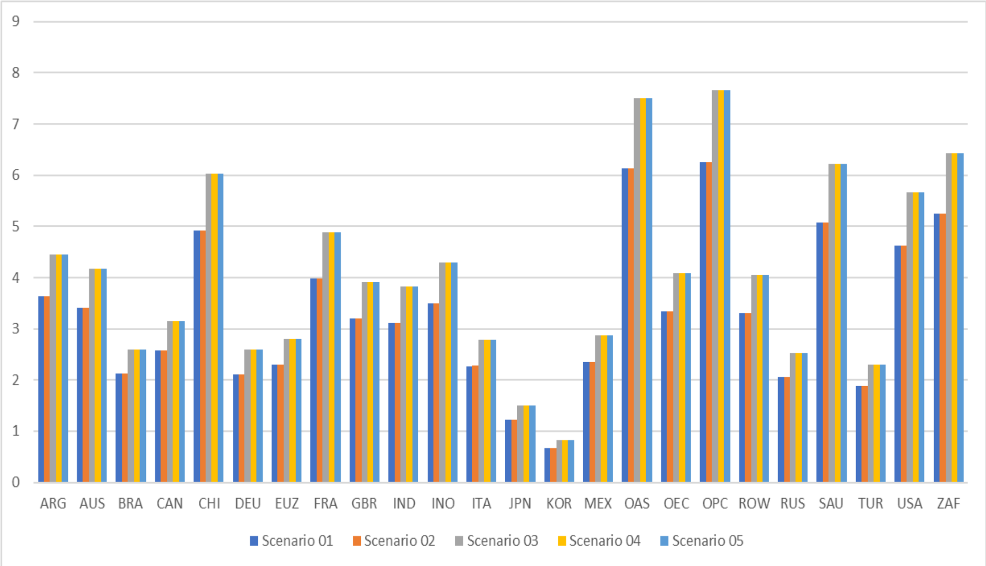


Figure 4 - Increase in Risk Premium on Human Wealth for the First Year under each Scenario



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University (2019), is used to develop the Index of Health Security. The Global Health Security Index covers six categories which include the ability to prevent, detect and respond to outbreaks and diseases. It also assesses the health and political systems in a given country and evaluates the country's compliance with international health standards. Figure 5 presents the Index of Health Risk for the regions in the model. A higher value indicates a higher health risk.

The Index of Governance Risk is calculated using the International Country Risk Guide (ICRG) (PRSGroup 2020). The ICRG Index scores countries based on performance in 22 variables categorised under political, economic and financial dimensions. The political dimension accounts for government stability, the rule of law and the prevalence of conflicts. The economic dimension is composed of GDP per capita, real GDP growth and inflation, among others. Exchange rate stability and international liquidity are the two main variables constituting the financial dimension. Figure 6 presents the Index of Governance relative to the US. A higher value indicates a higher governance risk.

The Index of Financial Risk utilises the IMF data on Current Account Balance as a proportion of GDP to demonstrate the financial risk associated with countries. Figure 7 presents the value of the index relative to the US. The Index of Country Risk is the arithmetic average of the three indices and Figure 8 shows the value of the index relative to the US, due to the prevalence of well-developed financial markets there (Fisman & Love 2004).

We then estimate the average variation of the Nasdaq, Dow Jones and S&P 500 stock market indices in the US financial markets for four months after the outbreak. After that, using the standard deviation in the US financial markets as a benchmark, we obtain estimates for other countries by scaling for the lengths of lockdowns and the Index of Country Risk. Figure 9 shows the magnitude of the country risk premium shock in the first year for different scenarios.

We then scale the risk premia for a given country across scenarios by adjusting for changes in the length of lockdowns.

The shock to the sector risk premia is calculated using the movement of the sector indices in the Australian Stock Exchange (ASX) during the four months following the outbreak. The risk premia shocks are scaled across countries and scenarios according to the length of economic shutdowns. When scaling across sectors, we consider the impact on productivity in different sectors compared to the Australian sectors. Figure 10 presents the magnitude of the sector premium shock for the first year under Scenario 01.

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Figure 5 - Index of Health Risk

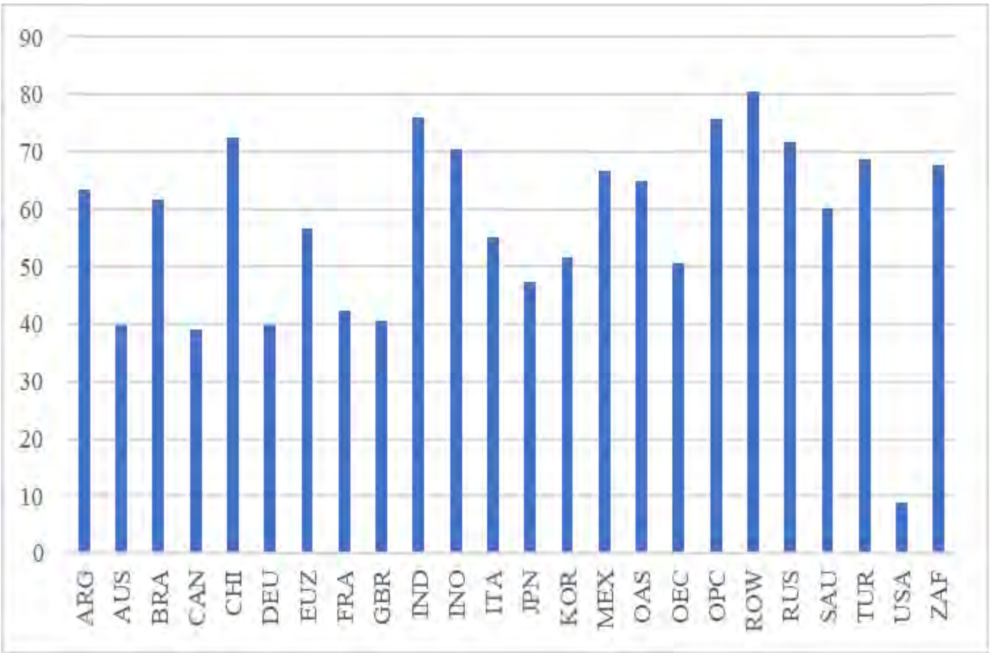

Figure 6 - Index of Governance Risk

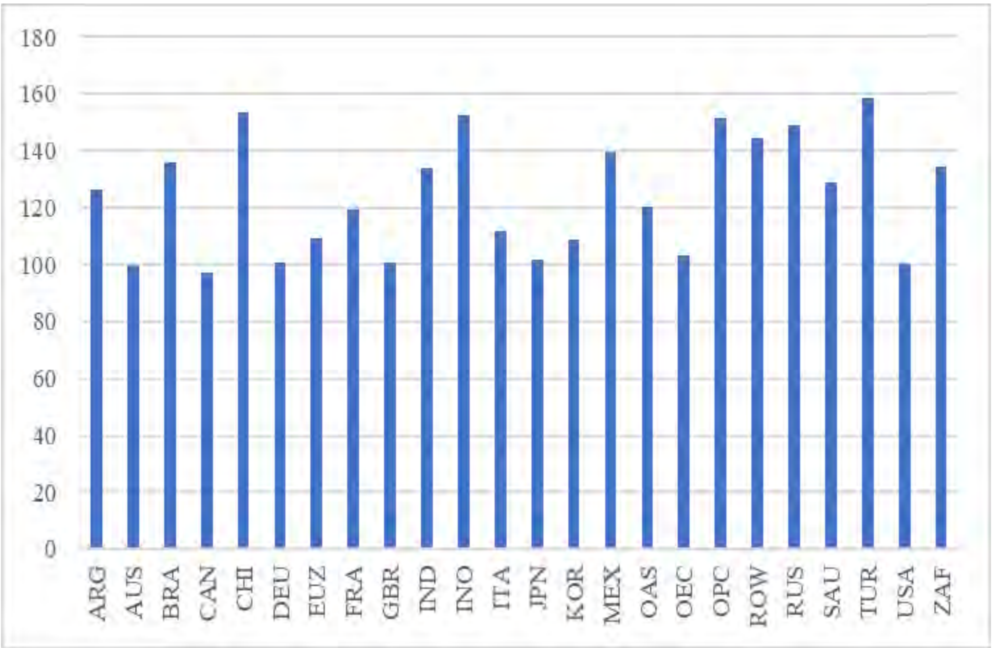

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Figure 7 - Index of Financial Risk

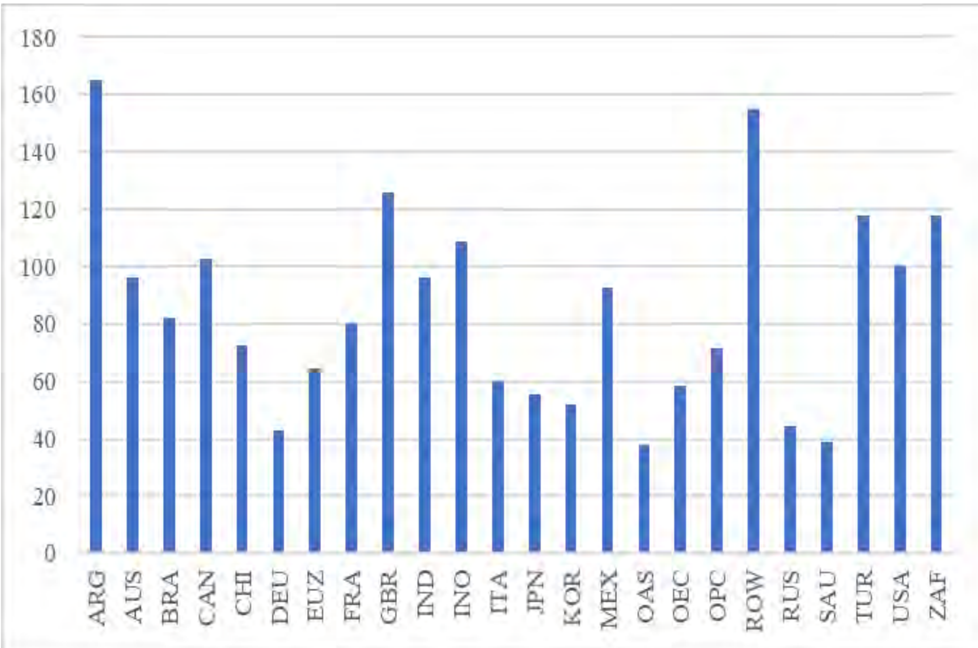

Figure 8 - Net Country Risk Index relative to the US

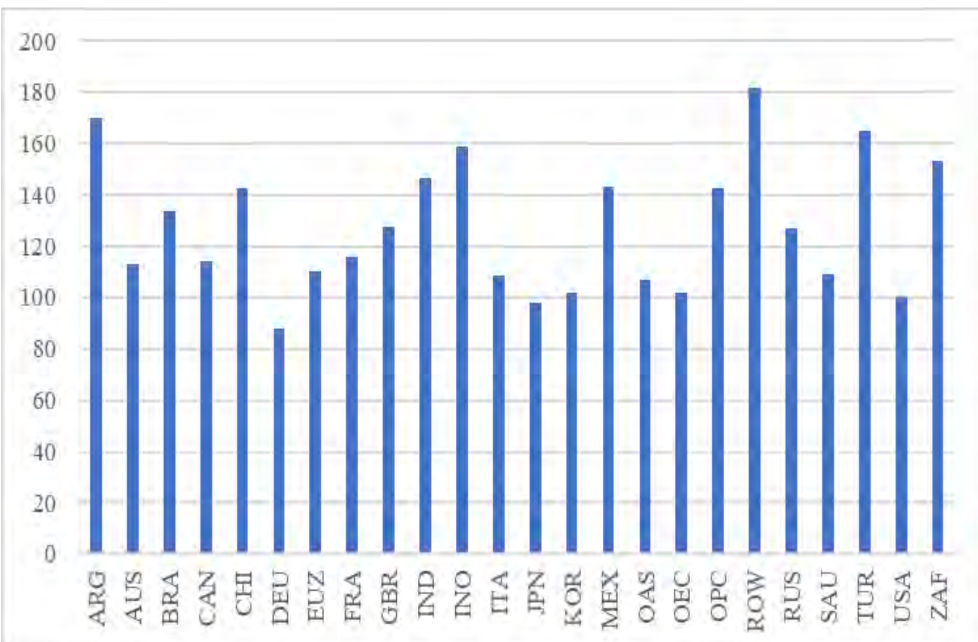

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Figure 9 - Country Risk Premium Shock for the First Year under each Scenario

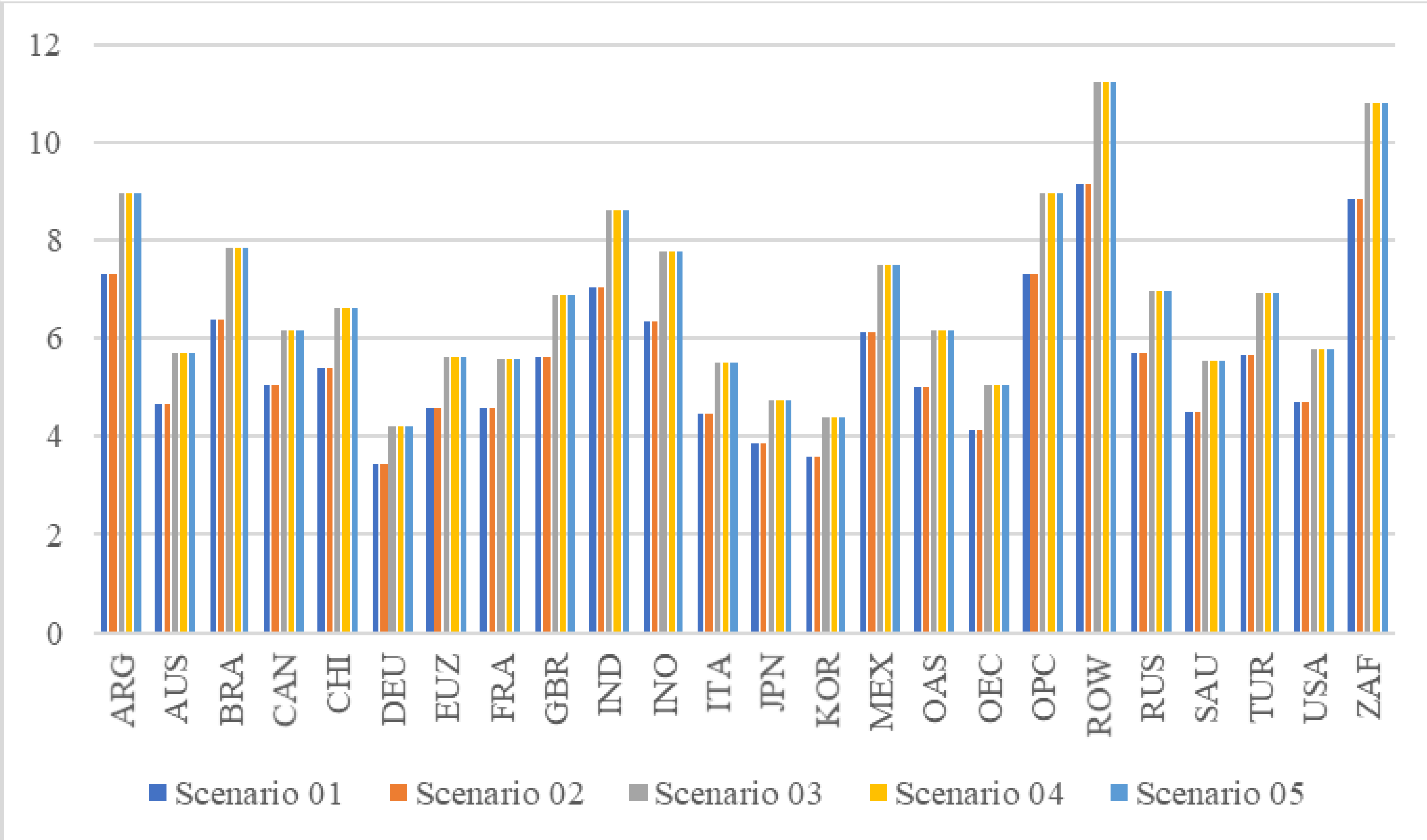

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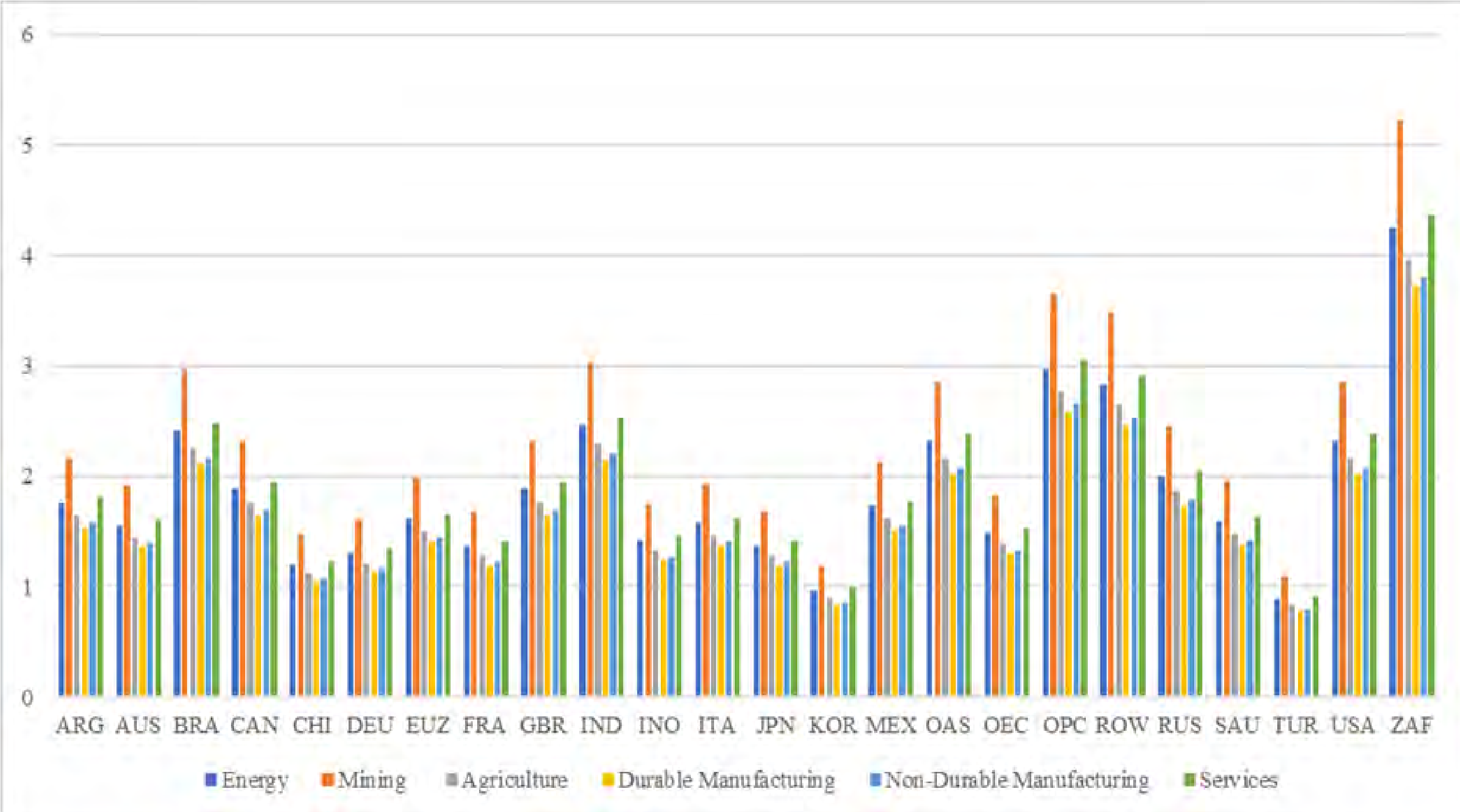
Figure 10 - Sector Equity Risk Premium Shock for the First Year for Scenario 01



4.2.5 Shock to Government Expenditure

In the model, there are endogenous changes in fiscal variables as well as exogenous changes that we impose in the form of shocks. Each country follows the same fiscal rule. The budget deficit is endogenous. The fiscal rule is that a lump sum tax is levied on all households to cover the interest servicing costs of changes in net government debt caused by a change in the fiscal deficit in response to the shocks we impose on the model. Government debt can permanently change after a shock, but debt levels eventually stabilise. National government expenditure is exogenous, while transfers respond to change in economic activity as do tax revenues. There are taxes on household income, corporate income and imports. These fiscal variables all respond when shocks occur in the model. The ultimate change in the budget deficit is a combination of exogenous changes in government spending, transfers and wage subsidies where they occur, and endogenous fiscal stabilisers operating via the fiscal rule.

While imposing the lockdown measures, many governments have implemented a range of fiscal measures to cushion the impact on the economy emanating from the virus, the change in household and firm behaviour and the economic shutdowns. The IMF (2020a) compilation of the policy responses of different countries to COVID-19 reveals that the fiscal measures to support firms include relieving firms from paying tax and social contributions, targeted subsidies to hard-hit sectors, exemptions for paying utility bills and credit guarantees. The fiscal measures to support households include relief from tax payments, exemptions for settling utility bills and direct transfers. Wage subsidies have also been an essential component in the assortment of fiscal measures worldwide. As well as supporting targeted firms and households, governments have also reallocated their current budgets to increase spending on the healthcare sector. Some governments have also increased expenditure on infrastructure projects.

In this paper, we try to capture as much of the difference in policies across countries as possible. We decompose the overall fiscal response into three parts. The first is an increase in general government spending decomposed for the broad sectors. The second is a wage subsidy, and the third is an exogenous increase in transfers to the households. While the data on the rise in general government expenditure is generally available for all the countries, the magnitude of the wage subsidies and transfers are not explicitly apparent for all countries. In this case, we estimate these variables.

Even though the fiscal stimulus packages have been announced, there is uncertainty about what proportion of those packages would actually be spent. Therefore, when calculating the increase

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Figure 11 - Increase in Government Expenditure excluding the Wage Subsidies & Transfers for Households (% GDP)

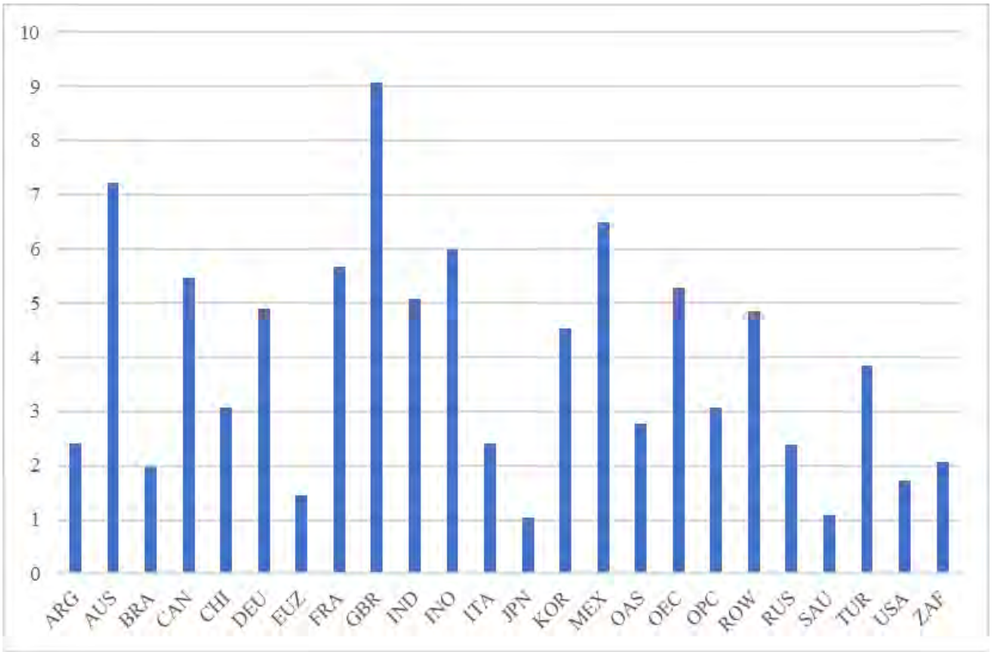

Figure 12 - Wage Subsidies Announced (% GDP)

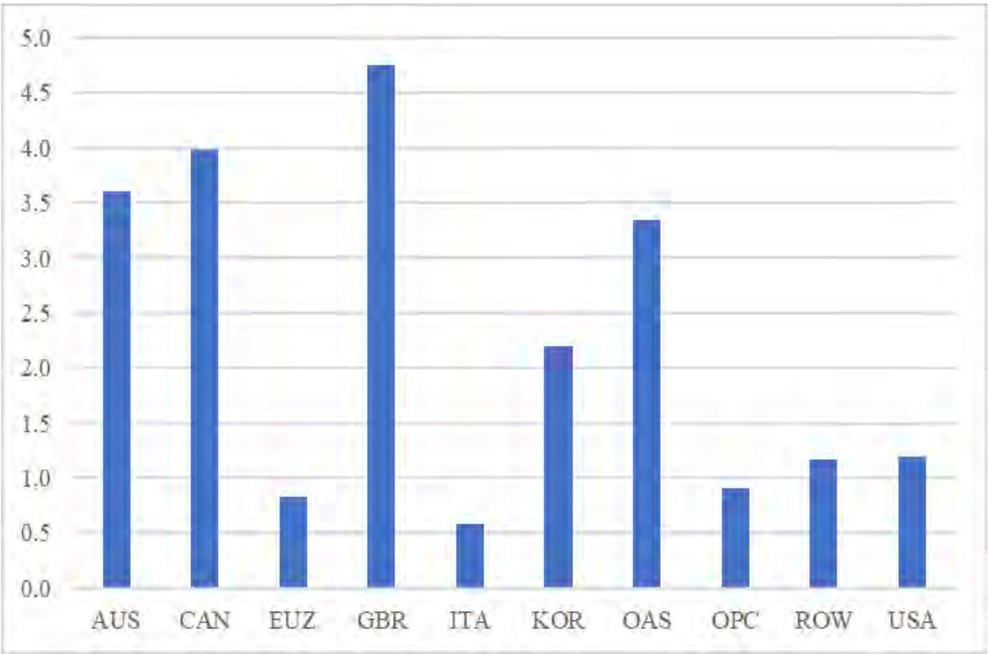

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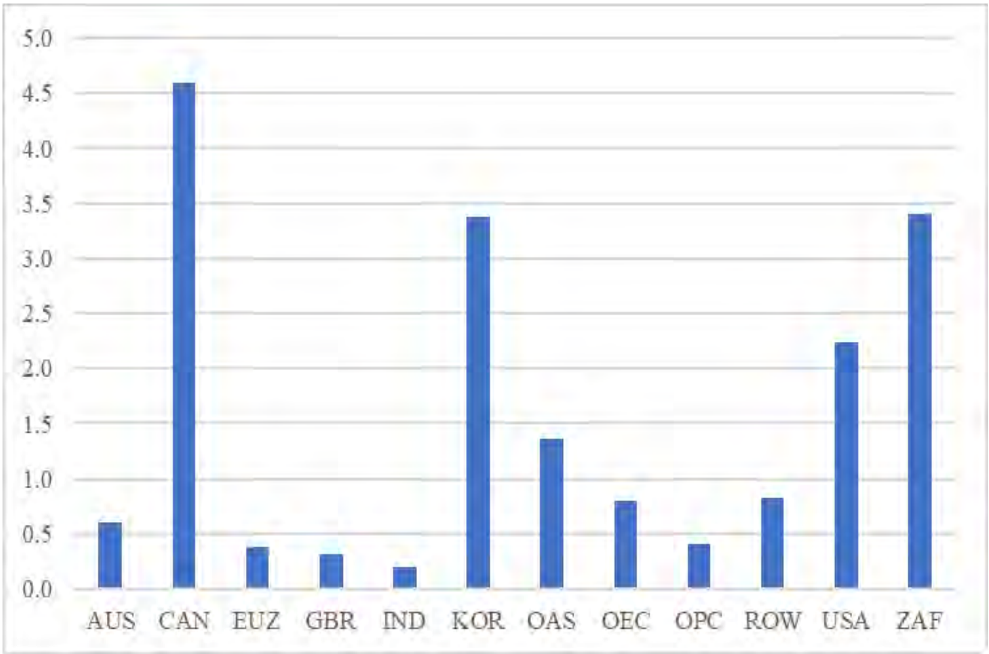
Figure 13 - Household Transfers Announced (% GDP)



in government expenditure, we utilise the changes in fiscal deficit projected by the IMF in its April 2020 issue of the Fiscal Monitor. Figure 11 presents the increase in government expenditure for different regions in the model in response to the pandemic in early 2020 as a proportion of GDP, excluding wage subsidies and transfers for countries where the explicit data is available. Figure 12 and Figure 13 show the Wage Subsidy and Household Transfers as a proportion of GDP for countries where the data is explicitly available.

Data on the Household Transfers as a proportion of GDP is available for 12 regions in the model. While these details feed into Scenario 1, for the subsequent waves and scenarios they were scaled depending on the duration of economic shutdowns compared to the current wave.

The increase in government spending is allocated across sub-sectors depending on the preferences governments would have to support the sub-sectors. We then aggregate this spending to calculate expenditure by government across the broad model sectors. We assume these preferences for spending in different sectors are determined by the expected impact on the sub-sectors during the pandemic. The proportions of government spending on the broad sectors are then scaled across scenarios depending on the length of shutdowns. Figure 14

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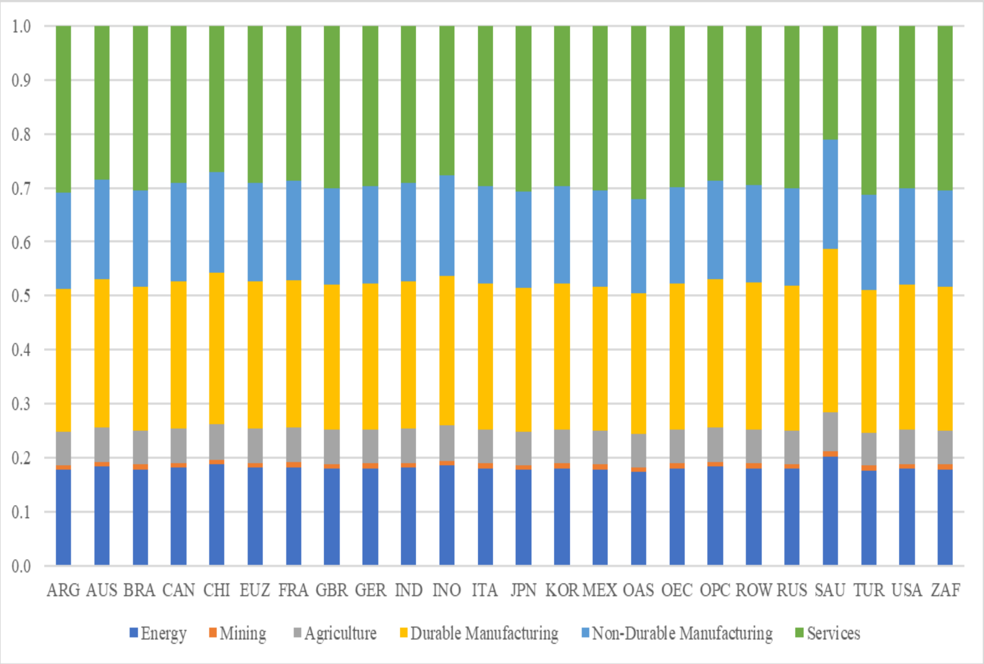
presents the proportions of increased government spending each broad model sector would receive in a given country based on our estimations of government allocation of its expenditure across the sub-sectors. Building on the Figures 11 and 14, Figure 15 presents the increase in government spending for different sectors across different scenarios.

Figure 14 - Government Spending Allocation across Broad-sectors



One of the notable elements in the fiscal responses to the pandemic has been the wage subsidies introduced by different governments. Governments in the model can employ workers directly, or they can generate employment in the private sector via demand for goods and services or investments in infrastructure. The motive of the wage subsidies during the pandemic is to directly support workers in jobs while preventing the rise in unemployment. Due to this unprecedented nature of the wage subsidy, we calibrate the wage subsidy shock closely approximating the Australian case and using the estimates by the Australian Treasury for the employment effects of the wage subsidy.

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Figure 15 - Increased Government Spending across Sectors for the First Year in Scenario 01

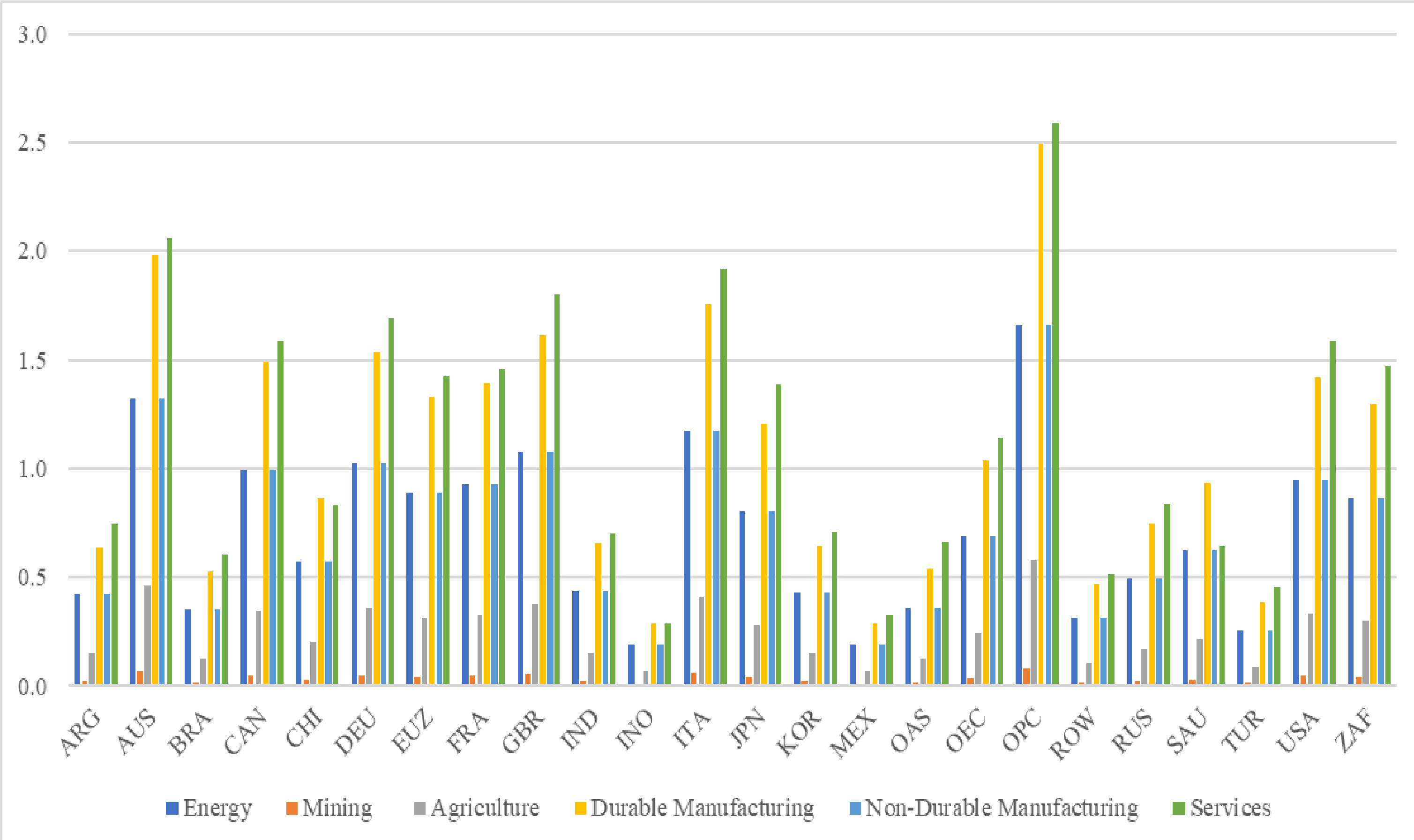

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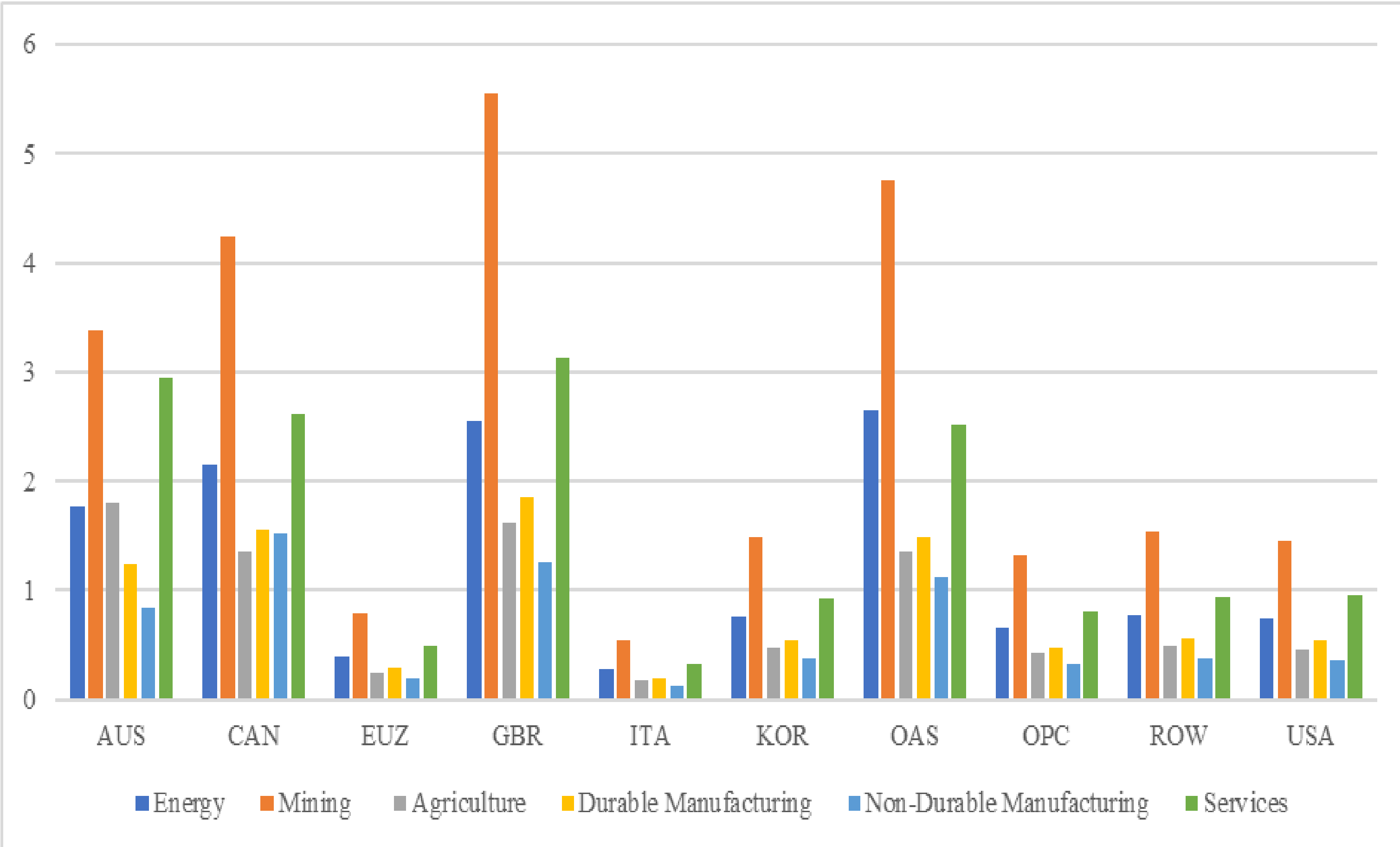
Figure 16 - Wage Subsidy Shock for the First Year for Scenario 01



We observe the fall in employment with all the shocks except for the wage subsidy shock in the model and obtain a calibration factor for each sector to achieve the forecasted overall employment benefit given the wage subsidy. We then scale the shock across countries depending on the respective wage subsidy packages. We also scale the shock across scenarios depending on the length of the shutdowns. Figure 16 presents the wage subsidy each sector receives for the first year in Scenario 1.

5 Simulation Results

5.1 Baseline scenario

The baseline of the model is the same as that used in McKibbin and Fernando (2020a & 2020b). To summarise, the model is solved from 2016 to 2100 with 2015 as the base year for calibrating parameters. The key inputs into the baseline are the initial dynamics from 2015 to 2016 and subsequent projections from 2016 forward for labour-augmenting technological progress by sector and by country. The labour-augmenting technology projections follow the approach of Barro (1991, 2015).

In the alternative COVID-19 scenarios, we incorporated the range of shocks discussed above to model the economic consequences of different epidemiological assumptions. All results begin in 2020 and are the difference between the COVID-19 scenario and a baseline of the model in which there is no COVID-19 pandemic. It is important to stress that because the results are either percentage change or per cent of GDP difference from the non-COVID, the interpretation of the numbers can easily be misunderstood. For example, suppose for country X that the change in GDP in 2020 is -20%. This number means that GDP in 2020 is 20% lower than it otherwise would have been in 2020. If the country was growing at 5% in the baseline, then the change in GDP from 2019 to 2020 is not -20% but it is -15% relative to 2019. GDP is 20% lower than the baseline in 2020.

A full set of results are presented in the model dashboard available at:
https://cama.crawford.anu.edu.au/covid-19-macroeconomic-modelling-results-dashboard.

5.2 Results for 2020

Table 10 contains the results for the $US value of GDP change in 2020 for all countries for all scenarios. The loss to the global economy in 2020 under scenario 01 is $US14.7 trillion. The more waves are assumed, the larger the loss. By scenario 04 which has four waves, two each in 2020 and 2021 and a replication of the policies seen in the first wave across all countries, the loss rises to $US 21.8 trillion. In scenario 05, where lockdowns only occur in the first wave for

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Table 10: Change in Real GDP in 2020 in $US Billion

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-122.18	-123.55	-182.64	-181.49	-144.85	-134.43
Australia	-117.02	-125.93	-170.16	-172.31	-147.42	-127.25
Brazil	-607.08	-620.63	-908.91	-905.35	-723.23	-631.86
Canada	-134.94	-145.12	-200.38	-200.06	-178.99	-151.27
China	-1,935.94	-2,131.80	-2,787.65	-2,831.90	-2,346.65	-2,046.49
France	-367.75	-395.55	-520.43	-537.29	-392.87	-374.99
Germany	-475.29	-496.50	-666.01	-694.99	-513.61	-548.93
India	-1,075.59	-1,089.88	-1,610.37	-1,605.81	-1,280.35	-1,163.17
Indonesia	-261.62	-270.66	-390.57	-388.97	-315.82	-276.69
Italy	-340.14	-355.12	-491.37	-502.20	-393.97	-348.35
Japan	-782.72	-785.97	-1,120.64	-1,160.27	-790.03	-841.37
Mexico	-170.83	-174.59	-258.12	-257.01	-203.49	-180.71
Other Asia	-236.56	-241.84	-353.60	-352.88	-278.88	-257.08
Other oil producing countries	-305.64	-317.50	-449.92	-454.02	-382.00	-350.56
Republic of Korea	-105.45	-108.42	-155.91	-156.91	-122.45	-115.91
Rest of Euro Zone	-129.49	-135.24	-187.94	-191.05	-145.44	-134.81
Rest of OECD	-260.38	-270.80	-373.47	-383.56	-295.92	-296.45
Rest of the World	-292.95	-296.65	-442.39	-440.74	-352.00	-309.08
Russia	-2,830.25	-2,895.40	-4,176.30	-4,211.51	-3,285.58	-2,997.29
Saudi Arabia	-243.36	-288.79	-332.18	-336.55	-300.84	-207.74
South Africa	-1,377.70	-1,390.12	-2,057.97	-2,063.74	-1,574.52	-1,450.38
Turkey	-376.00	-382.80	-559.15	-559.10	-441.04	-408.64
United Kingdom	-141.19	-144.79	-205.47	-209.07	-166.19	-164.55
United States of America	-2,043.62	-2,149.39	-2,967.76	-2,985.18	-2,490.50	-2,136.57
Total for the World	**-14,733.67**	**-15,337.04**	**-21,569.33**	**-21,781.99**	**-17,266.63**	**-15,654.55**

Table 11: Cumulative Change in Real GDP between 2020 and 2025 in $US Billion

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-97.90	-142.96	-133.20	-144.15	-217.77	-105.23
Australia	-151.62	-206.04	-194.11	-223.98	-306.63	-164.96
Brazil	-601.72	-850.06	-803.42	-894.06	-1,271.31	-629.38
Canada	-157.81	-235.79	-199.68	-232.82	-397.54	-169.24
China	-2,632.94	-3,729.39	-3,335.64	-3,853.41	-4,924.32	-2,712.79
France	-453.07	-579.95	-574.24	-660.97	-785.72	-464.21
Germany	-572.43	-661.79	-724.20	-835.99	-989.42	-639.92
India	-1,305.01	-2,002.01	-1,710.71	-1,919.82	-2,914.95	-1,368.91
Indonesia	-346.52	-482.43	-466.02	-513.16	-650.71	-356.93
Italy	-441.37	-564.64	-572.68	-651.65	-830.45	-442.69
Japan	-915.44	-1,134.07	-1,171.28	-1,349.83	-1,561.81	-1,000.38
Mexico	-239.44	-331.70	-328.78	-352.55	-573.36	-225.87
Other Asia	-367.02	-500.63	-484.77	-547.04	-690.66	-368.81
Other oil producing countries	-515.42	-755.64	-672.22	-752.39	-1,046.04	-528.27
Republic of Korea	-139.00	-156.05	-183.12	-208.24	-280.84	-141.60
Rest of Euro Zone	-159.95	-215.83	-205.96	-234.89	-339.61	-162.60
Rest of OECD	-317.50	-411.33	-397.68	-467.34	-585.80	-355.28
Rest of the World	-356.24	-580.25	-461.47	-527.31	-777.83	-368.28
Russia	-3,699.76	-5,099.90	-4,830.93	-5,490.82	-6,968.17	-3,868.80
Saudi Arabia	-535.23	-630.72	-681.46	-749.36	-845.95	-438.49
South Africa	-2,039.51	-3,012.59	-2,609.24	-3,024.52	-3,678.91	-2,068.51
Turkey	-460.45	-598.97	-612.95	-686.76	-687.51	-462.08
United Kingdom	-161.24	-214.32	-209.89	-238.15	-381.39	-179.97
United States of America	-901.53	-1,106.08	-1,115.56	-1,263.40	-3,653.80	-1,026.25
Total for the World	**-17,568.13**	**-24,203.14**	**-22,679.19**	**-25,822.62**	**-35,360.49**	**-18,249.44**

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countries that had lockdowns, the pandemic continues to re-emerge. This continuing emergence of the pandemic causes a permanent increase in global risk. The global loss of GDP in 2020 is $US17.3 trillion. However, the GDP loss in future years continues to acccumulate, given the permanent risk shock. Table 11 shows the cumulative GDP loss from 2020 to 2025.

Table 12 gives a better indication of the relative decline of economic activity across countries. This table has the change in GDP scaled by the size of GDP for each country measured relative to the baseline in which there is no COVID-19 pandemic. (Note that these results for GDP are not the growth rate of GDP.) The numbers in the tables are results for the percentage change in the level of GDP relative to the baseline. For example, the Australian economy in scenario 01 is estimated to shrink by 8.57% relative to what would have been the case in 2020. The change in the growth rate in 2020 would be the growth that would have occurred in 2020 less the number in this table. For example, if Australia's growth rate in 2020 would have been 2.57%, then the new growth rate for Australia for 2020 is estimated to be -6%.

For all countries, Scenario 1, which is optimistic given current data, has a significant contraction in the global economy. The US Congressional Budget Office [CBO] (2020) most recent projection is for GDP over 2020 to be 7.6% lower than previously forecast. However, CBO estimates that GDP in the second quarter of 2020 is 14.2% lower than otherwise. Much of this difference to the results in this paper can be attributed to the longer implied persistence of the economic slowdown relative to the CBO estimates. The current state of all economies is highly uncertain. The results for Scenario 1 are consistent with the estimates from the World Bank and IMF discussed in section 2, although the current results are, on average several percent more negative. Given the current state of uncertainty about the scale of the shock and the evolution of the pandemic, it is unclear which set of estimates are more realistic. However, all the studies predict a dramatic shock to the global economy much larger than the global financial crisis a decade ago.

It is clear from the results that if the waves of the pandemic re-occur the GDP losses mount. This mounting loss from recurring pandemic waves is even in the case where lockdowns are not part of the policy response (in Scenario 5). It is also clear from comparing Scenario 6 with scenario 01 that even if a country can contain the pandemic within its borders the loss to own GDP continues to rise if the rest of the world loses control. For example, under scenario 01 for all countries, Australia's GDP is 8.6% lower. If we assume Australia follows scenario 01 but the rest of the world is in Scenario 4 (i.e. Scenario 6) then Australia GDP is a further 0.7% lower than when all countries experience Scenario 1.

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Table 12: Percent Change in Real GDP in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-11.42	-11.55	-17.07	-16.96	-13.54	-12.56
Australia	-8.57	-9.22	-12.46	-12.62	-10.79	-9.32
Brazil	-14.99	-15.32	-22.44	-22.35	-17.85	-15.60
Canada	-7.09	-7.62	-10.52	-10.51	-9.40	-7.94
China	-6.48	-7.14	-9.34	-9.48	-7.86	-6.85
France	-11.46	-12.33	-16.22	-16.75	-12.25	-11.69
Germany	-10.45	-10.92	-14.65	-15.28	-11.30	-12.07
India	-8.02	-8.13	-12.01	-11.97	-9.55	-8.67
Indonesia	-6.12	-6.33	-9.13	-9.09	-7.38	-6.47
Italy	-12.26	-12.80	-17.71	-18.10	-14.20	-12.55
Japan	-13.63	-13.69	-19.52	-20.21	-13.76	-14.66
Mexico	-5.56	-5.68	-8.40	-8.37	-6.62	-5.88
Other Asia	-9.88	-10.10	-14.77	-14.74	-11.65	-10.74
Other oil producing countries	-7.05	-7.32	-10.38	-10.47	-8.81	-8.09
Republic of Korea	-5.40	-5.55	-7.98	-8.03	-6.27	-5.93
Rest of Euro Zone	-13.21	-13.80	-19.17	-19.49	-14.84	-13.75
Rest of OECD	-10.05	-10.45	-14.41	-14.80	-11.42	-11.44
Rest of the World	-9.00	-9.11	-13.59	-13.54	-10.81	-9.49
Russia	-13.34	-13.65	-19.69	-19.85	-15.49	-14.13
Saudi Arabia	-4.26	-5.05	-5.81	-5.89	-5.26	-3.64
South Africa	-23.06	-23.27	-34.45	-34.55	-26.36	-24.28
Turkey	-6.93	-7.06	-10.31	-10.31	-8.13	-7.54
United Kingdom	-6.75	-6.93	-9.83	-10.00	-7.95	-7.87
United States of America	-12.10	-12.73	-17.58	-17.68	-14.75	-12.65

Table 13: Percent Change in Employment in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-15.89	-16.13	-23.74	-23.53	-19.39	-18.31
Australia	-6.08	-7.33	-8.31	-8.66	-8.99	-7.67
Brazil	-14.64	-15.31	-21.80	-21.70	-18.29	-15.93
Canada	-5.25	-6.30	-7.62	-7.64	-8.66	-7.06
China	-4.27	-5.55	-5.64	-5.95	-5.96	-5.05
France	-12.75	-14.65	-17.00	-18.15	-12.84	-13.25
Germany	-11.52	-12.48	-15.27	-16.52	-12.08	-14.68
India	-8.35	-8.59	-12.46	-12.40	-10.50	-9.65
Indonesia	-6.41	-6.88	-9.48	-9.44	-8.40	-7.37
Italy	-12.24	-13.53	-16.75	-17.67	-14.50	-12.93
Japan	-13.50	-13.74	-18.49	-19.77	-12.52	-15.47
Mexico	-8.32	-8.67	-12.57	-12.53	-10.44	-9.41
Other Asia	-6.62	-7.17	-9.75	-9.73	-8.73	-8.61
Other oil producing countries	-8.40	-9.09	-12.08	-12.33	-11.75	-11.33
Republic of Korea	-3.90	-4.41	-5.43	-5.65	-4.87	-5.23
Rest of Euro Zone	-13.89	-15.23	-19.37	-20.10	-15.53	-15.09
Rest of OECD	-8.96	-9.76	-12.13	-12.89	-10.28	-11.67
Rest of the World	-8.88	-9.15	-13.48	-13.39	-11.58	-10.00
Russia	-13.22	-14.08	-18.89	-19.38	-16.23	-15.59
Saudi Arabia	-5.97	-8.97	-6.87	-7.14	-8.52	-5.16
South Africa	-10.89	-11.31	-16.00	-16.24	-12.68	-13.49
Turkey	-8.29	-8.65	-12.17	-12.21	-10.21	-9.84
United Kingdom	-8.05	-8.42	-11.45	-11.81	-9.63	-10.22
United States of America	-14.46	-15.49	-20.75	-20.93	-17.96	-15.35

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Table 13 contains results for the employment impacts of the different scenarios. These numbers are the change in hours worked. Employment reductions are significant globally. For some countries, such as Australia, Canada, China, South Korea and Other Asia, that either contained the pandemic or implemented wage subsidies, the employment losses are still substantial. However, for countries such as the United States, the loss of employment is estimated to be 14.5% in 2020 under the current information. If further waves emerge this rise sharply to 20.9% in scenario 04 under a repeat of policies or 18% if lockdowns are discontinued in subsequent waves (Scenario 5).

A significant part of the economic shock is the substantial collapse in consumption (Table 14) and Investment (Table 15). The consumption shock is partly due to shifts in preferences for transactions associated with human contact, but falling consumption is also due to the loss of income and wealth caused by the pandemic. Higher risk through the increase in the household risk premium cause private savings to rise and consumption to fall. Loss of employment income reduces consumer spending. In addition, some of the income loss is policy-induced due to the shutdown of specific activities in some countries, but much is caused by the change in the behaviour of households and firms.

Investment (Table 15) also falls sharply reflecting the recessions in many economies. Higher risk and falling output cause the firm's profitability to decline, which reduces the return to capital and therefore, investment drops sharply. As with consumption, the more severe the pandemic, the larger the decline in investment. The more significant the decline in investment, the larger the reduction in future output since firms require capital as an input into production.

Table 16 shows the implications for budget deficits in all countries. For most economies, budget deficits increase significantly because of policy changes in spending, taxes and wage subsidies as well as endogenous changes in tax revenue and unemployment benefits. For some countries which have substantial government debt (such as Argentina and Brazil), the sharp fall in real interest rates and the economy collapses cause the fiscal position to improve.

Table 17 shows the changes in trade balances as a result of the different COVID-19 scenarios. Trade is affected by large swings in exports and imports, and the overall trade balance is driven by changes in savings and investment. Countries that are deeply impacted will tend to have a rise in private savings and fall in private investment. If the government does not respond, then there is likely to be a capital outflow. To the extent that government increase the budget deficit, then some of this capital will flow into the government balance sheet. The net effect is that countries that do well will tend to attract foreign capital. Therefore, these countries will

Table 14: Percent Change in Real Consumption in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-22.08	-22.50	-32.99	-32.66	-24.00	-22.83
Australia	-12.36	-13.18	-18.69	-18.24	-15.47	-12.86
Brazil	-22.83	-22.93	-34.91	-34.16	-25.93	-22.84
Canada	-9.21	-9.74	-14.65	-13.72	-12.48	-9.30
China	-11.54	-12.67	-16.69	-16.75	-12.62	-12.14
France	-15.14	-15.68	-21.55	-22.09	-14.70	-15.96
Germany	-16.09	-15.62	-22.48	-23.57	-14.69	-18.69
India	-17.16	-17.44	-26.00	-25.62	-19.64	-17.72
Indonesia	-9.80	-10.18	-15.07	-14.49	-10.90	-9.02
Italy	-17.20	-17.30	-25.28	-25.50	-18.44	-17.79
Japan	-20.00	-18.63	-28.63	-29.67	-16.73	-21.52
Mexico	-12.26	-12.25	-18.88	-18.54	-13.64	-11.92
Other Asia	-12.38	-12.54	-19.74	-18.63	-15.65	-12.10
Other oil producing countries	-21.63	-23.33	-31.65	-31.87	-27.08	-25.34
Republic of Korea	-4.44	-3.97	-7.51	-6.87	-5.41	-4.54
Rest of Euro Zone	-19.60	-19.76	-29.19	-29.07	-20.96	-20.29
Rest of OECD	-15.54	-15.82	-21.96	-22.75	-15.78	-17.61
Rest of the World	-15.67	-16.15	-23.77	-23.35	-18.21	-15.97
Russia	-26.92	-27.01	-40.22	-40.07	-29.11	-27.92
Saudi Arabia	-10.28	-11.60	-14.56	-14.54	-10.39	-10.22
South Africa	-32.10	-33.39	-47.69	-47.51	-35.53	-33.31
Turkey	-13.78	-13.69	-20.92	-20.53	-14.33	-13.67
United Kingdom	-16.63	-16.83	-24.40	-24.60	-17.54	-17.84
United States of America	-17.48	-17.37	-26.35	-25.90	-20.21	-17.71

Table 15: Percent Change in Real Investment in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-17.78	-21.95	-24.07	-25.62	-20.88	-14.45
Australia	-18.79	-19.38	-27.53	-27.92	-25.06	-15.36
Brazil	-24.04	-27.10	-33.55	-35.22	-29.70	-21.18
Canada	-16.31	-16.65	-23.61	-23.62	-20.77	-11.92
China	-7.01	-8.08	-10.06	-10.20	-9.89	-4.92
France	-38.89	-43.39	-54.84	-57.33	-38.96	-31.66
Germany	-25.96	-26.34	-36.91	-38.97	-27.59	-23.61
India	-11.54	-13.18	-15.98	-16.56	-13.92	-9.75
Indonesia	-7.56	-8.30	-10.81	-10.96	-8.25	-5.19
Italy	-33.04	-35.06	-47.15	-49.37	-41.65	-26.33
Japan	-34.86	-36.15	-49.35	-52.19	-37.61	-32.55
Mexico	-9.09	-9.99	-12.55	-13.00	-10.75	-5.35
Other Asia	-21.10	-22.34	-30.51	-31.37	-26.18	-17.61
Other oil producing countries	-17.15	-20.33	-23.64	-24.11	-25.17	-13.98
Republic of Korea	-4.68	-2.60	-8.01	-7.63	-7.04	-1.80
Rest of Euro Zone	-34.98	-37.43	-49.93	-52.02	-39.45	-28.29
Rest of OECD	-19.54	-20.64	-28.30	-29.19	-22.14	-16.88
Rest of the World	-20.33	-24.76	-27.43	-28.92	-25.50	-18.65
Russia	-21.86	-24.60	-30.62	-32.02	-28.98	-17.65
Saudi Arabia	-5.36	-6.32	-7.61	-7.16	-5.97	-1.03
South Africa	-38.39	-45.85	-52.31	-55.34	-51.77	-35.37
Turkey	-7.53	-7.70	-11.11	-11.22	-5.90	-4.44
United Kingdom	-25.39	-28.21	-35.60	-37.35	-28.81	-23.49
United States of America	-32.70	-32.41	-47.88	-50.01	-34.80	-30.94

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experience trade deficits while those that are losing private capital, will experience improving trade balances as the exchange rate depreciates and exports rise and imports fall. Countries like Argentina, Brazil, India, Indonesia, Russia and the rest of the world have improving trade positions due to the capital flight. Countries like Australia, Canada and South Korea tend to experience trade deficits due to the capital inflows. The United States has almost no impact on the trade balance because the usual safe-haven status when the increase in global risk is offset by the worse performance of the US in dealing with the virus.

The trade balance adjustment is also consistent with the results in Table 18, which shows the change in real effective exchange rates. A rise in the real effective exchange rate is an appreciation. Those countries losing capital experience a depreciation and those attracting capital experience an appreciation.

Table 19 contains results for inflation defined as the change in the consumer price index. For some countries, the COVID-19 pandemic is mildly inflationary, and for others, it is deflationary. Even more interesting is that for some sectors in some countries, relative prices may rise and in other sectors, relative prices may fall. The key is whether demand falls by more than supply due to the disruptions to production. If demand falls by more than supply in some sectors or some countries the inflation will fall. If supply falls by more than demand, then inflation can initially rise. What matters for inflation over time is the response of central banks. In the model, all central banks follow Henderson-McKibbin-Taylor type monetary rules and inflation eventually returns to baseline. Central banks cut interest rates in response to the pandemic (Table 20). Fiscal deficits are eventually contained through a lumpsum tax on households. In practice countries may not follow these sensible monetary rules or maintain fiscal solvency in which case the results can be very different over time.

Table 20 contains results for short-term real interest rates across all countries and Table 21 shows the change in the real return on ten-year bonds for all countries. The short-term interest rate falls sharply. This sharp drop in interest rates is mostly due to the response of monetary authorities that loosen monetary policy quickly. We do not impose a zero-lower bound on the nominal policy interest rate. We treat negative nominal rates as if they are shadow policy rates becoming negative to reflect the range of policies, including loan guarantees that different central banks follow to stabilise the economy. Note that the real rate on ten-year bonds (Table 21) falls by much less than short-term real interest rates, so there is a steepening of the real yield curve. Short interest rates recover over time. The long-term real interest rate encompasses the expected future path of short real interest rates.

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Table 16: Percent of GDP Change in Fiscal Deficit in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-0.69	-0.72	-1.03	-1.03	-1.00	-0.72
Australia	6.95	7.08	10.28	10.38	6.64	7.28
Brazil	-3.38	-3.33	-5.16	-5.08	-3.85	-3.24
Canada	9.22	9.27	13.77	13.83	8.99	9.38
China	0.99	1.05	1.44	1.48	0.83	1.04
France	2.87	3.01	4.18	4.25	2.58	2.77
Germany	2.82	2.82	4.16	4.19	2.40	2.75
India	-0.90	-0.91	-1.37	-1.35	-1.20	-0.88
Indonesia	-1.11	-1.12	-1.72	-1.66	-1.29	-0.95
Italy	5.27	5.39	7.76	7.84	5.26	5.19
Japan	0.31	0.45	0.40	0.41	-0.11	0.42
Mexico	0.79	0.85	1.16	1.19	0.94	0.98
Other Asia	3.69	3.81	5.47	5.50	3.81	3.89
Other oil producing countries	7.83	7.87	11.68	11.71	8.01	8.12
Republic of Korea	5.15	5.46	7.46	7.61	5.09	5.51
Rest of Euro Zone	3.42	3.56	4.98	5.05	3.21	3.32
Rest of OECD	2.72	2.81	3.95	4.03	2.54	2.89
Rest of the World	1.20	1.23	1.80	1.81	1.14	1.24
Russia	0.52	0.60	0.67	0.74	0.48	0.94
Saudi Arabia	3.20	3.59	4.54	4.58	3.55	3.57
South Africa	2.71	2.65	4.06	4.10	2.25	2.97
Turkey	0.43	0.50	0.57	0.61	0.58	0.61
United Kingdom	5.80	5.82	8.65	8.67	5.53	5.78
United States of America	1.59	1.60	2.39	2.42	0.66	1.49

Table 17: Percent of GDP Change in Trade Balance in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	4.64	5.65	6.39	6.61	4.39	3.24
Australia	-3.85	-3.91	-5.40	-5.76	-2.79	-5.26
Brazil	2.96	3.40	4.30	4.32	3.25	1.56
Canada	-3.86	-4.04	-5.34	-5.88	-3.49	-5.65
China	-2.12	-1.92	-3.21	-3.29	-1.94	-3.15
France	-1.15	-0.94	-2.01	-1.80	-2.22	-2.23
Germany	-2.62	-3.29	-4.15	-3.83	-3.96	-3.29
India	3.13	3.68	4.46	4.45	3.71	2.23
Indonesia	0.76	1.01	1.22	0.99	0.28	-0.90
Italy	-1.61	-1.73	-2.51	-2.35	-1.21	-2.85
Japan	1.30	0.68	1.45	1.99	-0.23	0.63
Mexico	3.80	3.88	5.72	5.63	4.02	2.29
Other Asia	0.05	0.17	0.62	0.15	1.30	-1.72
Other oil producing countries	0.96	2.32	0.78	0.91	4.00	1.50
Republic of Korea	-4.29	-5.35	-5.53	-6.05	-4.05	-5.70
Rest of Euro Zone	-1.78	-1.91	-2.53	-2.58	-2.00	-3.10
Rest of OECD	-2.51	-2.60	-3.95	-3.79	-3.33	-3.42
Rest of the World	6.07	7.34	8.52	8.59	7.38	5.42
Russia	2.60	2.85	3.73	3.75	2.94	1.38
Saudi Arabia	-2.02	-2.12	-2.85	-3.06	-2.98	-2.94
South Africa	0.57	2.89	-0.50	-0.01	2.39	-0.68
Turkey	2.28	2.11	3.66	3.41	1.08	0.99
United Kingdom	2.07	2.45	2.69	2.92	1.97	1.41
United States of America	-0.13	-0.91	0.31	0.23	-0.61	-0.82

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Table 18: Percent Change in Real Exchange Rate in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-11.44	-13.40	-16.06	-16.36	-11.45	-11.27
Australia	2.83	2.78	3.86	4.32	1.27	3.13
Brazil	-4.28	-5.24	-6.13	-6.10	-4.51	-2.97
Canada	2.53	2.35	3.60	4.14	1.73	3.05
China	1.84	1.40	2.96	2.94	1.32	1.60
France	1.95	1.92	2.97	2.89	2.68	1.20
Germany	0.76	1.17	1.31	1.05	1.31	-0.73
India	-5.32	-6.27	-7.53	-7.58	-6.25	-5.38
Indonesia	-2.83	-3.28	-4.24	-3.95	-2.13	-2.23
Italy	1.76	1.91	2.64	2.53	1.52	1.00
Japan	-2.93	-2.03	-3.51	-4.44	-0.81	-3.47
Mexico	-8.75	-9.42	-12.73	-12.77	-10.09	-8.66
Other Asia	-0.14	-0.37	-0.42	-0.19	-0.85	-0.98
Other oil producing countries	-1.41	-2.92	-1.36	-1.50	-4.55	-3.40
Republic of Korea	2.11	2.72	2.57	2.92	1.27	1.88
Rest of Euro Zone	1.21	1.32	1.69	1.76	1.21	0.18
Rest of OECD	1.52	1.57	2.39	2.30	2.03	0.81
Rest of the World	-4.80	-6.41	-6.40	-6.48	-5.89	-4.83
Russia	-2.58	-2.80	-3.70	-3.70	-2.95	-3.07
Saudi Arabia	-1.25	-1.49	-1.87	-1.75	-1.20	-3.17
South Africa	3.19	0.87	6.13	5.67	1.99	2.68
Turkey	-3.59	-3.62	-5.55	-5.28	-2.51	-3.47
United Kingdom	-2.65	-3.04	-3.59	-3.76	-2.31	-3.39
United States of America	3.90	6.20	4.20	4.57	6.16	4.77

Table 19: Percentage point Change in Inflation in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-3.11	-3.00	-4.76	-4.53	-4.58	-4.65
Australia	0.44	-0.48	1.19	1.00	-0.43	-0.91
Brazil	-0.54	-0.70	-0.97	-0.71	-1.64	-1.52
Canada	1.88	1.14	2.86	2.91	0.54	0.64
China	0.47	-1.12	1.68	1.34	-0.34	-0.62
France	-2.88	-3.98	-2.88	-3.58	-1.96	-3.28
Germany	-4.09	-4.58	-4.44	-5.43	-2.97	-6.40
India	-0.07	0.02	-0.31	-0.11	-1.18	-1.60
Indonesia	-1.01	-1.36	-1.57	-1.38	-2.37	-2.06
Italy	-2.70	-3.62	-2.84	-3.43	-3.04	-3.17
Japan	-2.66	-2.58	-2.88	-3.60	-0.53	-4.08
Mexico	-3.85	-4.15	-6.22	-5.98	-5.71	-5.21
Other Asia	0.69	0.15	1.03	1.27	-0.46	-0.98
Other oil producing countries	-1.16	-1.37	-1.46	-1.67	-2.66	-4.23
Republic of Korea	0.03	-0.96	0.68	0.41	-0.09	-1.53
Rest of Euro Zone	-2.78	-3.62	-3.23	-3.60	-2.81	-3.42
Rest of OECD	-1.15	-1.69	-0.61	-1.23	-1.10	-3.18
Rest of the World	2.61	3.02	3.28	3.57	1.65	1.54
Russia	-0.53	-0.93	-0.30	-0.55	-1.27	-2.51
Saudi Arabia	-4.90	-8.49	-4.83	-5.21	-7.17	-4.27
South Africa	7.85	8.13	11.62	11.66	9.10	5.87
Turkey	-1.00	-1.36	-1.23	-1.31	-2.54	-2.59
United Kingdom	-1.26	-1.39	-1.49	-1.68	-1.41	-2.94
United States of America	-1.32	-2.20	-1.30	-1.27	-2.77	-1.96

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Table 20: Percentage point Change in Real interest rate in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-8.05	-8.29	-12.68	-11.86	-10.04	-10.05
Australia	-2.35	-2.61	-1.55	-3.14	-0.42	-4.19
Brazil	-5.38	-5.74	-7.34	-7.85	-6.07	-6.68
Canada	-2.23	-2.64	-1.77	-3.15	-1.08	-4.11
China	-1.99	-1.80	-0.86	-2.75	1.17	-4.30
France	-2.04	-1.65	-0.82	-2.82	1.50	-4.36
Germany	-3.58	-3.09	-3.12	-4.89	0.25	-5.91
India	-4.64	-4.87	-6.35	-6.85	-4.47	-6.61
Indonesia	-3.82	-4.12	-5.08	-5.57	-4.03	-5.69
Italy	-3.56	-3.41	-2.97	-4.98	-0.26	-6.13
Japan	-4.58	-3.86	-4.81	-6.53	0.11	-6.00
Mexico	-8.66	-9.31	-13.53	-12.95	-12.34	-11.05
Other Asia	-4.01	-4.34	-4.38	-5.69	-2.93	-6.68
Other oil producing countries	-3.66	-3.70	-3.59	-5.33	-0.11	-7.23
Republic of Korea	-3.77	-3.90	-3.76	-5.15	-2.20	-6.24
Rest of Euro Zone	-3.27	-3.18	-2.95	-4.59	-0.74	-6.04
Rest of OECD	-3.16	-2.81	-2.40	-4.34	0.51	-5.25
Rest of the World	-3.29	-3.72	-4.19	-5.14	-2.35	-4.76
Russia	-5.75	-5.82	-7.29	-8.27	-4.39	-8.46
Saudi Arabia	-4.95	-4.76	-6.06	-7.08	-3.73	-8.77
South Africa	-0.62	-0.80	2.55	-0.93	4.81	-3.02
Turkey	-5.04	-5.13	-7.07	-7.33	-5.19	-7.01
United Kingdom	-3.69	-3.55	-4.09	-5.36	-0.89	-5.47
United States of America	-4.68	-4.64	-5.13	-6.39	-3.59	-5.43

Table 21: Percentage point Change in real 10-year interest rate in 2020 relative to baseline

Country/Region	S01	S02	S03	S04	S05	S06
Argentina	-1.33	-1.64	-1.87	-2.00	-2.39	-1.71
Australia	-0.02	-0.52	0.14	0.04	-1.06	-0.29
Brazil	-0.62	-0.98	-0.80	-0.92	-1.67	-0.81
Canada	0.13	-0.19	0.26	0.20	-0.91	-0.11
China	-0.06	-0.49	0.10	-0.03	-0.98	-0.41
France	-0.19	-0.73	-0.04	-0.20	-1.13	-0.55
Germany	-0.54	-1.23	-0.48	-0.68	-1.43	-1.01
India	-0.53	-0.79	-0.68	-0.80	-1.75	-0.82
Indonesia	-0.39	-0.69	-0.47	-0.56	-1.26	-0.62
Italy	-0.28	-0.82	-0.16	-0.34	-1.37	-0.68
Japan	-0.74	-1.23	-0.77	-1.02	-1.36	-1.05
Mexico	-0.89	-1.10	-1.30	-1.41	-2.04	-1.17
Other Asia	-0.28	-0.75	-0.25	-0.37	-1.44	-0.66
Other oil producing countries	-0.07	-0.33	0.02	-0.11	-1.66	-0.64
Republic of Korea	-0.34	-0.95	-0.28	-0.42	-1.38	-0.69
Rest of Euro Zone	-0.30	-0.82	-0.23	-0.38	-1.34	-0.73
Rest of OECD	-0.30	-0.89	-0.18	-0.36	-1.29	-0.69
Rest of the World	-0.10	-0.09	-0.14	-0.23	-1.30	-0.29
Russia	-0.55	-0.95	-0.63	-0.78	-1.67	-0.94
Saudi Arabia	-0.56	-1.12	-0.60	-0.75	-1.73	-1.09
South Africa	0.70	0.61	1.15	1.03	-0.62	0.30
Turkey	-0.63	-1.00	-0.79	-0.90	-1.69	-0.94
United Kingdom	-0.45	-0.84	-0.48	-0.64	-1.49	-0.80
United States of America	-0.88	-1.87	-0.97	-1.16	-1.90	-1.01

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5.3 Dynamic Results

The results for all countries exhibit similar patterns because of the nature of the economic shocks we have imposed. It is possible that the COVID-19 pandemic has caused a major structural change to the world economy and that the pattern of recovery in the scenarios considered in this paper does not ensue. Scenarios 1-4 imply an eventual recovery of the global economy, whereas scenario 5 implies the persistence of higher risk, which causes the countries to have a permanent output loss. In this paper, we do not consider any major benefits of the implementation of new technologies that may follow the recovery to the COVID-19 pandemic. McKibbin and Triggs (2018) use the same model as in this paper to consider a range of global productivity scenarios unrelated to the COVID-19 pandemic but which is illustrative of how different the world evolves depending on productivity changes due to technology.

In this section, we will focus on results for Australia to explain the economic adjustments over time. The economic story is similar for all countries given the initial differences for 2020 discussed above. A complete set of all dynamic results for all countries are available on the Dashboard.

Figure 17 shows the dynamic path of Real GDP, real consumption, real investment and the trade balance. It is clear, that as the pandemic worsens across the scenarios, the falls in year 1 GDP, consumption and investment increase. It takes three years on average for real GDP to return to the pre COVID-19 baseline under most scenarios. Under scenario 5, in which there is a permanent change in risk, Australian GDP (and that of all other countries) never returns to baseline. One exception to the more substantial falls across scenarios is the Australian trade balance, which worsens by less as the pandemic worsens. This result is not surprising as the world economy is increasingly negatively impacted; the impact on the Australian economy, which is exposed to global trade becomes less attractive as an investment destination. Figure 18 contains results for the other key macroeconomic variables: employment, inflation, the real short-term interest rate and the real effective exchange rate.

Figures 19 and 20 show the sectoral output and employment results for energy, mining, agriculture, durable manufacturing, non-durable manufacturing and services. All sectors are negatively impacted by the sharp reduction in demand and supply except for energy output because the fall in energy prices increases energy use. Services and non-durable manufacturing have larger output and employment losses. In the case of a permanent rise in global risk (Scenario 5), there is a permanent structural change induced by the pandemic. Higher risk means a lower global capital stock and those sectors that feed heavily into investment activities such as durable manufacturing and mining experience permanent relative contractions.

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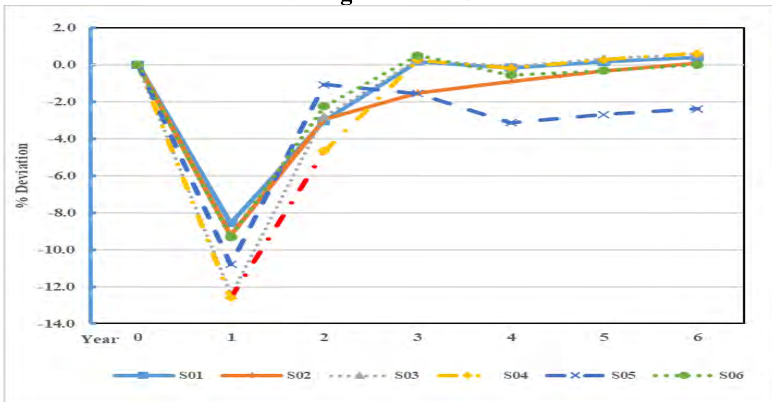
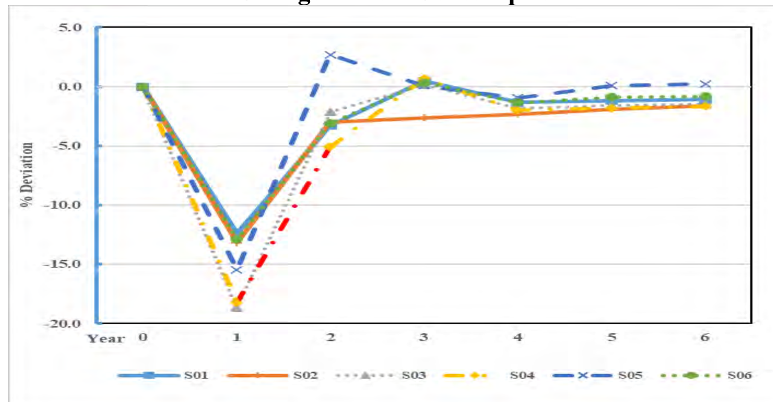
Figure 17: Dynamic Results for Australia

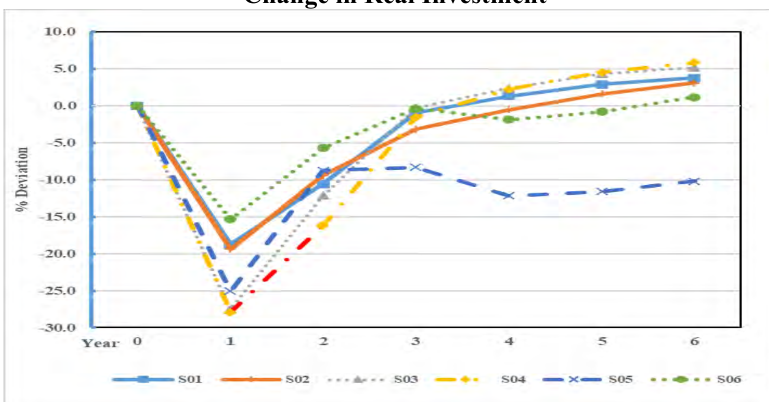
Change in Real GDP



Change in Real Consumption



Change in Real Investment



Change in Trade Balance (% GDP)

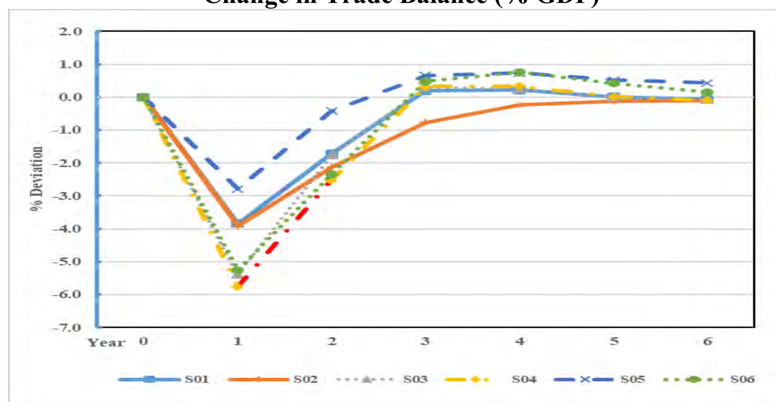


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Figure 18: Dynamic Results for Australia (Contd.)

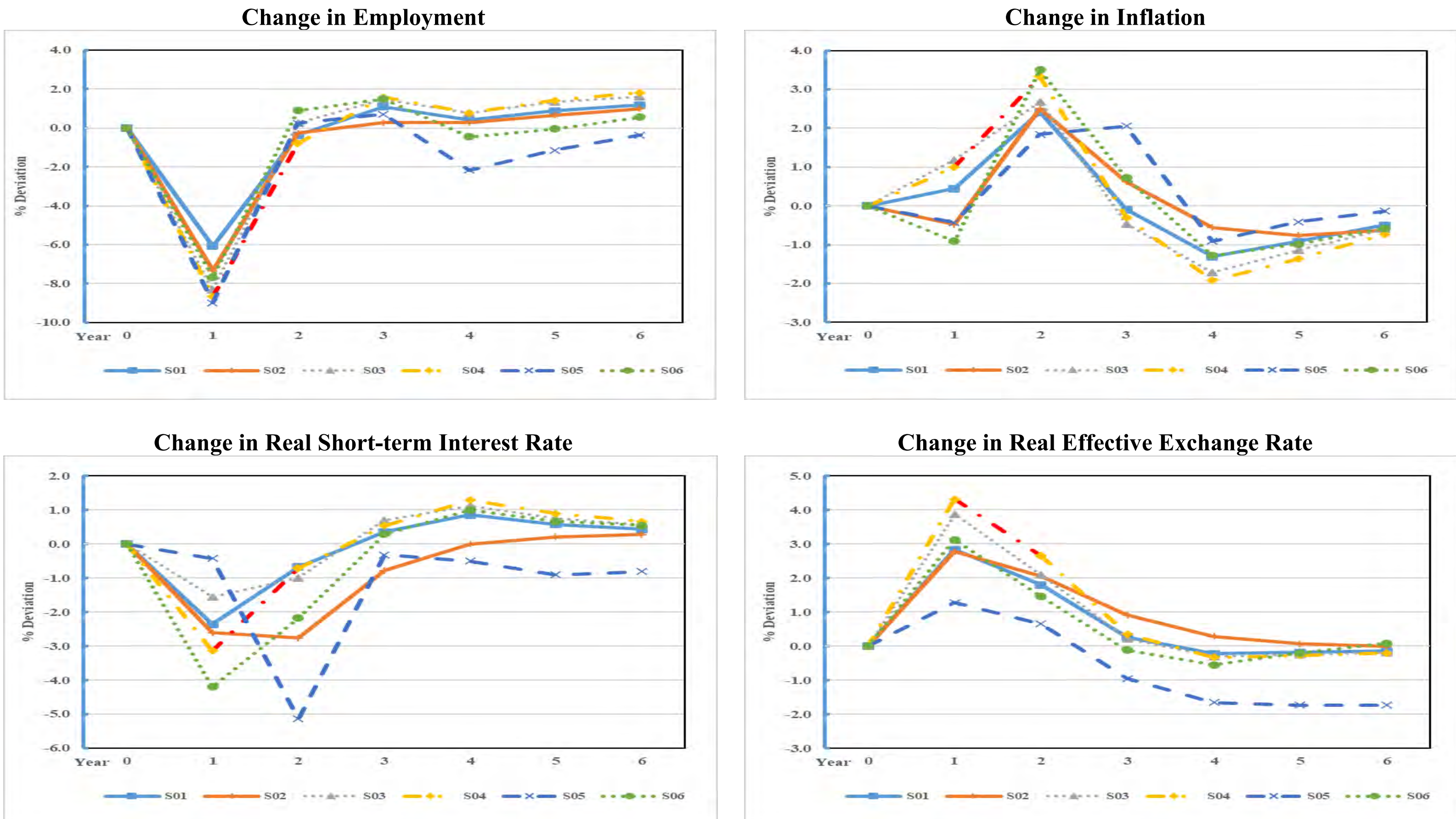

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Figure 19: Dynamic Results for Australia (Contd.)

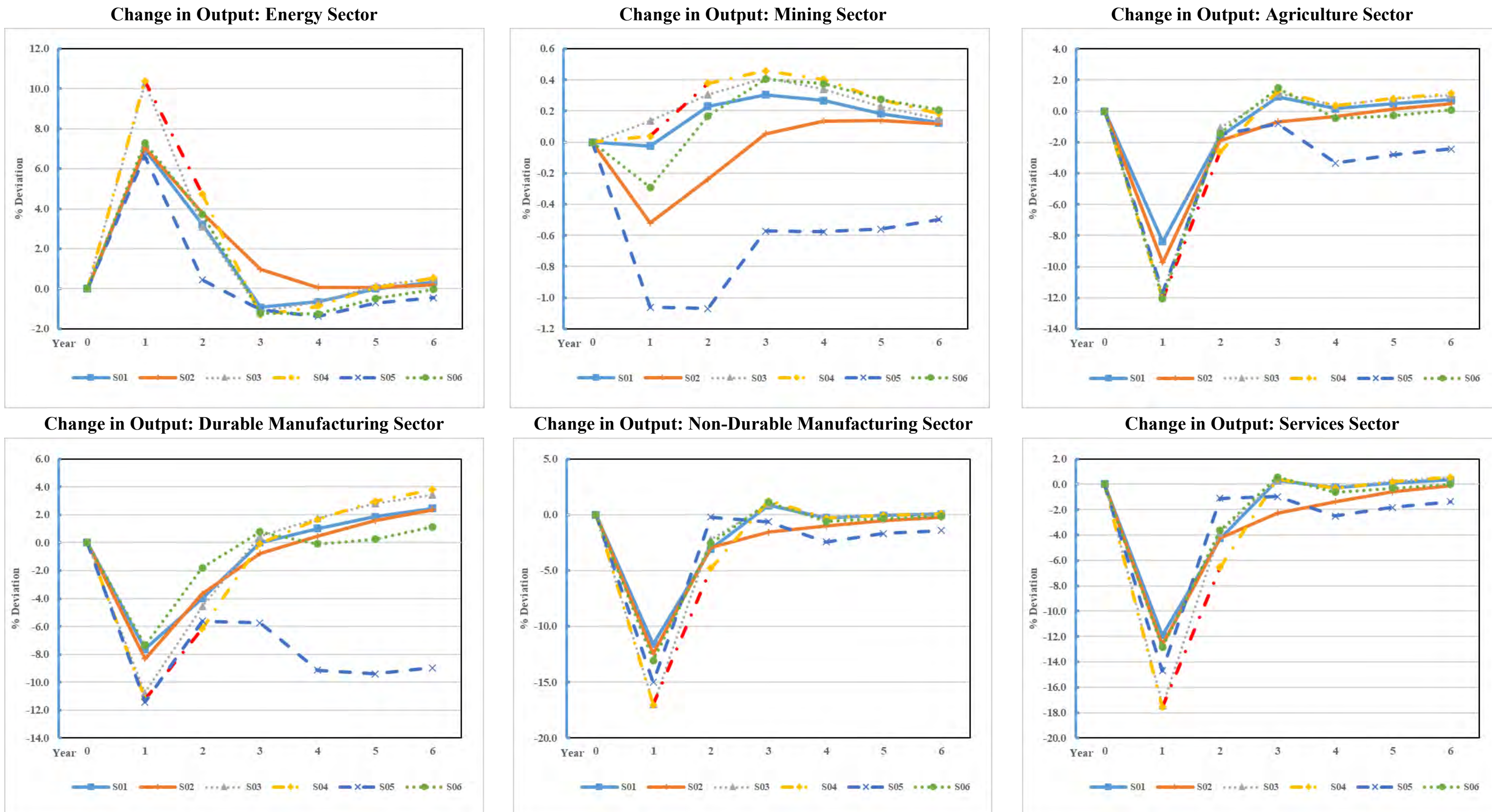
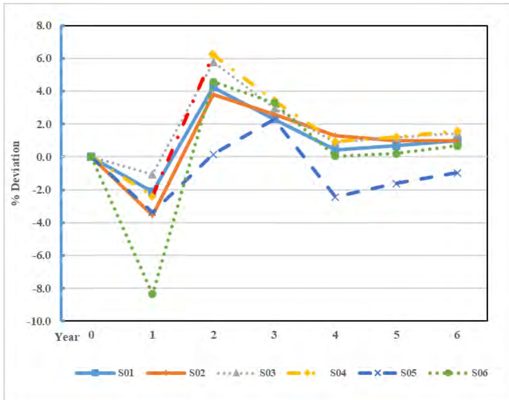
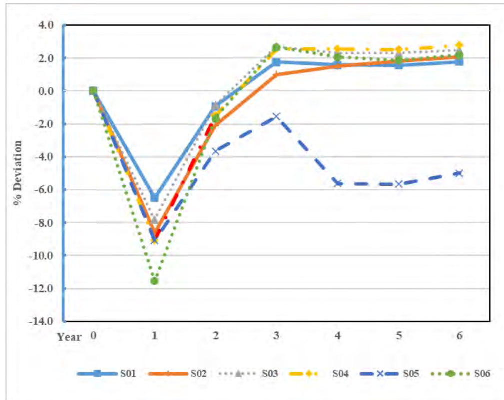


Figure 20: Dynamic Results for Australia (Contd.)

Change in Employment: Energy Sector



Change in Employment: Mining Sector



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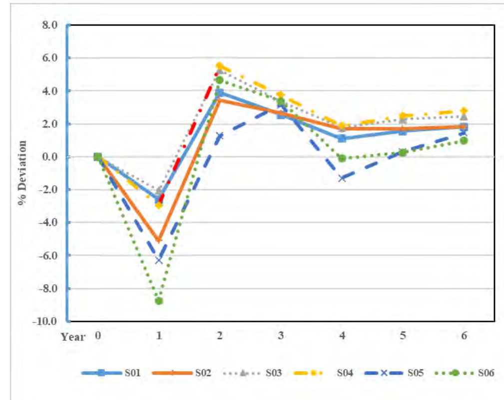
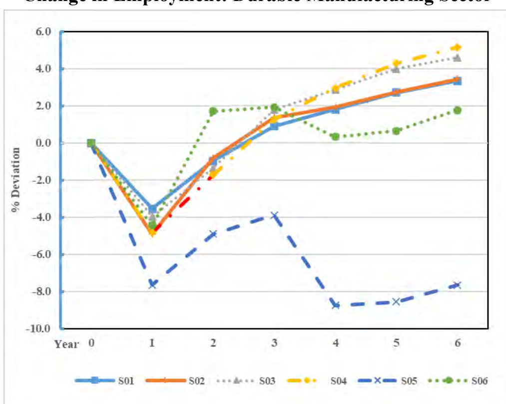
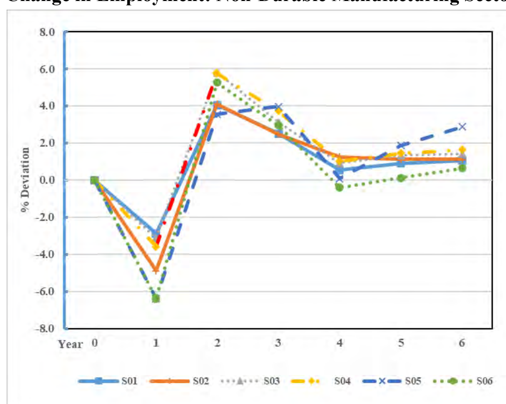


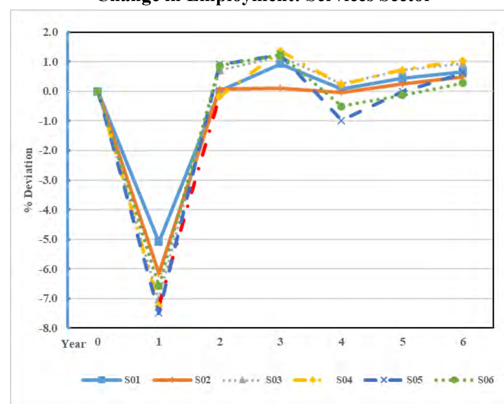
Change in Employment: Durable Manufacturing Sector



Change in Employment: Non-Durable Manufacturing Sector



Change in Employment: Services Sector



6 Conclusion & Policy Implications

This paper applies recent data on the different epidemiological experiences of COVID-19 and recent observations on the extent of economic shocks in early 2020 across countries to explore six different scenarios for the evolution of the world economy over the next few years. There is still enormous uncertainty about the future course of the pandemic, whether a vaccine will be available and effective in the near term, and whether countries will change their policies in response to the economic adjustments already experienced, if new waves of the pandemic emerged. There is no doubt that COVID-19 is a significant negative shock to the world economy. The health policy responses and the economic policy responses have been very different across countries. As a result, some countries have done much better in responding to the pandemic. It is also very likely that there will be future waves of COVID-19 just as there were waves of the 1918/19 flu pandemic. The basis of the scenarios explored in this paper revolve around how many future waves there might be and how countries will respond to those outbreaks in terms of public health responses and changes in economic policies.

Even under the first scenario, which assumes that the worst of COVID-19 is over by mid-2020, the global economy experiences a major recession in 2020. Some countries are impacted far more than others. The results from this paper and recent IMF and World Bank forecasts make it clear that health and economic policies will have to be carefully designed and adapted to get through the current phase of the pandemic. Withdrawing macroeconomic support and creating 'fiscal cliffs' through setting expiration dates on critical fiscal support policies in economies is likely to worsen the uncertainty and increase the economic costs. Preventing countries from undertaking more substantial fiscal stimulus measures either through institutional arrangements or by lack of access to financing also increase the cost of the pandemic. In McKibbin and Vines (2020), we explore the benefits of an additional globally coordinated fiscal response for constrained countries through G20 policy cooperation in the case of scenario 5 from this paper. The gains (or avoided losses) are significant for the global economy.

While the short-term public health and macroeconomic policy responses are critical to the shape of the world economy in 2020, the evolution of the global economy over future decades will depend on longer-term policy decisions. As argued in McKibbin and Fernando (2020a & 2020b), investment in global public health, particularly in developing economies is a crucial ingredient in avoiding future devastation from pandemics. The experience of pandemic emergence over the past two decades shows that COVID-19 is not an isolated event. Given the scientific knowledge about zoonotic diseases and emerging spillovers of viruses from current hosts to humans, there is a strong case for investment in pandemic preparedness at the national

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and global levels. Global cooperation is fundamental since pandemics do not respect borders. Therefore, the institutional design at the global level is critical to success. A World Health Organization, in some form, is vital to a cooperative global public health response. Also, the role of the G20, as it was in the global financial crisis a decade ago, is critical. Design and financing of macroeconomic policy responses will need to be better coordinated over the coming years.

COVID-19 is one amongst many challenges that the world will face in the coming decades. These problems include ongoing pandemics, the increasing prevalence of antimicrobial resistance and the need to deal with the impacts of climate change and the impact of transitional policies to address climate change. The current experience with the COVID-19 pandemic has revealed deep problems in existing institutions at the supernational level and within countries. While policies need to be designed and implemented at the national level, for most foreseeable problems, there needs to be greater cooperation across countries. COVID-19 shows the folly of isolationist politics and policies when the natural world ignores artificial boundaries.

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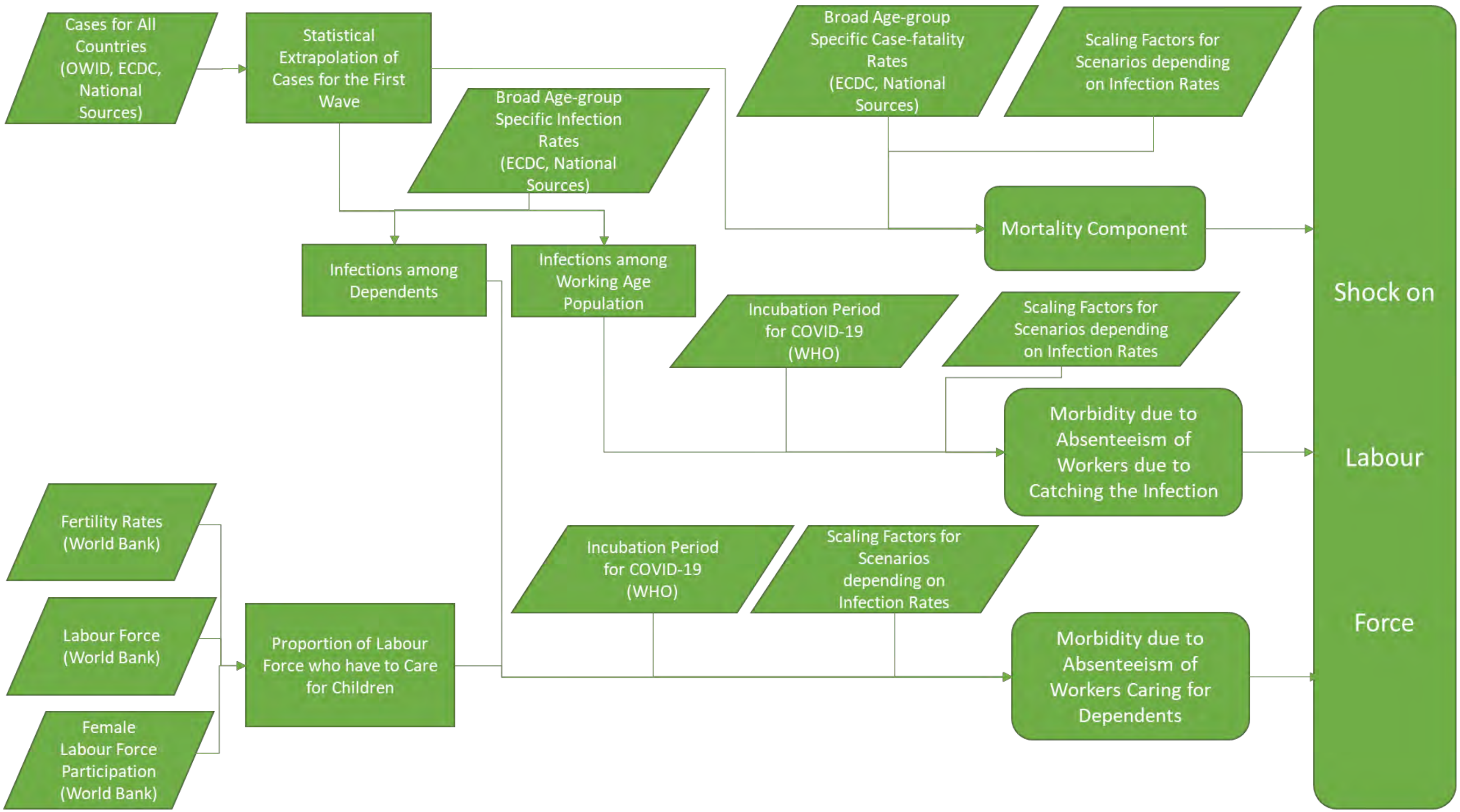
Appendix A: Flowcharts for formulating shocks



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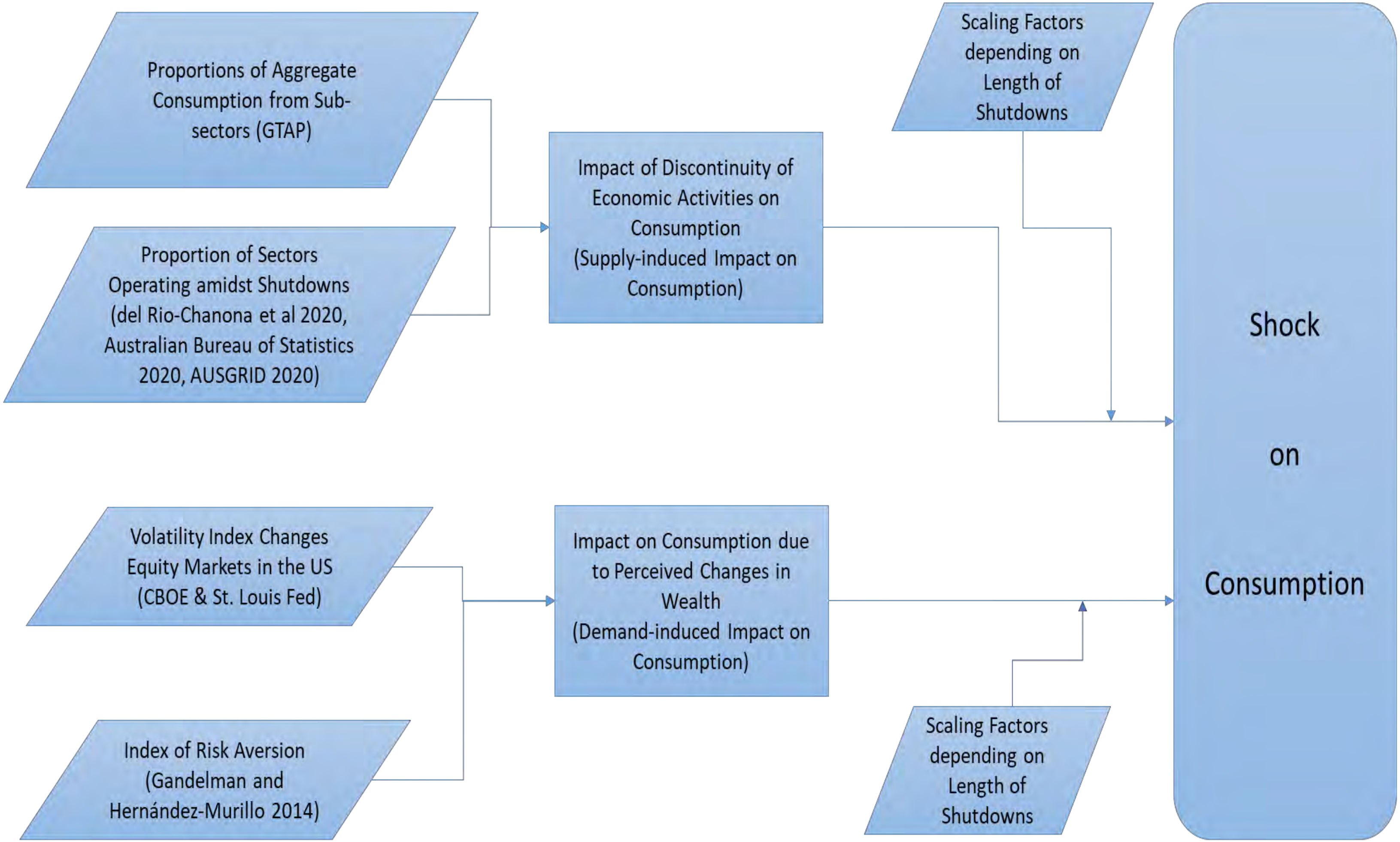

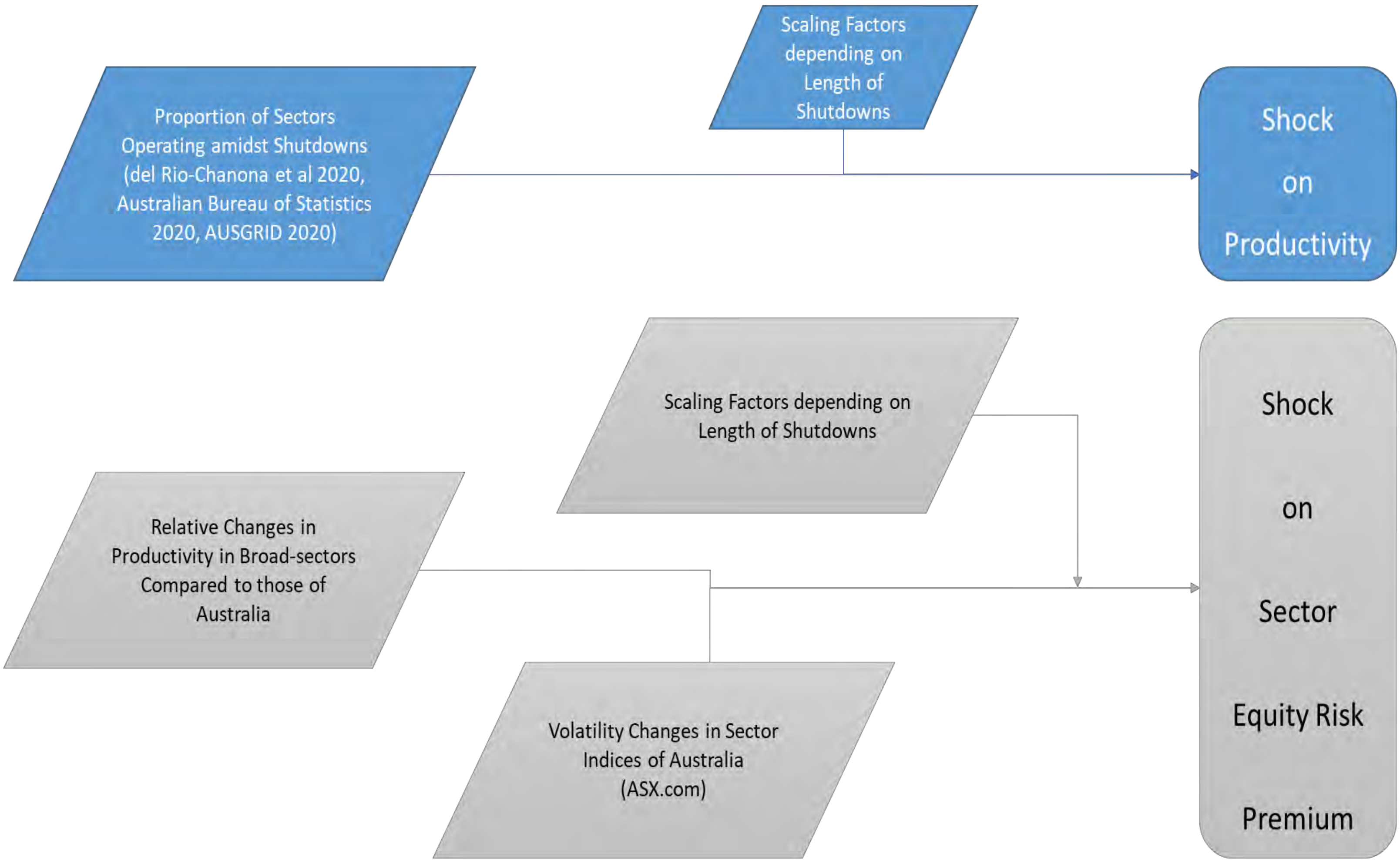
Scaling Factors depending on Length of Shutdowns
Proportion of Sectors Operating amidst Shutdowns (del Rio-Chanona et al 2020, Australian Bureau of Statistics 2020, AUSGRID 2020)
Shock on Productivity
Scaling Factors depending on Length of Shutdowns
Relative Changes in Productivity in Broad-sectors Compared to those of Australia
Volatility Changes in Sector Indices of Australia (ASX.com)
Shock on Sector Equity Risk Premium

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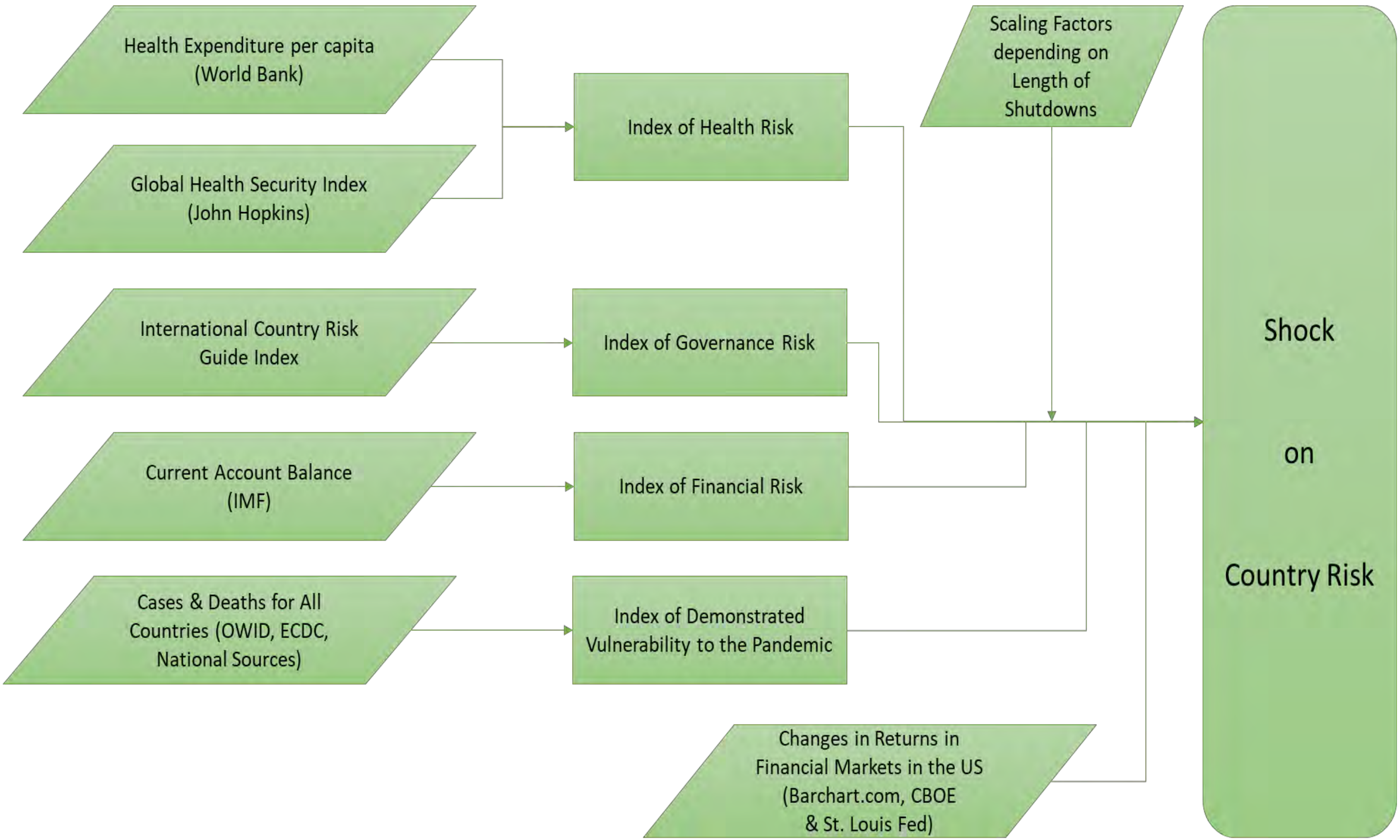

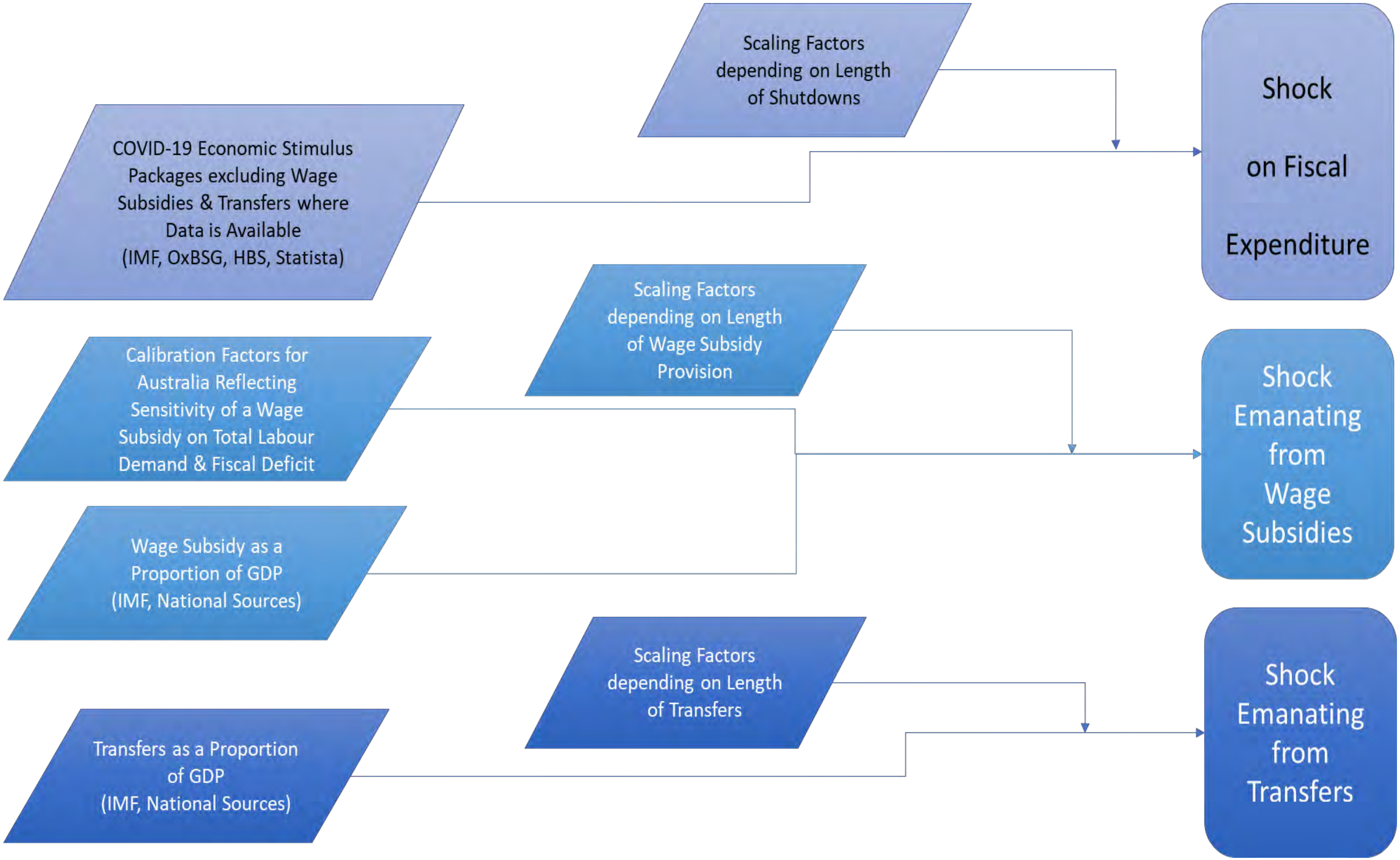

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Covid Economics **Issue 39, 23 July 2020**

Take me out: De facto limits on strict lockdowns in developing countries

Eduardo Levy Yeyati[1] and Luca Sartorio[2]

Date submitted: 16 July 2020; Date accepted: 17 July 2020

In the COVID-19 pandemic, lockdowns and containment measures were a fundamental tool to control the spread of the virus. In this article, we analyze data from 120 countries seeking to assess the stringency of de jure lockdown policies, comparing them with their de facto compliance and empirically analyzing the determinants of social distancing noncompliance. We find that, from a de jure perspective, almost all the strictest and longest lockdowns took place in emerging or developing economies. However, when analyzing its de facto compliance, we document a generalized and increasing non-compliance over time, which is significantly higher in emerging and developing economies. We show that lockdown compliance declines with time, and is lower in countries with stricter quarantines, lower incomes and higher levels of labor precariousness.

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Generalized lockdowns have been the first line of defense against the COVID-19 pandemic, but the lengthening of the expected duration of the pandemic and the tax that labor restrictions impose on the economy by strict quarantines have moved the consensus towards a "learning-to-live-with-the-COVID-19" mix of social distancing with widespread testing and tracing and localized suppression.

That said, the rigidity of isolation policies, as measured nationally by the Oxford Stringency Index (OSI) compiled by the University of Oxford, continues to be high in many quarters, particularly in emerging and developing countries, increasing the already high social and economic costs of the pandemic (Figures 1a and 1b)[1].

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[1] The data of this article is taken from the CEPE-DiTella COVID program database and is available upon request.

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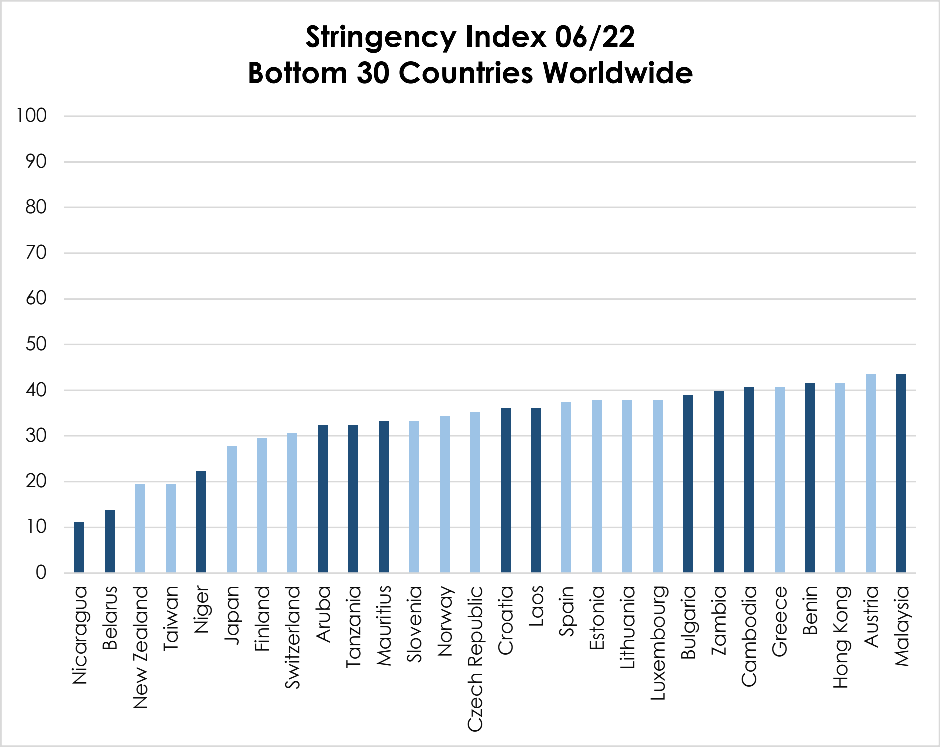
Figure 1. Oxford Stringency Index (OSI), June 22th



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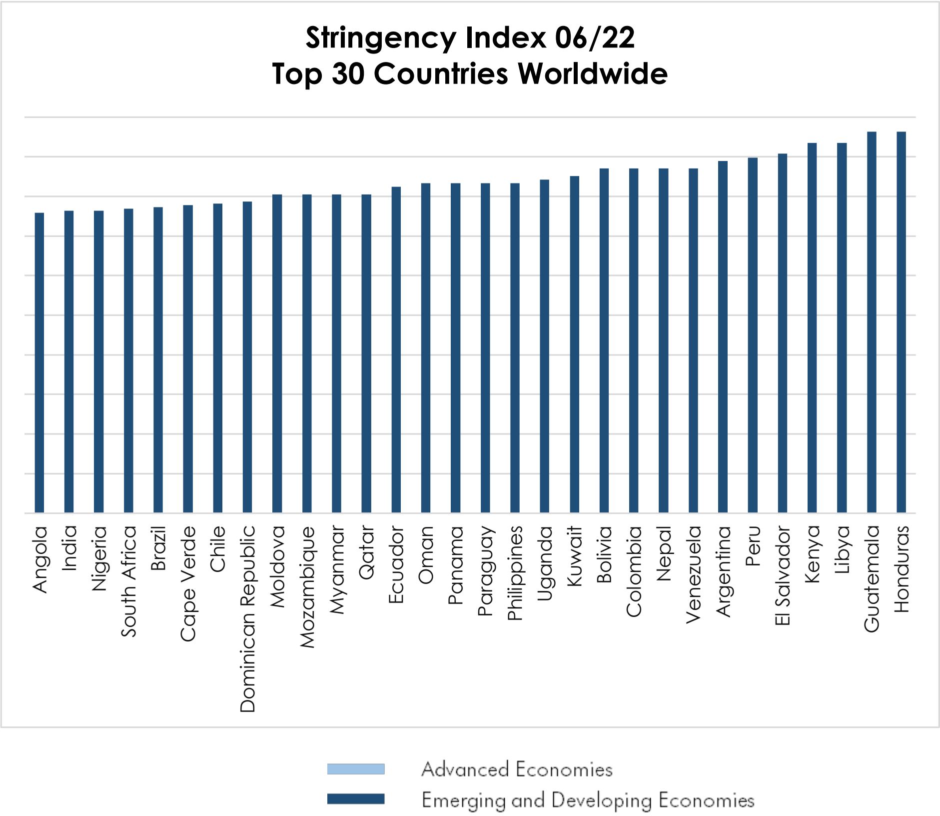

Source: Oxford COVID-19 Government Response Tracker (OxCGRT)

Moreover, many developing economies are not only hit by the stringency of the lockdowns but also by a length that far exceeds that of a traditional quarantine. In fact, Israel is the only advanced economy in the world's 30 longest strict lockdowns (Figures 2a and 2b).

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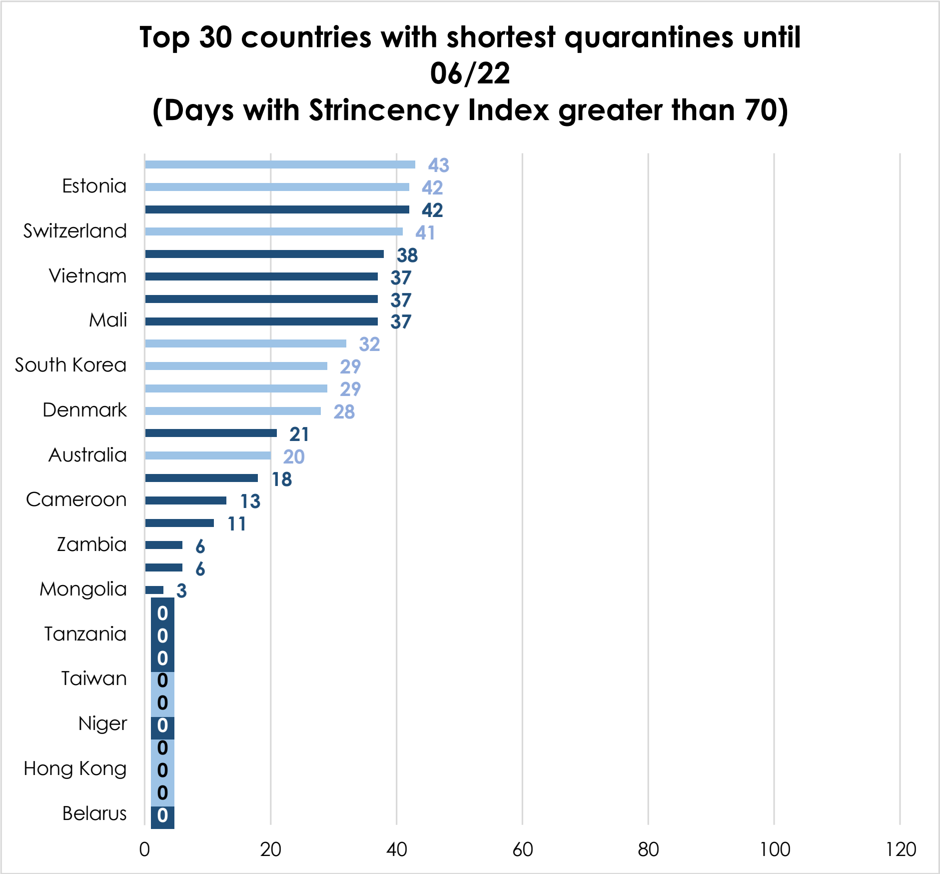
Figure 2. Lockdown duration per country: Days accumulated until June 22th with an Oxford Stringency Index (OSI) greater than 70 points.



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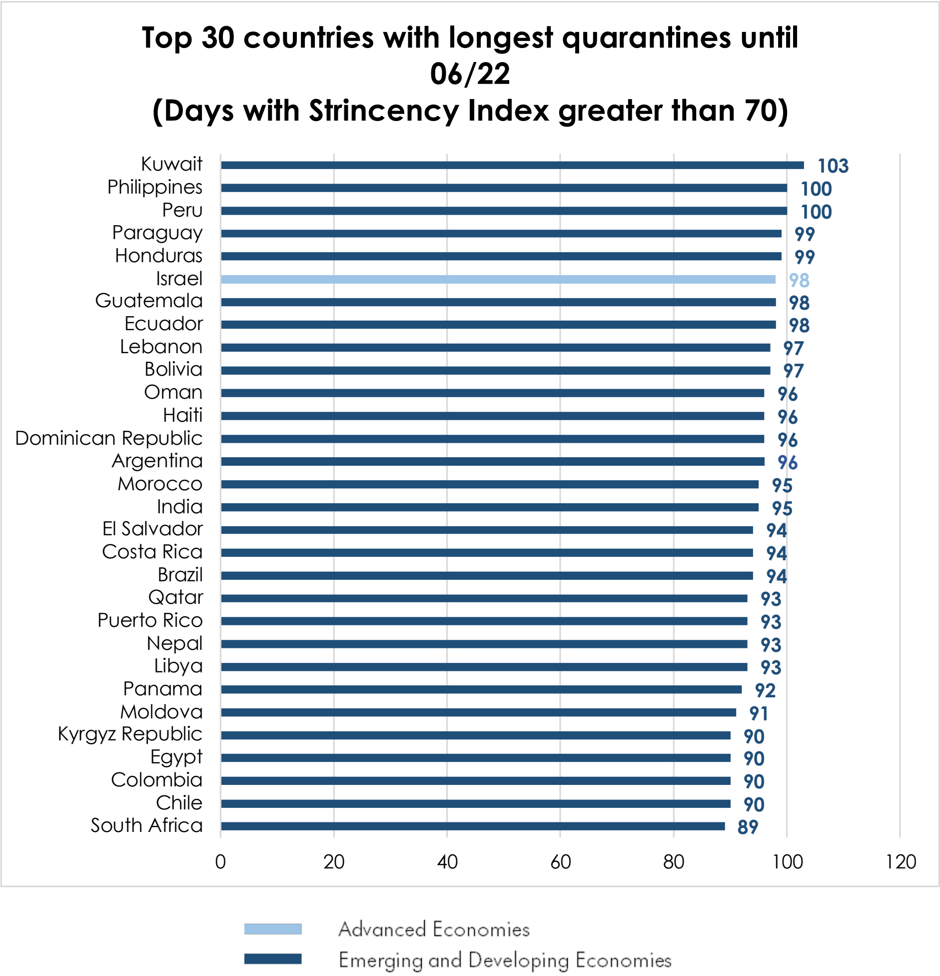
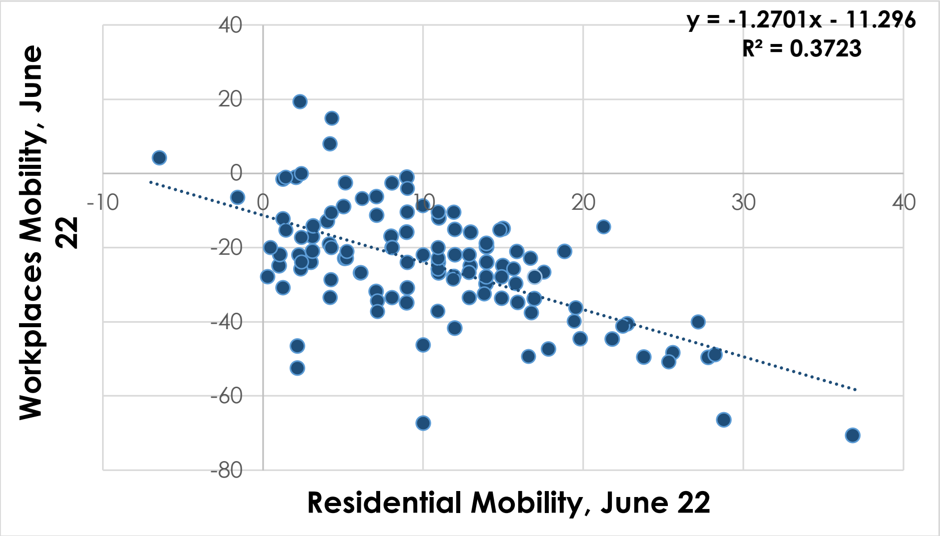


Source: Oxford COVID-19 Government Response Tracker (OxCGRT)

The OSI has been recently used to assess the effectiveness of the lockdown in containing the virus spread (Ostry et al., 2020; Goldstein et al., 2020). However, the ultimate incidence of the lockdown is intimately related to its impact on actual mobility, particularly workplace mobility, which is mostly associated with closed common spaces and public transportation and thus more likely to influence the spread. Indeed, a point to highlight is that residential mobility often correlates negatively with workplace mobility –and in most countries increased with the lockdown– as it works as a compensatory escape valve (Figure 3). This suggests that strict lockdowns on productive activities are partially "diluted" in non-productive activities. Additionally, workplace mobility is likely the one most closely related to the economic costs of the pandemic. As a result, a measure of total mobility, by averaging both types, may underestimate the health and economic impact of the lockdown.

Figure 3. Work Mobility and Residential Mobility, percentage change relative to baseline, June 22th



Source: Google COVID-19 Community Mobility Reports

De jure rigidity and de facto noncompliance

It seems natural to distinguish between the formal (de jure) rigidity of lockdown policies and its de facto compliance, and to explore the determinants of this compliance to evaluate the convenience of either extending or gradually lifting the current restrictions.

It is possible to approximate the distance between these two based on mobility data garnered from the movement of cell phones; in our case, Google´s Mobility Index (GMI), which estimates the variation of mobility relative to a baseline date previous to the pandemic (January 2020), distinguishing (approximately) by mobility types. To compare the evolution of de jure and de facto lockdowns at the national level across countries (Figures 4a and 4b), we normalize the GMI to zero for the week from March 3rd to March 10th to avoid an unnecessary bias in countries in the Southern Hemisphere, where labor mobility falls during the holiday season in January.

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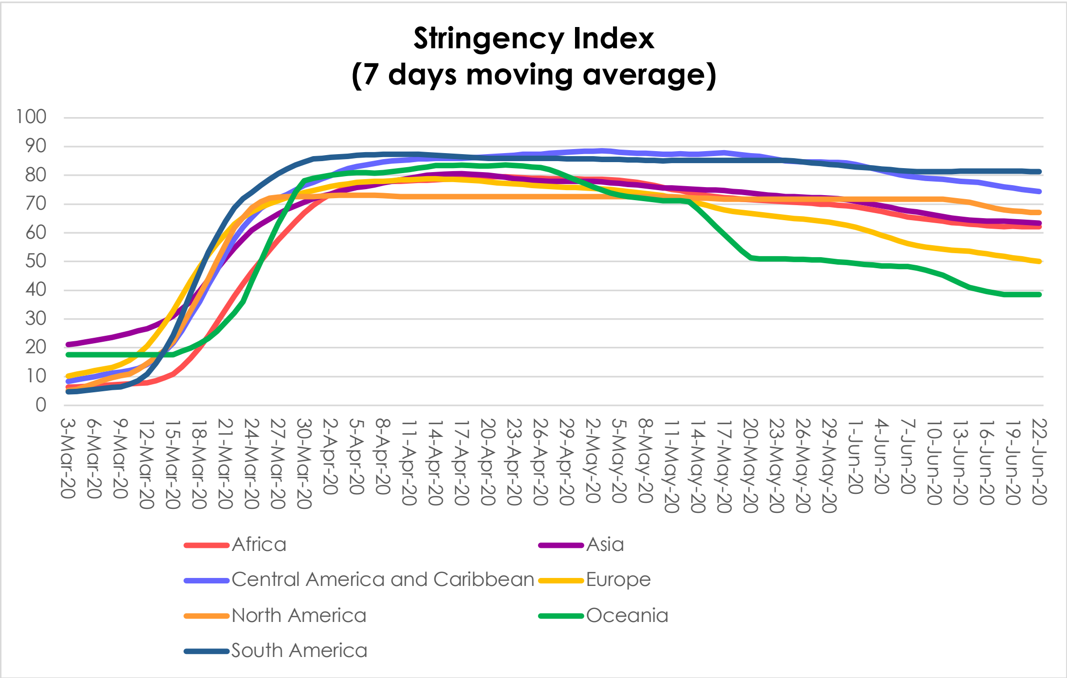
Figure 4. De jure rigidity (OSI) and de facto compliance (GMI, percentage change relative to baseline) of lockdown policies



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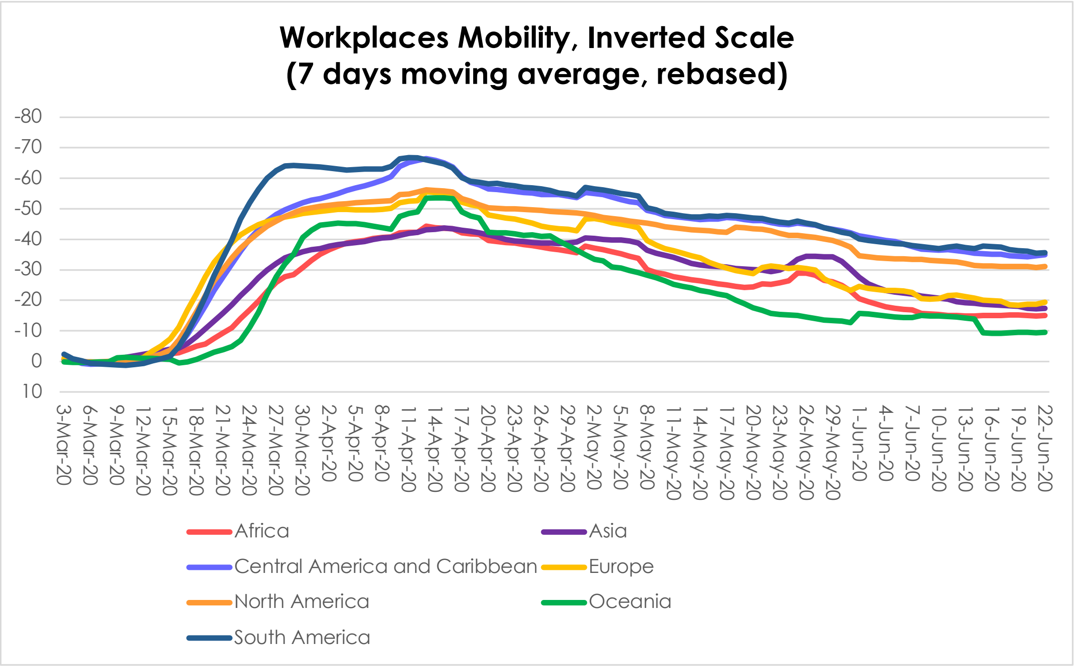
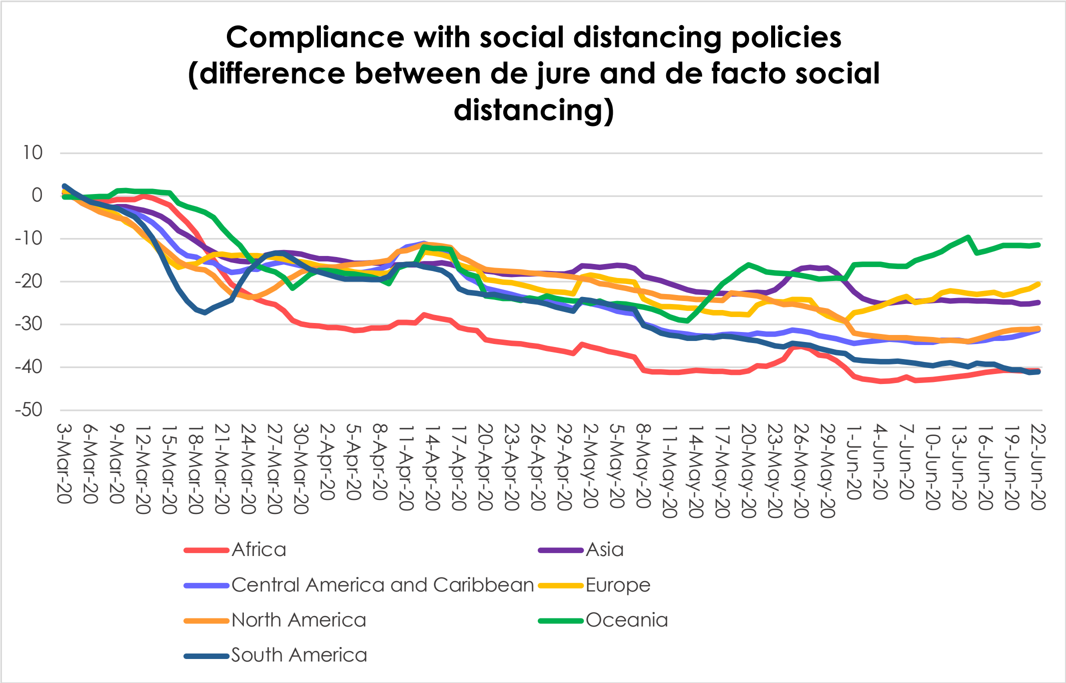


Sources: Oxford COVID-19 Government Response Tracker (OxCGRT) and Google COVID-19 Community Mobility Reports

When the restrictions on mobility de jure and de facto are both analyzed, several interesting findings are observed. First, with the exception of North America, government-imposed lockdowns were tighter and more sustained during the course of the epidemic in emerging and developing economies. However, despite the de jure restrictions, de facto labor mobility grew steadily over time: for instance, current activity in work areas in Asia and Africa is even higher than in Europe despite having stricter legal lockdowns.

To estimate the degree and evolution of compliance in each country, we normalize the OSI to zero on March 3rd, 2020 and subtract it from the normalized GMI. As can be seen, non-compliance with lockdown policies increased over time and was higher in developing economies, particularly in Africa and Latin America (Figure 5).

Figure 5. Standardized discrepancy of the Oxford Stringency Index (OSI) with Google's Work Mobility.



Sources: Oxford COVID-19 Government Response Tracker (OxCGRT) and Google COVID-19 Community Mobility Reports

What is behind the lack of compliance?

The previous analysis highlights the policy conundrum faced by many emerging and developing economies: long and strict but increasingly breached lockdowns, a measure of the limits that the socioeconomic reality imposes on social distancing measures.

Is a sustained tightening of the quarantine going forward still viable? The question is doubly relevant to developing countries in the South: 1) the winter season heightens the circulation risk and puts pressure on the capacity of local governments to relax mobility restrictions; 2) precarious labor markets (largely comprised of independent or informal workers) and poor and overcrowded habitats deepen the welfare impact of lockdowns and limit governments´ income support programs and stay-at-home campaigns (Levy Yeyati and Valdés, 2020). Not surprisingly, compliance correlates with per capita income and labor precariousness in urban centers (Figures 6a and 6b).

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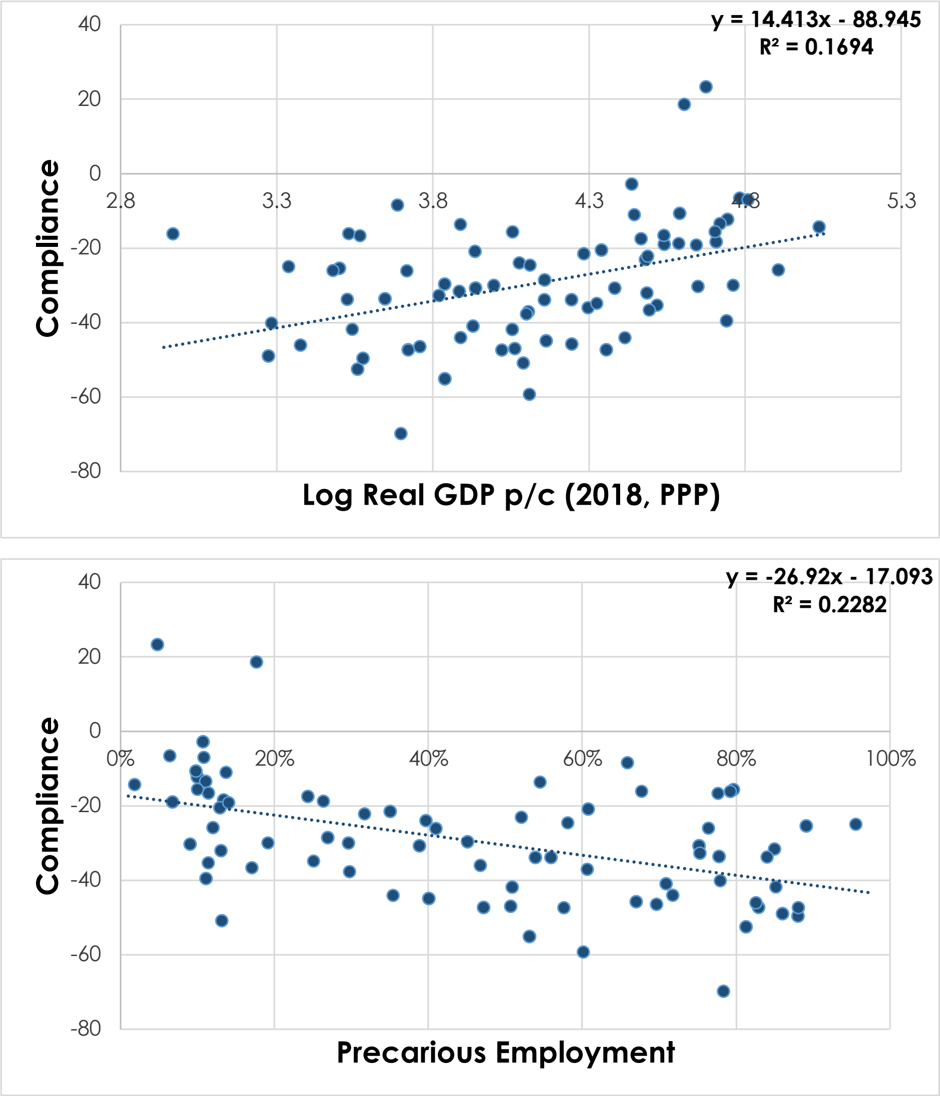
Figure 6. Correlations between compliance with Real GDP p/c and Urban Precarious Employment, June 22th



Sources: Oxford COVID-19 Government Response Tracker (OxCGRT), Google COVID-19 Community Mobility Reports, World Bank and International Labor Organization

To address the question about the determinants of lockdown compliance more rigorously, we ran a simple model of our measure of non-compliance against a number of potential drivers:

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1) The stringency of the lockdown, measured by the OSI (we expect that harder lockdowns correlated with lower compliance);[2]
2) GDP per capita, PPP measured in constant 2017 international dollars and expressed in logs using World Bank data (lower incomes should correlate with poorer compliance);[3]
3) Urban labor precariousness, defined as the share of non-agricultural informal employment in non-agriculture, estimated by the International Labour Organization (more precariousness, less compliance)[4]
4) The length of the pandemic measured as a simple time trend to capture the lockdown fatigue (non-compliance increases over time);
5) The daily COVID death count reported by Our World in Data (to control for "fear factor": the larger, the stronger the compliance).[5]

The results confirm our priors: stronger and longer lockdowns, in countries with lower incomes and higher levels of labor informality have significantly lower levels of compliance, whereas the rise of the COVID-19 death toll contributes to the effectiveness of the quarantine (Table 1).

Table 1. What is behind the lack of compliance? Pooled regressions of Lockdown Compliance.

VARIABLES	(1) Compliance	(2) Compliance	(3) Compliance
Stringency	-0.164***	-0.166***	-0.172***
	(0.00712)	(0.00716)	(0.00708)
Timetrend	-0.0864***	-0.0939***	-0.0892***
	(0.0111)	(0.0114)	(0.0115)
Stringency * Timetrend	-0.00186***	-0.00174***	-0.00182***
	(0.000179)	(0.000184)	(0.000184)
GDP per capita (Log)	4.340***	3.496***	3.131***
	(0.133)	(0.283)	(0.288)
Urban Informal Employment		-3.567***	-3.447***
		(1.027)	(1.028)
Daily Deaths (per million of people)			0.582***
			(0.0569)
Constant	-40.75***	-31.02***	-27.64***
	(1.279)	(3.136)	(3.183)
Observations	8,736	8,736	8,736
R-squared	0.429	0.430	0.436
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

[2] Data available in https://covidtracker.bsg.ox.ac.uk/
[3] Data available in https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD.
[4] Data available in https://www.wiego.org/sites/default/files/publications/files/Women%20and%20Men%20in%20the%20Informal%20Economy%203rd%20Edition%202018.pdf.
[5] Data available in https://ourworldindata.org/covid-deaths.

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Note: Stringency is measured by the OSI, GDP per capita is measured in logarithms (Source: World Bank), Urban Informal Employment measures the share of informal and self-employed employment over total employment outside rural areas (Source: International Labor Organization) and Daily Deaths per million measures the number of daily deaths from COVID-19 per million people (Source: Our World in Data).

What next? A socially and economically viable transition

The previous findings identify the multiple dimensions behind the lockdown fatigue (time, stringency, precariousness, income) highlighting the practical limits of implementing stringent social distancing policies in developing countries with dual labor markets and a considerable portion of the population living in congested neighborhoods with poor habitats. This suggests that, moving forward, lockdowns will likely be increasingly ineffective –especially in low and middle-income countries from Asia, Africa and Latin America that still have strict restrictions in place. Additionally, this also hints at the difficulty of resorting to new lockdowns in the event of a second wave: none of the 120 countries in our database has so far reestablish equally strong restrictions on labor mobility after they have been lifted.

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From fear to hate: How the COVID-19 pandemic sparks racial animus in the United States[1]

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We estimate the effect of the coronavirus (COVID-19) pandemic on racial animus as measured by Google searches and Twitter posts, including a commonly used anti-Asian racial slur. Our empirical strategy exploits the plausibly exogenous variation in the timing of the first COVID-19 diagnosis across regions in the United States. We find that the first local diagnosis leads to an immediate increase in racist Google searches and Twitter posts, with the latter mainly due to existing Twitter users posting the slur for the first time. This increase could indicate a rise in future hate crimes as we document a strong correlation between the use of the slur and anti-Asian hate crimes using historic data. Moreover, we find that the rise in animosity is directed at Asians rather than other minority groups and is stronger in hours and on days when the connection between the disease and Asians is more salient, as proxied by the number of President Trump's tweets mentioning China and COVID-19 simultaneously. In contrast, the negative economic impact of the pandemic plays little role in the initial increase in racial animus. Our results suggest that de-emphasizing the connection between the disease and a particular racial group can be effective in curbing current and future racial animus.

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1. Introduction

Racial animus can affect welfare in measurable ways, as economists have noted since the seminal work of Becker (1957). Recent papers have shown that racial animus can hinder economic development, affect political institutions, and induce social unrest.[1] To prevent further fueling of racial animus and reduce its damage to society, it is fundamental to rigorously identify how racial animus forms and spreads.

The coronavirus (COVID-19) pandemic provides a natural experiment allowing us to study why and how racial animus against certain groups can rise rapidly. It has long been argued that the risk of infection can foster xenophobia (Schaller and Neuberg, 2012). While COVID-19 may have originated in China, the Centers for Disease Control and Prevention (CDC) has emphasized that people of Asian descent are at no greater risk of spreading the virus than are other Americans. Nonetheless, since the outbreak of the virus, multiple incidents of Asian Americans being verbally or physically attacked have been reported by major news outlets,[2] and hundreds more have been recorded by organizations that track hate incidents (Mullis and Glenn, 2020). These are telltale signs that the current pandemic may have sparked racial animus against Asians. The challenge is to measure and understand this phenomenon rigorously and expediently.

In this paper, we exploit variation in the timing of the first local COVID-19 diagnosis across regions in the United States to causally identify how infectious diseases can trigger racial animus against Asians. We focus on the timing of the *first* COVID-19 diagnosis for two reasons. First, the first diagnosis in an area represents a salient increase in the infection risk. Lab experiments have shown that a more salient threat of infectious diseases leads to stronger xenophobia (Faulkner et al., 2004). Second, the exact timing of the first diagnosis is plausibly exogenous; whether an area has its first diagnosis this week or the next is largely unpredictable and is unlikely to be correlated with other factors that simultaneously change local racial animus.[3]

To proxy for an area's racial animus against Asians, we use the percentage of Google searches

[1] For example, the racial wage gap, residential racial segregation, the costs of being minority political candidates, and the death of Gorge Floyd and the resulting protests across the United States can all find their roots more or less in racism or racial animus (Charles and Guryan, 2008; Card et al., 2008; Stephens- Davidowitz, 2014; BBC, 2020).

[2] For example, anti-Asian incidents have been reported on *NBC News* (https://www.nbcnews.com/news/asian-america/video-shows-passenger-defending-asian-woman-facing-racism-new-york-n1162296), *New York Times* (https://nyti.ms/3ccvHzO), and *USA Today* (https://www.usatoday.com/story/news/politics/2020/05/20/coronavirus-hate-crimes-against-asian-americans-continue-rise/5212123002/).

[3] Papers like Egorov et al. (2020) have noted that areas with larger population sizes or better medical systems tend to have first diagnoses earlier. We thus include area fixed effects to control for these time-invariant characteristics.

and Twitter posts (tweets) that include the word "chink" or "chinks". The proxy based on Google searches was first used by Stephens-Davidowitz (2014), who shows a negative relationship between an area's Google search rate of the word "nigger" or "niggers" and the vote share for Barack Obama in 2008, even after controlling for a number of demographic, economic and political variables. This proxy can capture *hidden* racial animus because searches are mostly private and unlikely to suffer from social censoring. This proxy has since been used to measure racial animus in papers such as Depetris-Chauvin (2015) and has been shown to have a positive relationship with economic downturn and anti-African American hate crimes (Anderson et al., 2020). To capture *public* display of racial animus, we use a proxy based on public tweets, which has been used by Nguyen et al. (2018), among others, to measure sentiment towards minorities.

We focus on the use of the c-word, the most salient and unambiguously pejorative racial slur against people of Asian descent, to properly capture racial animus against Asians and to avoid data mining.[4] Google searches and tweets including the epithet are mostly negative. "Chinked eye" and "chink virus" are common terms in such Google queries, and over 53.4 percent of such tweets are categorized as showing "anger" or "disgust" between November 2019 and April 2020. Moreover, an area's monthly Google searches for the epithet is positively correlated with monthly anti-Asian hate crimes between 2014 and 2018 and negatively correlated with monthly visits to Chinese restaurants between 2018 and 2019, controlling for area and year-month fixed effects.

Our first finding is that the COVID-19 pandemic leads to a surge in racial animus against Asians. In the week after the first local COVID-19 diagnosis, on average, an area's racially charged Google search rate increases by 22.6 percent of the area's maximum search rate in the sample period, and an area's racially charged Twitter post rate increases by 100 percent of the average post rate across all areas in the sample period. The result is robust to using a more general definition of "hate" tweets against Asians, to excluding early- and hard-hit states, and to controlling for area and year-month fixed effects, the severity of COVID-19 infection, and an area's use of terms like "Asian(s)".

An analysis using unique Twitter user identifiers reveals that the increase in racially charged tweets mainly comes from existing Twitter users who post the racial epithet for the first time rather

[4]According to Philadelphia Bar Association (2014), the epithet "originated in the 19th Century as a racial slur against people of Chinese descent", and "is now widely used throughout the United States as a racial slur against people of Asian descent." The epithet is as racist and hurtful to Asian Americans as the n-word is to African Americans (Richburg, 2008). Importantly, it has not been reclaimed by the Asian American community, as exemplified by the 2018 incident when TBS analyst Ron Darling, who himself is of partial Chinese descent, had to quickly issue a public apology after receiving criticism for his use of "chink in the armor" when referring to the performance of a Japanese pitcher playing for the New York Yankees.

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than those who have previously used the term. In the four weeks after the first local diagnosis, 2,064 Twitter users who were not newly registered tweeted the epithet for the first time, potentially exposing their four million followers to racially charged content. This can create a multiplier effect on racial animus via persuasion (DellaVigna and Gentzkow, 2010) or by changing the social norms of publicly expressing anti-Asian sentiment (Bursztyn et al. 2020; Müller and Schwarz, 2019). Our findings also broadly relate to a growing body of literature on the role of social media in propagating animosity against minorities (Bursztyn et al. 2020; Müller and Schwarz, 2020).

Next, we turn our attention to the factors that fuel racial animus. First, fear of infectious diseases could motivate racial animus. Evolutionary psychologists have argued that the desire to avoid harmful communicable diseases contributes to contemporary prejudices against subjective outgroups (Schaller and Neuberg, 2012). Second, the salience of the connection between COVID-19 and the Asian population is also a key factor. We find that the increase in animus is directed at Asians rather than other minority groups. Moreover, this racial animus is stronger in hours and on days when the connection is more salient, as proxied by the number of President Trump's tweets mentioning China and COVID-19 simultaneously. This time series relationship remains robust after we control for the severity of the pandemic and for general attention to Asians. Third, we find little evidence that the negative economic impact of the pandemic motivates the initial increase in racial animus. Areas with a more severe economic impact from the pandemic do not exhibit a higher increase in racial animus than do those with a less severe impact. This finding is consistent with surveys administered in early March and April 2020 which show that Americans are more worried about the effect of COVID-19 on their health than on their personal finances (Binder, 2020; Saad, 2020). Individuals may not fully comprehend the economic impact of COVID-19 at its onset.

This paper contributes to the literature on the origin of racial animus. Past papers have documented that the deterioration of economic conditions can lead to animosity towards minorities. For example, Anderson et al. (2017) show that colder temperatures reduce agricultural production and intensify the persecution of Jewish people in Europe. Anderson et al. (2020) document that states hit harder by the Great Recession experience larger increases in racist Google searches and hate crimes against African Americans. In addition, evolutionary psychologists argue that the fear of and desire to avoid health threats can motivate racial bias (Schaller and Neuberg, 2012). Earlier studies were mostly correlational and based on surveys (e.g., Kim et al., 2016) or were conducted only in lab settings (Faulkner et al., 2004; O'Shea et al. 2020). We contribute by providing causal evidence that fear of infectious diseases and its link to a certain group lead to animus against the

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group, while the economic impact of the disease plays a weaker role in the current pandemic.

Our paper also contributes to the emerging literature on the relationship between COVID-19 and racial attitudes online and offline. Most papers are descriptive or correlational. For instance, Schild et al. (2020) characterize the evolution of Sinophobic slurs in the wake of the pandemic, Lyu et al. (2020) compare the characteristics of Twitter users who use or do not use controversial terms when talking about the pandemic, and Ziems et al. (2020) characterize how counter-hate speech can mitigate the spread of racial hate related to COVID-19 on Twitter. One exception is the paper by Bartoš et al. (2020). They use a controlled money-burning task among subjects in the Czech Republic to show that elevating the salience of COVID-related thoughts magnifies hostility against foreigners living in Asia. We use a different empirical strategy and complement their paper by showing that infection risk gives rise to racial animus outside the lab as well. The fact that COVID-19 induces racial animus in both the United States and the Czech Republic suggests that the phenomenon documented in our papers may be generalizable globally.

Finally, our work speaks to the literature on the role of political rhetoric. Political rhetoric has been shown to influence public opinions and behavior, such as presidential approval (Druckman and Homes, 2004) and public perception of a foreign country (Silver, 2016). In particular, Müller and Schwarz (2019) find that President Trump's tweets about Islam lead to anti-Muslim hate crimes. Our findings add to theirs by showing that the president's tweets also relate to anti-Asian sentiment, implying the generalizability of such a relationship to other racial attitudes.

Animosity between racial groups could severely hinder initiatives to tackle the current pandemic and slow economic recovery. Our results suggest that educating the public about the dissemination of COVID-19 and de-emphasizing the connection between the disease and a particular racial group can be an effective way to curb racial animus.

2. Data and Sample

2.1. Google and Twitter Proxy for Racial Animus

We use two measures to proxy for an area's racial animus against Asians — the percentage of Google searches and tweets that include the word "chink" or "chinks". The c-word is not uncommon in Google searches or in tweets. Between June 2019 and June 2020, the racial epithet was included in more than a quarter million searches and 60,000 tweets.[5] This is approximately the same number

[5]The number of Google searches are approximations from https://searchvolume.io/, a free-of-charge substitute for Google AdWords. The data are only available for the 12-month period before our query on June 8, 2020.

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of searches as "democrat" and 75 percent of the number of tweets as "UCSD".

We obtain the data from two sources. First, Google search data are obtained using Google Trends. We download weekly Google search data for the c-word at the media market level between July 2019 and April 2020.[6] The data are not the raw number of searches but the weekly percentage of searches including the term (hereafter, search rate), taken from a random sample of total searches, scaled by the highest weekly search rate in the same market during the entire time period for which data are extracted – in our case, between July 2019 and April 2020. In particular, the racially charged Google search index for media market m at time t extracted over period T is approximately:

$$\text{Search Index}_{mt,T} = 100 \times \frac{\frac{\text{Searches including "chink(s)"}_{mt}}{\text{Total searches}_{mt}}}{\max\limits_{t \in T}\{\frac{\text{Searches including "chink(s)"}_{mt}}{\text{Total searches}_{mt}}\}} \tag{1}$$

We are able to extract the racially charged Google search index for 60 of 210 media markets, covering approximately 40 percent of the U.S. population in 33 states. We are not able to extract the data for other media markets because Google returns value zero when the search index for a given area and time is below an unreported threshold. Compared to media markets with no racially charged search index, those in our sample tend to have a higher population and exhibit a quadratic relationship with the percentage of Asian population but do not differ in other measurable dimensions, such as the local unemployment rate or support for democratic parties (Table A1).[7] Analyses using Google data are conducted at the media market level.

It is worth noting that the above metric can capture the timing of a change in an area's search index but not the absolute level of the change. As an alternative, we rescale the search index so that the index in different media markets is normalized using the same base search rate. However, as detailed in Appendix A, rescaling will drop many media markets whose search rate is zero on the date when the base search rate occurs (*benchmark date*). We thus report the estimates using the original search index as the main results and those using the rescaled versions in the appendix.

Second, Twitter data are obtained from Crimson Hexagon, which houses all public tweets through a direct partnership with Twitter. We downloaded all geo-located tweets that included the c-word between November 2019 and April 2020. Crimson Hexagon does not provide data on

[6] An extraction period shorter than this will return daily rather than weekly search data.

[7] The quadratic relationship between the percentage of Asian population and racial animus is consistent with the theory of racial threat (Glaser, 1994). In communities with no Asians, race is not salient, and racial animus is less likely to form. In communities where Asians account for almost 100 percent of the population, there are very few non-Asian individuals, and those with racial animus are unlikely to choose such a community.

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the total number of tweets posted in a given area and time. We thus extract the number of all public tweets that include the word "the", the most common word on Twitter, in a given area and time. The assumption is that the proportion of tweets including "the" is stable across areas, and the number of tweets including "the" can approximate total Twitter activity in each area. We define the racially charged Twitter post index for a given area and time as the number of tweets that include the c-word per 100,000 tweets including "the".

We have valid Twitter post indexes for 612 counties across 51 states, encompassing 59.5 percent of the U.S. population. Some counties are not included in the sample because their residents do not use Twitter, do not disclose geo-identifiers on Twitter, or did not tweet the word "the" in the sample period.[8] Counties with a valid Twitter post index tend to have a larger population, more educated residents and slightly higher support for democratic parties than counties without the data (Table A1). Analyses using Twitter data are conducted at the county level unless noted otherwise.

Admittedly, Google and Twitter data suffer from sample selection due to either low search activities or missing geo-identifiers. However, given that areas with Google data and those with Twitter data are not highly correlated (correlation=0.053 at the county level), using both data sources can alleviate the concern about the external validity of our findings.

2.2. Relationship between Racial Animus, Hate Crimes, and Consumer Decisions

For the racially charged Google search index and Twitter post index to be meaningful proxies for racial animus, the only assumption we need is that an increase in racial animus makes one more likely to use the c-word. Under this assumption, higher racial animus will result in a higher percentage of Google searches and tweets that include the racial epithet. Existing papers that use a similar proxy for racial animus suggest that the assumption is likely to hold (Anderson et al., 2020; Depetris-Chauvin, 2015; Stephens-Davidowitz, 2014). Common terms in racially charged Google searches and tweets also support the assumption. During our sample period, some of the most common terms in these searches are "chink eye" and "chink virus"; common terms in these tweets are phrases such as "chink virus" or directly addressing another individual as a "chink". Furthermore, more than 67 percent of these tweets are tagged with the emotion of "anger" or "disgust".[9]

We benchmark our proxies with common measurements of racial animus and consumer discrim-

[8]Information on location is voluntarily provided when users sign up for Twitter. Approximately 50 percent of tweets in our sample have valid geo-identifiers at the county level.

[9]Crimson Hexagon assigns each tweet emotion tag(s) generated via a natural language processing algorithm. Please refer to https://www.brandwatch.com/blog/understanding-sentiment-analysis for more details.

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ination. We begin by presenting the relationship between the proxies and anti-Asian hate crimes. Hate crime data come from the FBI Uniform Crime Reports (UCR) and are available up to 2018. Over 80 percent of the U.S. population is covered by police agencies that voluntarily report hate crime data to UCR (Ryan and Leeson, 2011). A majority of these hate crimes are personal crimes, including simple or aggravated assault (30 percent) and in-person intimidation (34 percent). Table 1, panel A, columns (1) through (4) report the media-market-level correlation obtained by regressing the monthly racially charged search index on the monthly anti-Asian hate crime rate, local unemployment rate, year-month fixed effects, and media market fixed effects between January 2014 and December 2018. On average, a one-standard-deviation increase in the racially charged search index (i.e., 29.6) is linked to an approximately 15 percent ($= 29.6 \times 0.00019/0.03746$) increase in the average monthly anti-Asian hate crime rate in each media market each month. The correlation is robust to controlling for the search index for "Asian(s)", which is related to the c-word but is neutral in connotation, as shown in columns (2) and (4). The relationship between the racially charged search index and hate crimes is mainly contemporaneous because the coefficient on the last month's search index is small and insignificant, as shown in columns (3) and (4).

Next, we change the dependent variable to monthly visits to Chinese restaurants per million population in each media market between January 2018 and December 2019 and additionally control for the monthly visits to all restaurants per million population in the area. The visit data are from Safegraph and are available starting in 2018.[10] As shown in Table 1, panel A, columns (7) and (8), a one-standard-deviation increase in the racially charged search index is linked to approximately 160 to 190 fewer visits to Chinese restaurants per million population in each media market each month. This decrease equals approximately 0.6 to 0.7 percent of the average monthly visit rate. The relationship between the search index and the visit rate is also mainly contemporaneous.

We replicate the above correlations using Twitter data in Table 1, panel B. We aggregate hate crimes to the media market level due to their low occurrence at the county level. To maintain consistency, we also aggregate restaurant visits to the media market level. Overall, the racially charged Twitter post index does not correlate with anti-Asian hate crimes or visits to Chinese restaurants. One potential explanation is that Twitter data represent the public display of racial animus and undergo more social censoring. We may only see a change on Twitter when the shift in racial animus is substantially large.

[10]Safegraph partners with mobile applications and collects anonymous user location data to calculate the foot traffic to approximately 4.1 million points of interest in the United States.

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Table 1: Relationship between Local Racial Animus, Hate Crimes, and Chinese Restaurant Visits

VARIABLES	(1) Incidents/1m	(2) Incidents/1m	(3) Incidents/1m	(4) Incidents/1m	(5) Visits/1m	(6) Visits/1m	(7) Visits/1m	(8) Visits/1m
Panel A: Google search index								
Google c-word(t)	0.00019**	0.00019**	0.00019**	0.00019**	-5.123	-5.402*	-6.298*	-6.526**
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(3.169)	(3.166)	(3.152)	(3.177)
Google c-word(t-1)			-0.00009	-0.00009			-2.773	-2.917
			(0.00009)	(0.00009)			(2.900)	(2.904)
Google Asian(s)(t)		-0.00005		-0.00009		-33.567**		-21.114**
		(0.00030)		(0.00038)		(15.637)		(9.296)
Google Asian(s)(t-1)				0.00014				-10.274
				(0.00061)				(10.078)
Total visits/1m					0.030***	0.030***	0.029***	0.029***
					(0.007)	(0.007)	(0.005)	(0.006)
Observations	3,600	3,600	3,600	3,600	1,440	1,440	1,380	1,380
R-squared	0.18620	0.18621	0.18642	0.18645	0.980	0.980	0.985	0.985
Outcome mean	.03746	.03746	.03746	.03746	26353.271	26353.271	26353.271	26353.271
Panel B: Twitter post index								
Twitter c-word	-0.00008	-0.00008	-0.00008	-0.00008	-3.25768	-6.22705	-15.11324	-15.83304
	(0.00016)	(0.00016)	(0.00015)	(0.00015)	(37.49299)	(36.73437)	(40.16780)	(39.91470)
Twitter c-word (t-1)			-0.00010	-0.00009			-15.36303	-15.03136
			(0.00007)	(0.00007)			(20.76872)	(20.60958)
Twitter Asian(s)(t)		-0.00000**		-0.00000***		1.44369		0.50875
		(0.00000)		(0.00000)		(0.93082)		(0.65215)
Twitter Asian(s)(t-1)				-0.00000				0.35386
				(0.00000)				(0.87810)
Total visits/1m					0.02591***	0.02589***	0.02495***	0.02493***
					(0.00525)	(0.00523)	(0.00424)	(0.00422)
Observations	12,104	12,104	11,847	11,847	4,932	4,932	4,698	4,698
R-squared	0.04462	0.04550	0.04517	0.04619	0.97053	0.97056	0.97499	0.97499
Outcome mean	.0033	.0033	.0033	.0033	23708.533	23708.533	23708.533	23708.533

Notes: The table correlates the racially charged Google search index and Twitter post index with anti-Asian hate crimes and visits to Chinese restaurants. All data are at the media market×year-month level. Outcome variables are the number of anti-Asian hate crimes per million population in each month between January 2014 and December 2018 (columns (1)-(4)) and the number of visits to Chinese restaurants per million population in each month between January 2018 and December 2019 (columns (5)-(8)). All regressions control for media-market-level unemployment rate, year-month fixed effects, and media market fixed effects, and are weighted by local population. *** p<0.01, ** p<0.05, * p<0.1.

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2.3. The Covid-19 Pandemic in the United States

Our empirical strategy relies on the plausibly exogenous variation in the timing of the first COVID-19 diagnosis across regions in the United States. We download the data on all COVID-19 cases and deaths in the United States between January 21 and April 26, 2020, from Johns Hopkins University Coronavirus Resource Center. We match the date of the first diagnosis in each county and media market to those with valid Google and Twitter data. All media markets in the Google sample have their first diagnoses in the sample period and have data for at least six weeks after the first local diagnosis. For the Twitter sample, we exclude seven counties that did not have diagnoses in the sample period and 18 counties whose first diagnosis was after March 29, 2020, to ensure that all counties have data for at least four weeks after the first local diagnosis. Our main regression sample for Google (Twitter) data is then a panel of media markets (counties) from six weeks before to six (four) weeks after the first local diagnosis. The predictors of being in the main sample are presented in Table A1. Figure A1 plots the location of the areas in the main sample by the timing of the first local diagnosis. Table A2 further shows the relationship between local characteristics and the timing of the first local diagnosis. Areas with larger population sizes and more males tend to have diagnoses earlier, but, interestingly, areas with more Asians do not.

We plot the number of counties and media markets by the week of their first COVID-19 diagnoses in Figure 1, panel A and the U.S. weekly racially charged Google search index and Twitter post index in Figure 1, panel B.[11] The sharp rise in the search index around early March and the rise in the post index around mid-March correspond well with the waves of first local COVID-19 diagnoses at the media market and the county levels.

[11]There is more variation in the timing of the first COVID-19 diagnosis measured in days, as shown in Figure A2. However, since the daily search index and post index are much noisier than the weekly ones, we present estimates at the weekly level as the main results and those at the daily level in the appendix.

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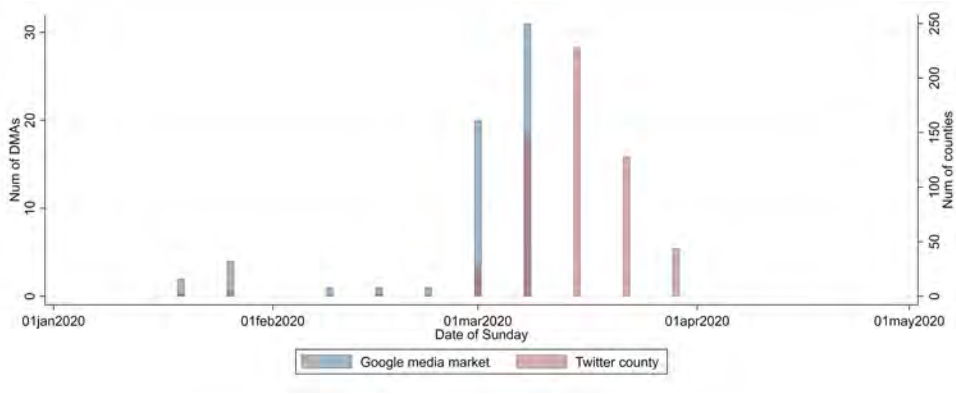
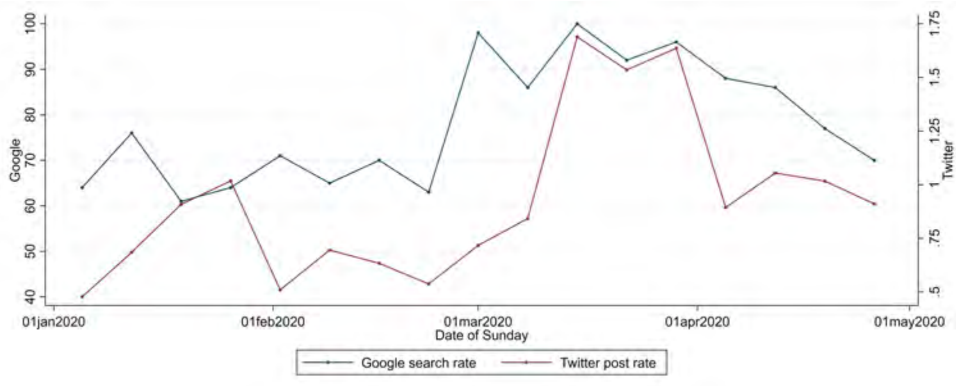


A: Number of media markets and counties by week of 1st local COVID-19 diagnosis



B: Racially charged Google search index and Twitter post index

Figure 1: Timeline of COVID-19 Diagnoses and C-word Usage in the U.S.

Notes: Panel A plots the number of media markets and counties in our main regression samples by the week of their first COVID-19 diagnoses. Panel B plots the weekly Google search index and Twitter post index for "chink(s)" in the United States.

3. Strategy and Results

3.1. Empirical Strategy

Our main strategy is a difference-in-differences event study in which the first COVID-19 diagnosis in a county or a media market is the event of interest. The specification is as follows:

$$\mathrm{Y}_{it} = \sum_{k=-6}^{-2} \beta_k \times 1\{k = t - E_i\} + \sum_{k=0}^{4 \text{ or } 6} \beta_k \times 1\{k = t - E_i\} + \gamma' X_{it} + \alpha_i + \alpha_{ym} + \epsilon_{it}, \tag{2}$$

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where Y_{it} is the racially charged Google search index or Twitter post index in county or media market i in week t. E_i is the week when i has its first COVID-19 diagnosis, and $1\{k = t - E_i\}$ is an event dummy equaling one if week t is k weeks from E_i. We include event dummies for six weeks before to six (or four) weeks after the first local diagnosis for the Google (or Twitter) sample, corresponding to the event periods included in our main regression sample. We omit the dummy for the week before the first diagnosis due to perfect collinearity. X_{it} is a vector of area-specific controls such as the number of diagnoses or deaths related to COVID-19, an indicator of a state-level stay-at-home order, and the search index or post index for "Asian(s)".[12] We include county or media market fixed effects (α_i) and year-month fixed effects (α_{ym}) to control for an area's average level of the racially charged search index and post index as well as the national trend in the indexes.[13] ϵ_{it} is the error term, and we cluster standard errors by media market for Google data and county for Twitter data. To understand how immediately the first local COVID-19 diagnosis has an effect on local racial animus, we also run regression 2 at the daily level and additionally control for day-of-week fixed effects.

The coefficients of interest are β_k's ($k \geq 0$), which represent the effects of the first local COVID-19 diagnosis on an area's racially charged Google search rate in week k as a percentage of the area's maximum search rate over the sample period or the effects on an area's racially charged Twitter post rate in week k. The identifying assumption is that the progression of the racially charged search index and post index in areas that have and have not yet had the first COVID-19 diagnosis share parallel trends in the absence of the diagnosis. This assumption is inherently untestable, but we can assess its plausibility by testing for parallel pre-trends. We provide evidence that the assumption is likely to hold in section 3.2.

3.2. The Effects of Covid-19 on Local Racial Animus

We start by examining how an area's search for the c-word on Google responds to the first local COVID-19 diagnosis. Figure 2, panel A plots the estimates of the coefficients on the event dummies from regression 2 using an area's racially charged Google search index as the outcome. The search index reaches the peak in the week after the first local diagnosis and decreases slightly in later weeks. Table A3, panel A reports the regression results. Note that the estimates should

[12] For a media market that crosses the state border, we assign it to the state where the highest fraction of its population resides.

[13] Although the Google search rate is normalized so that the maximum rate is 100 for each media market, there is still considerable variation in the sample mean, i.e., the average *actual* search rate over the *actual* maximum rate, ranging between 8 and 50.

be interpreted as a percentage of an area's maximum search rate in the sample period. Therefore, compared to the week before the first COVID-19 diagnosis, an area's racially charged search rate on average increases by 22.6 percent of the area's maximum search rate over the sample period in the first week after the diagnosis and remains at least 15 percent until six weeks afterward.[14] Given our findings in Table 1, the increase in the search index in the four weeks after the first COVID-19 diagnosis correspfloatonds to an increase of 0.0033 ($0.0002 \times (22.63 + 16.95 + 8.16 + 19)/4$) in anti-Asian hate crimes per million residents, or 10 percent of the average monthly anti-Asian hate crime rate between 2014 and 2018.

We also present estimates using various rescaled search indexes. We do so because the estimates using the original search index do not map to an increase over a national base. As detailed in Appendix A, rescaling will drop media markets whose racially charged search rate is zero on the benchmark date when the base search rate occurs. To alleviate concern over sample selection, we present results using search indexes rescaled by three different bases, i.e., Huntsville-Decatur (Florence)'s search rate on March 15, 2020, Wilkes Barre-Scranton's search rate on March 29, 2020, and Buffalo's search rate on April 5, 2020. We choose these benchmark dates and base search rates so as to back out rescaled search indexes for as many media markets as possible. We are able to back out rescaled search indexes for 35, 29 and 29 media markets, using each of the above base search rate respectively. Combined, they cover 50 media markets. Figure A3 plots the estimates using the rescaled indexes. These estimates share similar patterns as those using the original search index, but the magnitude of the former is approximately half of the latter because the search rates in Huntsville-Decatur (Florence), Wilkes Barre-Scranton, and Buffalo are generally higher than that of most media markets. Given the similar patterns, we present results using the original search index in the rest of the paper in the interest of the sample size.

[14]The increase during the week of the diagnosis is smaller than that in the following week because the diagnosis may occur late in the week and it takes time for the residents to obtain and react to the news. Consistent with these explanations, in untabulated results, we show that the increase in Google search index for terms such as "covid", "covid-19", and "coronavirus" is also smaller in the week of the diagnosis than in the following week, with the former equaling 40 percent of the latter.

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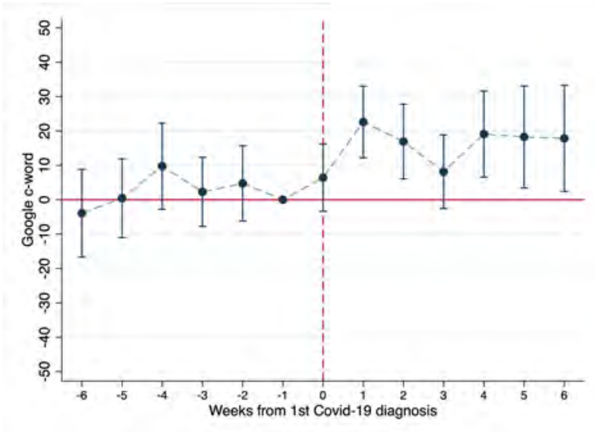
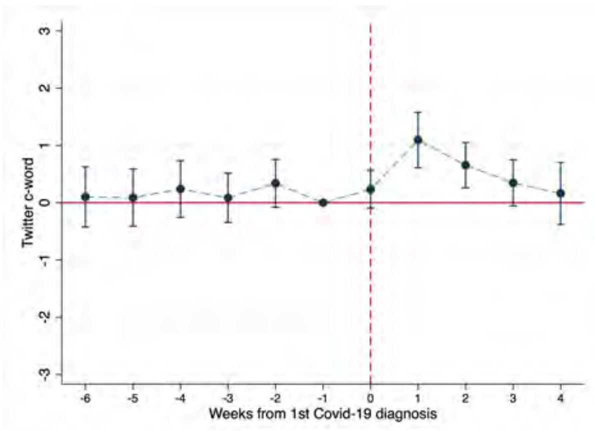


A: Google search index



B: Twitter post index

Figure 2: The Effect of 1st Local COVID-19 Diagnosis on Local Racial Animus

Notes: The figure presents the effect of the first local COVID-19 diagnosis on local racial animus. Panels A and B plot the coefficients and the 95 percent confidence intervals of the event time dummies from regression 2 using the racially charged Google search index and the racially charged Twitter post index as outcomes, respectively. Regressions control for year-month fixed effects and media market fixed effects (panel A) or year-month fixed effects and county fixed effects (panel B). Standard errors are clustered by media market (panel A) or by county (panel B).

To better understand how public expression of the c-word changes, we turn our attention to Twitter. Similar to the Google search index, the racially charged Twitter index also peaks in the week after the first local COVID-19 diagnosis and slowly decreases afterward, as plotted in Figure 2, panel B. Table A4, panel B further shows that relative to the week before the first diagnosis, racially

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charged tweets increase by 1 and 0.6 per 100,000 "the" tweets in the first and the second weeks after the first diagnosis. The increase amounts to roughly 100 and 66 percent of the average tweet rate in the sample period. In columns (2) through (4) in Table A3 and Table A4, we control for the weekly number of diagnoses and deaths related to COVID-19, whether a state-level stay-at-home order is in place, general interest in terms such as "Asian(s)", and excluding early- and hard-hit states such as New York, Washington, and California. The estimated effects change only slightly.

To understand the timing when the usage of the c-word starts to change, we run regression 2 using the daily search index and post index as outcomes and additionally control for day-of-week fixed effects. As shown in Figure A4, the effects start to appear two to three days after the first local diagnosis, implying that it takes some time for the locals to obtain and react to the news.

There may be concern that the increase in the usage of the c-word is driven by reasons other than higher animosity against Asians, such as an increase in online activities due to blanket stay-at-home orders, a rise in benign attention to China or Asia, seasonality in racist online activities, or "Twitter bots". These factors are unlikely to explain our findings. First, the search index and the post index are normalized by the total searches or tweets in a given area and time and thus already account for overall change in online activities. Second, Table A3, column (3) shows that our results are robust to controlling for the search index and the post index for terms that capture general attention to China or Asia but are neutral in connotation, such as "Asian(s)".[15] Third, to test the seasonality in racist online activities, we generate a "fake" COVID-19 diagnosis date for each area using the same calendar day and month of its actual diagnosis date but changing the year to 2019. Reassuringly, we find no increase in the racially charged search index or post index surrounding the "fake" dates, as shown in Figure A5. Finally, there may be concern that "Twitter bots" rather than local residents contribute to the increase in racially charged tweets. However, Twitter proactively identifies and removes automation-generated content (Roth and Pickles, 2020). In addition, based on 30 million tweets posted between January 15, 2020 and April 17, 2020, Ziems et al. (2020) show that only 10.4 percent users who posted anti-Asian tweets are likely bots. Furthermore, our results do not quantitatively change when we exclude users who are more likely to be bots, defined as those who tweeted the c-word for more than five times (99 percentile) between November 2019 and April 2020, as shown in Table A4, column (5).

We proxy for racial animus against Asians using only the c-word to avoid data mining. However,

[15]Results are also robust to controlling for the search index for "China" or "Asia" and are available upon request.

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since not all hateful searches or tweets include the c-word, our proxies may underestimate the effect of the COVID-19 pandemic on racial animus. We thus construct an alternative racially charged Twitter post index based on COVID-related hateful tweets against Asians classified via machine learning by Ziems et al. (2020), spanning between January 15 and April 17.[16] Figure A6 shows that the effect estimated using the alternative index shares a very similar pattern as that using the original Twitter index but is five times as large.[17] This finding suggests that the Twitter index based on the c-word is likely a conservative proxy.

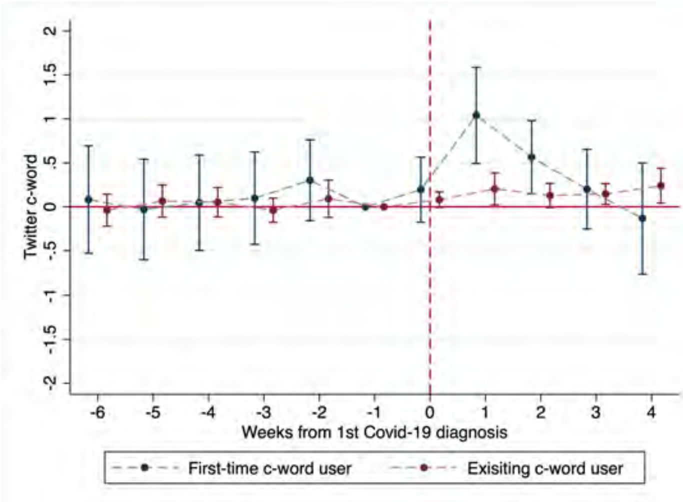

Figure 3: The Effect of 1st Local COVID-19 Diagnosis on Local Racially Charged Tweets by First-time and Existing C-word Users

Notes: The figure presents the heterogeneous effect of the first local COVID-19 diagnosis on the local racially charged Twitter post index. The blue line represents the number of racially charged tweets over the number of "the" tweets from *existing* c-word users, define as those who tweeted the c-word at least once between 2014 and the sixth week before the first local COVID-19 diagnosis. The red line represents those from *first-time* c-word users, defined as those who never tweeted the c-word between 2014 and the sixth week before the first local diagnosis and who posted at least 10 tweets before their first c-word tweet. The coefficients and the 95 percent confidence intervals of the event time dummies come from regression 2 using the racially charged Twitter post index as outcome. Both regressions control for year-month fixed effects and county fixed effects. Standard errors are clustered by county.

Thus far, we have shown that the COVID-19 pandemic increases both individuals' *hidden* animosity against Asians and their *public* display of this animosity. A natural next question is who

[16]Examples of tweets in this sample are hateful tweets including terms like "Chinese Virus", "Wuhan Virus", and "Kung Flu".

[17]We only include counties that had their first diagnoses between February 16 and March 22 and observations in these counties from five weeks before to four weeks after the first local diagnosis to ensure that the sample is balanced in event time.

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contributes to the rise. Do more individuals start to harbor the animus, or do a few existing racists increase their animosity? Taking advantage of unique Twitter user identifiers, we can break down the increase in racially charged tweets by whether their authors are first-time or existing c-word users. We define *existing* c-word users as those who tweeted the c-word at least once between 2014 and the sixth week before the first local COVID-19 diagnosis. We define *first-time* c-word users as those who never tweeted the c-word between 2014 and the sixth week before the first local diagnosis and who posted at least 10 tweets before their first c-word tweet. Importantly, this definition can avoid counting newly registered Twitter users as first-time users. Figure 3 plots the breakdown. The increase in racially charged tweets from first-time users is much higher than that from pre-existing users, especially in the first week (p=0.0094) and the second week (p=0.0627) after the first local diagnosis. This breakdown suggests that the COVID-19 pandemic induces more Twitter users to start publicly expressing animus against Asians. Specifically, in the four weeks after the first local diagnosis, 2,064 Twitter users started to use the racial epithet, which could expose their four million followers to racially charged content. This can create a multiplier effect on racial animus by persuading more individuals to hold racial animus via an increase in exposure to anti-Asian sentiment (DellaVigna and Gentzkow, 2010) or by changing the social norms of publicly expressing anti-Asian sentiment (Bursztyn et al. 2020; Müller and Schwarz, 2019). Moreover, only 25 percent of the c-word tweets posted after the first local diagnosis explicitly mention COVID-19, suggesting that the pandemic sparks racism beyond topics related to COVID-19.

3.3. Factors Fueling Local Racial Animus

In this section, we discuss several non-mutually exclusive explanations as to why the COVID-19 pandemic spurs animosity against Asians.

Fear of infectious diseases. Evolutionary psychologists have long argued that the desire to avoid harmful communicable diseases contributes to contemporary prejudices against subjective outgroups (Schaller and Neuberg, 2012). Lab experiments also show that xenophobia towards unfamiliar immigrant groups is stronger when the threat of infectious diseases is more salient (Faulkner et al., 2004). Moreover, surveys administered in March and April 2020 document that approximately 60 to 80 percent of Americans are worried about contracting COVID-19, suggesting that fear of the disease indeed exists among locals (Binder, 2020; Saad, 2020). Our main analysis indeed shows that racial animus responds to salient increases in infection risk.

Connection between Covid-19 and Asians. The salience of the connection between COVID-

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19 and the Asian population could also play a key role in fueling the animosity against Asians. First, if the salient connection is not a main driving force, the disease-avoidance theory would predict rising animus against all minorities, not just Asians. We construct the Google search index and Twitter post index for common racial epithets against major minority groups in the United States, such as "nigger(s)" against African Americans, "wetback(s)" against Hispanics, and "kike(s)" against the Jewish population.[18] We run regression 2 using racially charged searches and tweets against these minorities as outcomes. We include an indicator for the week of January 26, 2020, when using the n-word as the outcome because Kobe Bryant's death together with an MSNBC anchor using the n-word when broadcasting the news of the death led to a spike in its use. We also include an indicator for the week of February 23, 2020, when using the k-word as the outcome because the Los Angeles Dodgers player Enrique ("Kiké") Hernandez's performance in that week led to a spike in the use of the k-word. Coefficients on the event dummies are plotted in Figure A7. None of the examined racial epithets experience an increase in Google searches following the first local diagnosis; if anything, searches for the n-word demonstrate a slight decrease. A similar pattern is found for the w-word and the k-word on Twitter.[19] These findings suggest that the *connection* between COVID-19 and the Asian population, not just fear of contracting COVID-19 from unfamiliar outgroups, drives the rising animus against Asians.

[18] We do not use "spic(s)" as the racial epithet against Hispanics because the term is included in "Spic and Span", the name of an all-purpose household cleaner brand, which has experienced growing interest during the pandemic. Breakout Google queries and a substantial number of tweets, including the term, are about the brand and not the slur. In addition, we do not include "redskin(s)", a common racial epithet against Native Americans, because the term is included in the name of a professional American football team, "The Washington Redskins". Google queries and tweets including the term are mostly about the football team, such as "chase young redskins" and "redskins draft".

[19] We present the Twitter post index for the n-word separately in Figure A8 due to the seasonality in the use of the n-word on Twitter. The seasonality is evident when comparing the n-word usage between 2019 and 2020 in panel A. The seasonality may arise from a combination of Black History Month occurring in February and the n-word being reclaimed by African Americans (Croom 2011). These factors may invalidate the use of the term on Twitter as a proxy for racial animus. Note that we additionally include an indicator for the week of February 9, 2020, in panel A because a video tweet unrelated to COVID-19 but with n-words in the description went extremely viral on February 10 and contributed to 95 percent of the n-word tweets on that day.

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Table 2: Relationship between Racial Animus and Trump Tweets

VARIABLES	(1) Daily	(2) Daily	(3) Daily	(4) Hourly	(5) Hourly	(6) Hourly
China & Covid	0.0487*	0.0502**	0.0434**			
	(0.0278)	(0.0219)	(0.0214)			
China only	-0.0169*	-0.0031	-0.0074			
	(0.0093)	(0.0081)	(0.0081)			
Covid only	0.0104**	-0.0031	-0.0026			
	(0.0041)	(0.0053)	(0.0051)			
China & Covid*Post 1-4h				0.1012**	0.0693**	0.0635**
				(0.0413)	(0.0343)	(0.0312)
China only*Post 1-4h				-0.0462***	-0.0109	-0.0232
				(0.0160)	(0.0178)	(0.0168)
Covid only*Post 1-4h				0.0144**	-0.0088	-0.0051
				(0.0063)	(0.0066)	(0.0058)
New diagnoses			0.0000			-0.0000
			(0.0000)			(0.0000)
New deaths			0.0001			0.0001**
			(0.0001)			(0.0001)
Twitter Asian(s)			0.0005**			0.0005***
			(0.0002)			(0.0002)
Observations	123	123	123	2,952	2,952	2,952
R-squared	0.1938	0.5227	0.5547	0.0178	0.2660	0.2927
Outcome mean	.344	.344	.344	.340	.340	.340
Yw FE	N	Y	Y	N	Y	Y
DOW FE	N	Y	Y	N	Y	Y
Hour FE	N	N	N	N	Y	Y

Notes: The table presents the relationship between the US-level racially charged Twitter post index and the number of President Trump's tweets about Covid-19 or China between January 1, 2020 and May 2, 2020. The data are at the daily level in columns (1) through (3) and at the hourly level in columns (4) through (6). A tweet is defined to be about China if it contains any of "China", "Chinese", "Huawei", or "Xi" and about Covid-19 if it contains any of "covid", "covid-19", "corona", "coronavirus", "virus", "epidemic", or "pandemic". "New diagnoses" and "New deaths" are the total daily number of new COVID-19 diagnoses and deaths in the United States calculated using the data from Johns Hopkins University Covronavirus Resource Center. *Post 1-4h* equals one if the hour is between the first and the fourth hour following the president's tweet of a certain type. Standard errors in parentheses are clustered by date. *** p<0.01, ** p<0.05, * p<0.1.

Second, we examine how racial animus against Asians varies with the salience of the connection between COVID-19 and the Asian population. We proxy for the salience of this connection using the number of President Trump's tweets mentioning COVID-19 and China simultaneously.[20] President Trump has 82.4 million followers on Twitter, and his tweets have been shown to affect public behavior such as hate crimes (Müller and Schwarz, 2019). We expect to see more racially charged tweets on days when President Trump more frequently mentions COVID-19 and China at the same time. This is exactly what we find. Table 2, column (2) shows that there are one more racially charged tweet

[20]We define a tweet from the president to be related to China if it contains any of the words "China", "Chinese", "Huawei", or "Xi" and a tweet to be related to COVID-19 if it contains any of the words "covid", "covid-19", "corona", "coronavirus", "virus", "epidemic", or "pandemic". Table A5 presents examples of President Trump's tweets in each category, and Figure A8 plots the daily frequency of such tweets. We only include data after January 1, 2020, because President Trump did not tweet about Covid-19 until late January 2020.

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per million "the" tweets across the United States in a day when President Trump mentions China and COVID-19 simultaneously in two more tweets ($= 1/(0.0502 \times 10)$). The increase amounts to 30 percent of the average daily racially charged tweets per million "the" tweets across the United States ($= 1/(0.344 \times 10)$). Columns (4) through (6) show that the time series relationship holds even at the hourly level - there are more racially charged tweets across the United States in the hours immediately following President Trump's tweets simultaneously mentioning China and COVID-19. Importantly, the racially charged Twitter post index does not correlate with the president's tweets mentioning *only* China or *only* COVID-19, once we control for year-week and day-of-week fixed effects. Moreover, the findings remain quantitatively similar after we control for the daily number of new COVID-19 diagnoses and deaths in the United States and the Twitter post index for "Asian(s)". Therefore, an increase in the severity of the COVID-19 pandemic or benign attention to Asians cannot explain our findings. In sum, the salience of the connection between the disease and Asians propagates racial animus in the current pandemic.[21]

Economic Downturn. The COVID-19 pandemic imposes risks on both lives and livelihoods. Existing work has documented that the deterioration of economic conditions can fuel animus towards minorities (Sharma, 2015; Anderson et al., 2017, 2018). To understand this channel, we study the heterogeneity in response to the COVID-19 pandemic by the level of its negative impact on the local economy. We define an area to be more (less) susceptible to the negative impact if the proportion of the area's annual average employment in "leisure and hospitality" and "education and health services", the two hardest-hit industries in employment according to the Bureau of Labor Statistics, is above (below) the sample median (32 percent in Google data and 35 percent in Twitter data). Figure A10 shows that areas experiencing high versus low negative economic impact do not respond differently to the first local COVID-19 diagnosis. One potential reason is that the impact of the pandemic on the local economy was not well understood at the onset of the first diagnosis. According to surveys administered in early March and April 2020 (Binder, 2020; Saad, 2020), Americans were more worried about the effect of COVID-19 on their health than on their personal finances.

Taken together, our findings imply that the pressing infection risk and the salience of the connection between the disease and the Asian population play a larger part than the negative economic impact of the disease in motivating the initial racial animus in the current pandemic.

[21] There is no relationship between the racially charged Google search index and President Trump's tweets. A potential reason could be that not all Google users have Twitter accounts and may not respond to events on Twitter.

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4. Conclusion

In this paper, we estimate the effect of the COVID-19 pandemic on racial animus. We find that the first local diagnosis leads to an immediate increase in Google searches and Twitter posts including the c-word. Most of the racist tweets discuss issues beyond COVID-19 and come from Twitter users posting the slur for the first time. This can create a multiplier effect on racial animus via persuasion or by changing the social norms of publicly expressing anti-Asian sentiment. Moreover, the increase in racist online activities may indicate a rise in offline hate crimes as we document a strong correlation between the use of the the c-word and anti-Asian hate crimes using historic data. Our findings further suggest that the fear of infectious diseases and its link to a certain group is a stronger driver of the initial increase in racial animus than the economic impact of the disease in the current pandemic.

Animosity between racial groups could severely hinder initiatives to tackle the current pandemic and slow economic recovery. Our results suggest that educating the public about the dissemination of COVID-19 and de-emphasizing the connection between the disease and a particular racial group can be an effective way to curb current and future racial animus.

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Appendix A. Rescaled Google Search Index

Google Trends reports the search index in either a time series or a cross-sectional format. To construct a panel data for each media market and time, we need to extract the search index in each media market separately. However, the search index reported by Google Trends is the search rate normalized by the maximum search rate in an extraction and is not comparable across extractions. To build a panel of search indexes that are normalized by the same base, we rescale the search index using the following method.

In a time series extraction of the search index in media market m over period T, the search index in median market $m$at time t is approximately:

$$\text{Search Index}_{mt,T} = 100 \times \frac{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}}{\max\limits_{t \in T}\{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}\}} \tag{3}$$

Meanwhile, in a cross-sectional extraction of the search index at time t for all media markets $m \in M$, the search index in media market m at time t is approximately:

$$\text{Search Index}_{mt,M} = 100 \times \frac{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}}{\max\limits_{m \in M}\{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}\}} \tag{4}$$

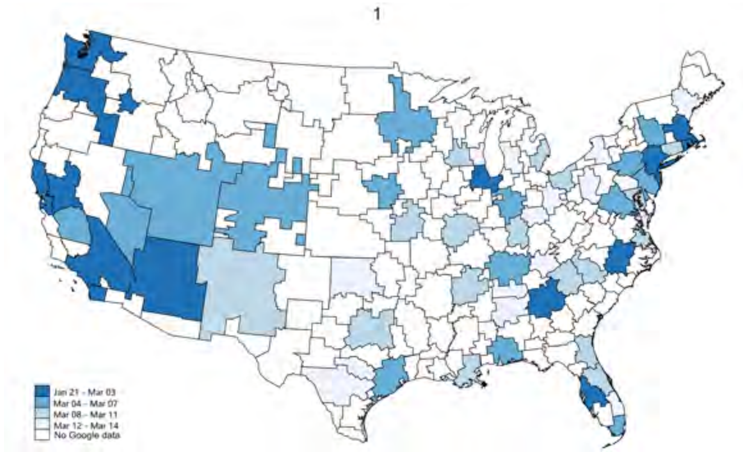
If we are willing to assume that the numerators in equations 3 and 4 are the same, we can calculate the ratio of the two denominators as:

$$Ratio_{m.MT} = \frac{\max\limits_{t \in T}\{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}\}}{\max\limits_{m \in M}\{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}\}} = \frac{\text{Search Index}_{mt,M}}{\text{Search Index}_{mt,T}} \tag{5}$$

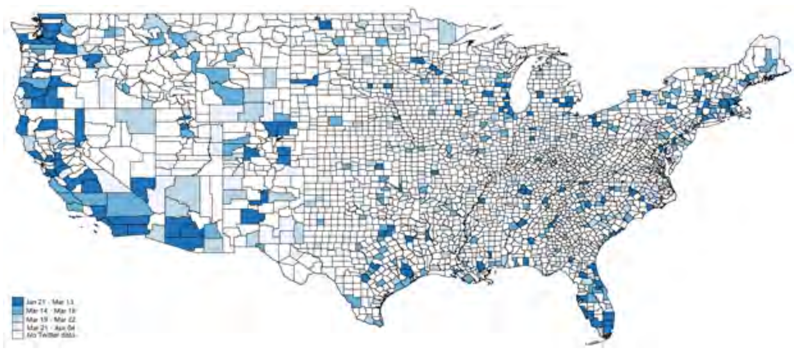
when both search indexes are non-zero. We can scale the time series search index over period T in each media market $m \in M$ by multiplying it with the corresponding $Ratio_{m,MT}$. The resulting time series are normalized by the same $\max\limits_{m \in M}\{\frac{\text{Searches including ``chink(s)''}_{mt}}{\text{Total searches}_{mt}}\}$. However, Google Trends returns value zero when the absolute level of search in a given media market and time is below an unreported threshold, under which the re-scaling does not work. After extracting cross-sectional search indexes on all possible weeks in the sample period, we can at best back out the rescaled search index for 35 media markets using Huntsville-Decatur (Florence) media market's search rate on March 15, 2020 as the base. Alternatively, we can back out 29 media markets using Wilkes Barre-Scranton media market's search rate on March 29, 2020 and 29 media markets using Buffalo media market's search rate on April 5, 2020 as the base. Combined, these three measures cover 50 media markets.

One point worth noting is that Google calculates the search index using a random sample of searches, which can be different across extractions. As a result, the numerators in equations 3 and 4 are similar but may not be exactly the same. To the extent that these two are not the same, we may introduce measurement errors to the dependent variable and attenuate the main effects.

Appendix B. Additional Figures & Tables



A: Google media markets



B: Twitter counties

Figure A1: Media Markets and Counties by Date of 1st Local COVID-19 Diagnosis

Notes: The figure presents a map of the media markets (panel A) and a map of the counties (panel B) in the main regression samples by the date of the first COVID-19 diagnosis in the local area. The darker the color, the earlier the first local diagnosis.

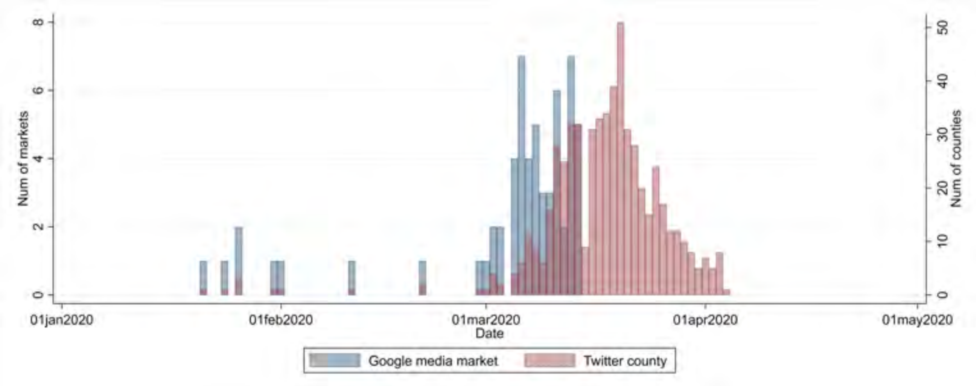
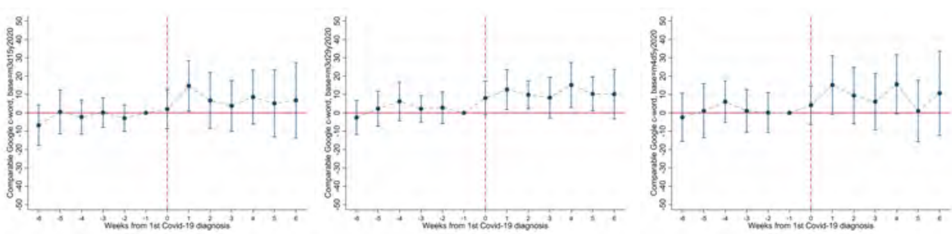


Figure A2: Number of Media Markets and Counties by Day of 1st Local COVID-19 Diagnosis

Notes: This figure plots the number of media markets (blue bar) and the number of counties (red bar) in the main regression samples by the date of the first COVID-19 diagnosis in the local area.



A: Benchmark 3/15/2020 **B:** Benchmark 3/29/2020 **B:** Benchmark 4/5/2020

Figure A3: Robustness - The Effect of 1st Local COVID-19 Diagnosis on Local Racial Animus Rescaled Google Search Index

Notes: The figure presents the effect of the first local COVID-19 diagnosis on local racial animus proxied by various *rescaled* Google search indexes. Panels A, B, and C plot the coefficients and the 95 percent confidence intervals of the event time dummies from regression 2 using an area's racially charged Google search rate scaled by Huntsville-Decatur (Florence) media market's search rate on March 15, 2020, by Wilkes Barre-Scranton media market's search rate on March 29, 2020, and by Buffalo media market's search rate on April 5, 2020 as outcomes, respectively. All regressions control for year-month fixed effects and media market fixed effects. Standard errors are clustered by media market.

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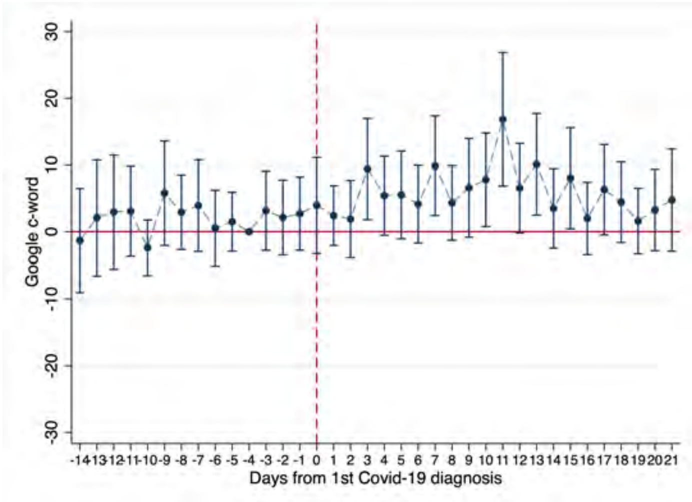
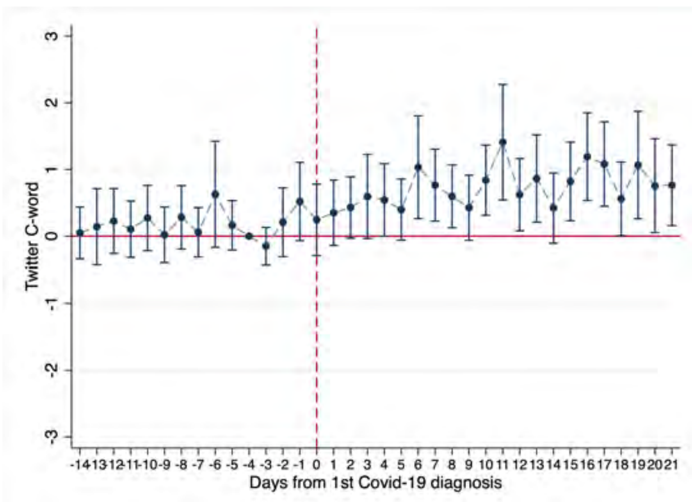


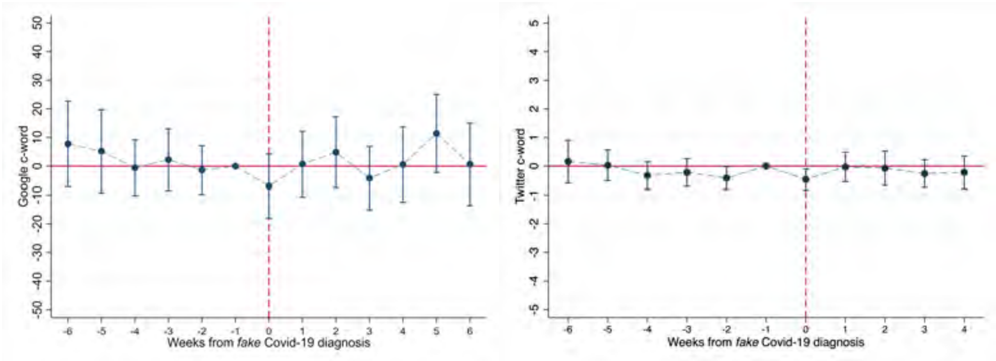
A: Google search index



B: Twitter post index

Figure A4: The Effect of 1st Local COVID-19 Diagnosis on Daily Local Racial Animus

Notes: The figures present the effect of the first local COVID-19 diagnosis on local racial animus at the daily level. Panels A and B plot the coefficients and the 95 percent confidence intervals on the event time dummies from 14 days before to 21 days after the day of the first COVID-19 diagnosis using the racially charged Google search index and the racially charged Twitter post index as outcomes, respectively. Regressions control for year-month fixed effects, day-of-week fixed effects, and media market fixed effects (panel A) or county fixed effects (panel B). Standard errors are clustered by media market (panel A) or by county (panel B).



A: Google search index **B:** Twitter post index

Figure A5: Placebo - The Effect of *fake* Local COVID-19 Diagnosis on Local Racial Animus

Notes: The figure presents a placebo test for the effect of the first local COVID-19 diagnosis on local racial animus. We replace the date of the first local COVID-19 diagnosis with a *fake* date which shares the same day and month as the actual date but in year 2019 instead of 2020. Panels A and B plot the coefficients and the 95 percent confidence intervals of the event time dummies based on the *fake* date from regression 2 using the racially charged Google search index and the racially charged Twitter post index as outcomes, respectively. Regressions control for year-month fixed effects and media market fixed effects (panel A) or year-month fixed effects and county fixed effects (panel B). Standard errors are clustered by media market (panel A) or county (panel B).

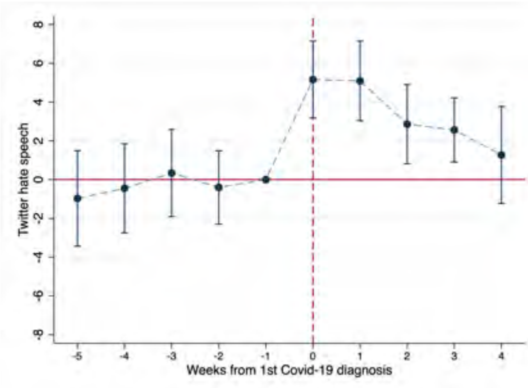


Figure A6: Robustness - The Effect of 1st local COVID-19 Diagnosis on Local Racial Animus Anti-Asian Hateful Tweets

Notes: The figure presents the effect of the first local COVID-19 diagnosis on local racial animus, using an area's number of anti-Asian hateful tweets per 100,000 "the" tweets as proxy. The hateful tweets are categorized via machine learning by Ziems et al. (2020). The figure plots the coefficients and the 95 percent confidence intervals of the event time dummies from regression 2 using the above proxy as outcome. The sample consists of 340 counties that had their first local diagnoses between February 16 and March 22, 2020, and is balanced in event time from five weeks before to four weeks after the first local diagnosis. All regressions control for county fixed effects and year-month fixed effects. Standard errors are clustered by county.

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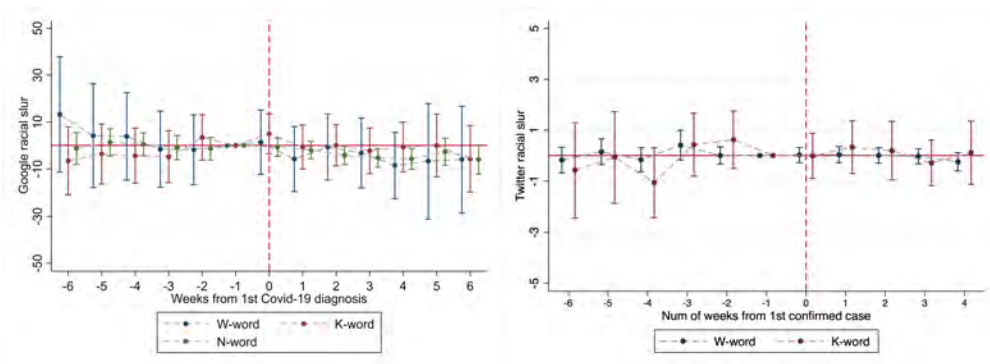
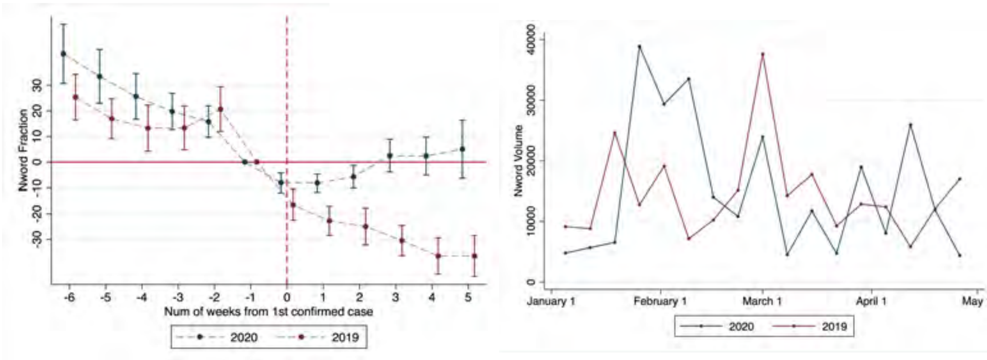


A: Google search index **B:** Twitter post index

Figure A7: The Effect of 1st Local COVID-19 Diagnosis on Local Racial Animus Against Other Minority Groups

Notes: The figure presents the effect of the first local COVID-19 diagnosis on local racial animus against the Hispanic, Jewish, and African American population, using the Google search indexes and Twitter post indexes for “wetback(s)”, “kike(s)”, and“nigger(s)” as proxies, respectively. Regression samples for the n-word, k-word, and w-word Google search indexes contain 203, 78, and 27 media markets (panel A). Regression samples for the w-word and k-word Twitter post indexes both contain 587 counties (panel B). The displayed coefficients and the 95 percent confidence intervals of the event time dummies are from regression 2 using the above racially charged Google search and Twitter post indexes as outcomes. All regressions control for year-month fixed effects and media market fixed effects (panel A) or year-month fixed effects and county fixed effects (panel B). We include an indicator for the week of January 26, 2020 in the regression for the n-word to control for a spike in its use due to Kobe Bryant’s death and MSNBC’s anchor using the n-word while reporting the news. We include an indicator for the week of February 23, 2020 in the regression for the k-word to control for a spike in its use due to the Los Angeles Dodges player Enrique ("Kiké") Hernandez’s performance in that week. Standard errors are clustered by media market (panel A) or by county (panel B).



A: Event study

B: National trend

Figure A8: Racial Animus Against African Americans on Twitter

Notes: Panel A plots the estimates and the 95 percent confidence intervals of the coefficients on the event dummies from regression 2 using the weekly Twitter post index for the n-word between November 2019 and April 2020 (blue line) and that between November 2018 and April 2019 (red line) as the outcomes. For the regression using the 2018-2019 data, we replace the date of the first local COVID-19 diagnosis with a *fake* date which shares the same day and month as the actual date in 2020 but with the year as 2019. For the regression using the 2019-2020 data, we include an indicator for the week of January 26, 2020 to control for Kobe Bryant's death on January 26, 2020 and an indicator for the week of February 9, 2020 to control for an extremely viral video tweet *unrelated* to COVID-19 but mentioning the n-word on February 10, 2020. Panel B plots time trends for US-level Twitter post indexes for the n-word in 2020 (blue line) and in 2019 (red line).

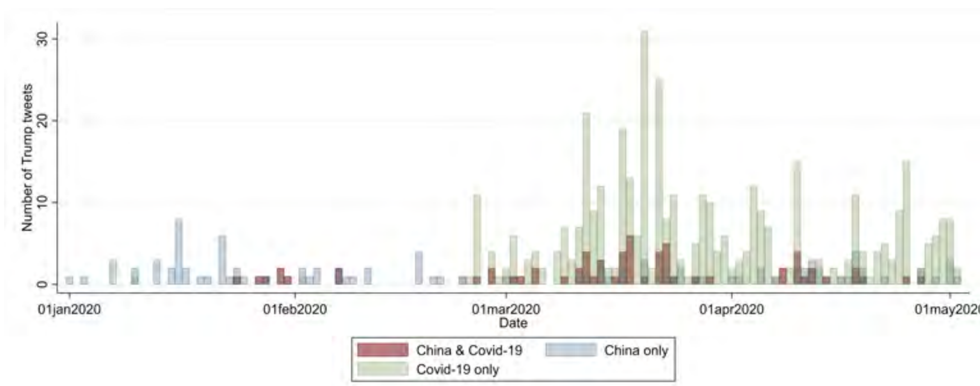


Figure A9: Number of President Trump's Tweets about China or COVID-19

Notes: This figure plots the number of President Trump's tweets on both China and COVID-19 (blue bar), only China (red bar), and only COVID-19 (green bar) on each day between January 1, 2020 and May 2, 2020. A tweet is defined to be about China if it contains any of "China", "Chinese", "Huawei", or "Xi" and about COVID-19 if it contains any of "indicator", "covid-19", "corona", "coronavirus", "virus", "epidemic", or "pandemic".

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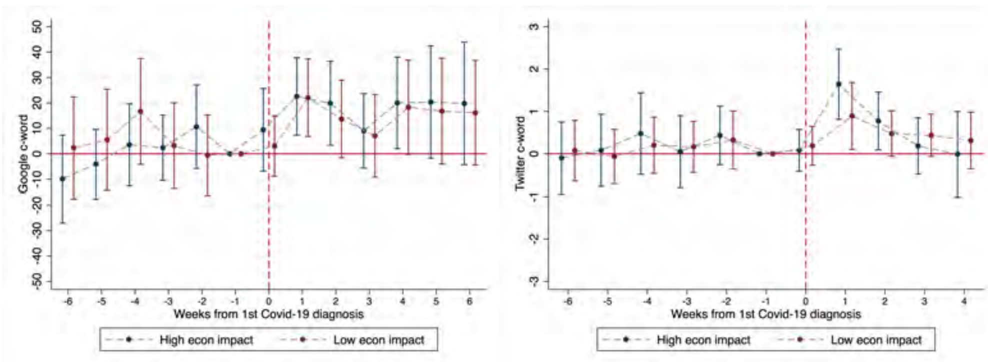

A: Google search index

B: Twitter post index

Figure A10: The Effect of 1st Local COVID-19 Diagnosis on Local Racial Animus by the Negative Economic Impact of COVID-19

Notes: The figures present the heterogeneous effect of first local COVID-19 diagnosis on local racial animus by the local labor market's susceptibility to unemployment caused by the COVID-19 pandemic. We define an area to be more (less) susceptible to the negative impact if the proportion of the area's annual average employment in "leisure and hospitality" and "education and health services", the two hardest-hit industries in employment according to the Bureau of Labor Statistics (BLS), is above (below) the sample median (i.e., 32 percent in the Google sample and 35 percent in the Twitter sample). The employment data is based on BLS's county-level QCEW NAICS-Based Data in 2018. Panels A and B plot the coefficients and the 95 percent confidence intervals of the event time dummies from regression 2 using the racially charged Google search index and Twitter post index as outcomes, respectively. All regressions control for year-month fixed effects and media market fixed effects (panel A) or year-month fixed effects and county fixed effects (panel B). Standard errors are clustered by media market (panel A) or county (panel B).

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Table A1: Sample Selection - Media Markets and Counties with Google and Twitter data

VARIABLES	(1) Google sample	(2) Google sample	(3) Twitter data	(4) Twitter data	(5) Twitter sample	(6) Twitter sample
Log(pop)	0.241***	0.224***	0.120***	0.145***	0.122***	0.145***
	(0.029)	(0.035)	(0.006)	(0.007)	(0.006)	(0.007)
% Asian	0.025	0.060*	0.005	0.009	0.006	0.009
	(0.019)	(0.031)	(0.008)	(0.009)	(0.008)	(0.009)
% Asian^2	-0.001*	-0.002*	-0.000	-0.001**	-0.000	-0.001**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% Male	-0.016	-0.007	0.003	-0.002	0.002	-0.002
	(0.026)	(0.040)	(0.002)	(0.002)	(0.002)	(0.002)
% 65+	0.002	-0.010	-0.002	-0.001	-0.002	-0.001
	(0.009)	(0.016)	(0.002)	(0.002)	(0.001)	(0.002)
% BA+	0.012***	0.007	0.003***	0.002**	0.003**	0.002*
	(0.004)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
% Unemp	0.002	-0.005	-0.007*	0.000	-0.009**	-0.002
	(0.011)	(0.020)	(0.004)	(0.005)	(0.004)	(0.005)
% VS dem-rep	-0.001	-0.001	0.001***	0.002***	0.001***	0.001***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	205	205	3,111	3,111	3,111	3,111
R-squared	0.581	0.678	0.279	0.351	0.292	0.357
Outcome mean	.292	.292	.193	.193	.186	.186
State FE	N	Y	N	Y	N	Y

Notes: The table presents the sample selection in Google and Twitter data. The data are at the media market level (columns (1)-(2)) or county level (columns (3)-(6)). Outcome is an indicator of having valid racially charged Google search index (columns (1)-(2)), an indicator of having valid racially charged Twitter post index (columns (3)-(4)), or an indicator of being in the final Twitter sample. Note that all media markets with valid Google data are in the final Google sample. "%Asian", "% Male", "% 65+", and "% BA+" are the percentage of Asians, males, population 65 years old or over, and population with Bachelor's or above degree in the local area from American Community Survey 2014-2018 five-year average. "%Unemp" is the average monthly local unemployment rate between 2014 and 2018 from the Bureau of Labor Statistics. "Log(pop)" is the logarithm of local population estimates in 2018 from Census Bureau. "% Vote share dem-rep" is the difference between the democratic and the republican vote shares in 2012 presidential election from Harvard Dataverse. The number of media markets and counties is less than 210 and 3141 due to missing covariates. Standard errors in parentheses are clustered by media market (columns (1)-(2)) or by county (columns (3)-(4)). *** p<0.01, ** p<0.05, * p<0.1.

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Table A2: Sample Selection - Timing of 1st Local COVID-19 Diagnosis

VARIABLES	(1) Google sample Weeks from Jan 19, 2020	(2) Google sample Weeks from Jan 19, 2020	(3) Twitter sample Weeks from Jan 19, 2020	(4) Twitter sample Weeks from Jan 19, 2020
Log(pop)	-0.838*	-0.835***	-0.586***	-0.575***
	(0.469)	(0.291)	(0.048)	(0.059)
% Asian	-0.184	0.004	-0.058	-0.068
	(0.166)	(0.184)	(0.039)	(0.041)
% Asian^2	0.002	-0.000	0.000	-0.000
	(0.005)	(0.004)	(0.001)	(0.001)
% Male	-0.841**	-0.943**	-0.036	-0.010
	(0.391)	(0.364)	(0.028)	(0.029)
% 65+	-0.128	-0.056	-0.014	-0.013
	(0.077)	(0.048)	(0.009)	(0.014)
% BA+	-0.039	0.040	-0.016***	-0.005
	(0.053)	(0.041)	(0.005)	(0.006)
% Unemp	-0.219	0.477**	-0.013	0.047
	(0.254)	(0.196)	(0.025)	(0.045)
% VS dem-rep	0.002	-0.019*	-0.001	-0.002
	(0.009)	(0.009)	(0.002)	(0.002)
Observations	60	60	581	581
R-squared	0.529	0.975	0.510	0.600
Outcome mean	5.983	5.983	7.913	7.913
State FE	N	Y	N	Y

Notes: The table presents the relationship between the timing of the first local COVID-19 diagnosis and characteristics of the local area. The data are at the media market level (columns (1)-(2)) or county level (columns (3)-(4)). Outcome is the number of weeks from the week of the first diagnosis in our sample, i.e., the week of January 19, 2020. "%Asian", "% Male", "% 65+", and "% BA+" are the percentage of Asians, males, population 65 years old or over, and population with Bachelor's or above degree in the local area from the 2014-2018 five-year average of the American Community Survey. "%Unemp" is the average monthly unemployment rate between 2014 and 2018 from the Bureau of Labor Statistics. "Log(pop)" is the logarithm of local population estimates in 2018 from the Census Bureau. "% Vote share dem-rep" is the percentage difference in the democratic and the republican vote shares in 2012 presidential election from Harvard Dataverse. The number of counties in columns (3) and (4) are smaller than 587 due to missing covariates. Standard errors in parentheses are clustered by media market (columns (1)-(2)) or by county (columns (3)-(4)). *** p<0.01, ** p<0.05, * p<0.1.

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Table A3: The Effect of 1st Local COVID-19 Diagnosis on Local Racial Animus Google Search Index

VARIABLES	(1) C-word index	(2) Severity control	(3) Asian control	(4) Exclude states
-6w	-3.920	-2.694	-4.265	-8.979
	(6.379)	(6.620)	(6.404)	(8.341)
-5w	0.431	1.100	-0.198	-2.575
	(5.722)	(5.820)	(5.699)	(7.083)
-4w	9.764	10.088	9.419	9.205
	(6.263)	(6.316)	(6.233)	(7.649)
-3w	2.282	2.503	2.247	2.458
	(5.023)	(5.085)	(5.020)	(5.912)
-2w	4.739	4.899	4.771	2.564
	(5.469)	(5.535)	(5.467)	(6.150)
+0w	6.421	6.326	6.274	6.574
	(4.898)	(4.911)	(4.864)	(5.127)
+1w	22.628***	22.442***	22.030***	22.771***
	(5.210)	(5.246)	(5.280)	(5.721)
+2w	16.945***	15.936***	16.727***	18.104***
	(5.439)	(5.443)	(5.407)	(5.621)
+3w	8.155	5.702	7.894	8.614
	(5.359)	(5.907)	(5.403)	(5.829)
+4w	19.106***	15.972**	18.873***	19.527**
	(6.265)	(6.999)	(6.253)	(7.461)
+5w	18.263**	15.375*	18.041**	14.709*
	(7.411)	(8.113)	(7.428)	(8.679)
+6w	17.861**	15.002*	18.125**	18.017*
	(7.726)	(8.046)	(7.751)	(9.267)
New cases(t)		0.000		
		(0.000)		
New deaths(t)		-0.006		
		(0.004)		
Post lockdown		3.691		
		(4.072)		
Observations	780	780	780	663
R-squared	0.190	0.192	0.193	0.180
Outcome mean	30.03	30.03	30.03	30.03
Outcome sd	28.501	28.501	28.501	28.501

Notes: The table presents the effect of the first local COVID-19 diagnosis on local racial animus. All estimates are from regression 2 using the racially charged Google search index as outcome. Event dummy for the week before the first local diagnosis is omitted. The first column corresponds to Figure A4, panel A. The second column controls for the number of new cases and new deaths related to COVID-19 and whether the state has any stay-at-home orders in place. The third column controls for the Google search index for "Asian(s)". The fourth column excludes early- and hard-hit states, i.e., Washington, New York, and California. All regressions control for media market fixed effects and year-month fixed effects. Standard errors are clustered by media market. *** p<0.01, ** p<0.05, * p<0.1.

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Table A4: The Effect of 1st Local COVID-19 Diagnosis on Local Racial Animus Twitter Post Index

VARIABLES	(1) C-word Fraction	(2) Severity control	(3) Asian control	(4) Exclude states	(5) Exclude bots
-6w	0.101	0.103	0.103	0.222	0.088
	(0.267)	(0.268)	(0.267)	(0.285)	(0.263)
-5w	0.089	0.090	0.086	0.173	0.071
	(0.254)	(0.254)	(0.254)	(0.267)	(0.253)
-4w	0.239	0.240	0.242	0.317	0.110
	(0.252)	(0.251)	(0.251)	(0.265)	(0.236)
-3w	0.086	0.086	0.100	0.175	0.065
	(0.218)	(0.219)	(0.219)	(0.240)	(0.215)
-2w	0.337	0.337	0.336	0.360	0.332
	(0.213)	(0.213)	(0.212)	(0.233)	(0.210)
+0w	0.233	0.228	0.137	0.264	0.246
	(0.166)	(0.163)	(0.171)	(0.185)	(0.164)
+1w	1.094***	1.076***	1.045***	0.937***	1.036***
	(0.246)	(0.236)	(0.238)	(0.242)	(0.242)
+2w	0.655***	0.610***	0.754***	0.589***	0.600***
	(0.201)	(0.219)	(0.202)	(0.221)	(0.192)
+3w	0.346*	0.272	0.497**	0.388*	0.331
	(0.205)	(0.234)	(0.211)	(0.230)	(0.204)
+4w	0.162	0.076	0.336	0.182	0.166
	(0.276)	(0.305)	(0.281)	(0.307)	(0.273)
New case(s)		0.000			
		(0.000)			
New death(s)		-0.001			
		(0.001)			
Post Lockdown		0.065			
		(0.199)			
Observations	4,796	4,796	4,796	4,251	4,796
R-squared	0.140	0.140	0.155	0.144	0.135
Outcome mean	.798	.798	.798	.798	.766
Outcome sd	2.875	2.875	2.875	2.875	2.772

Notes: The table presents the effect of the first local COVID-19 diagnosis on local racial animus. All estimates are from regression 2 using the racially charged Twitter post index as outcome. Event dummy for the week before the first local diagnosis is omitted. The first column corresponds to Figure A4, Panel B. The second column controls for the number of new cases and new deaths related to COVID-19 and whether the state has any stay-at-home orders in place. The third column controls for the Twitter post index for "Asian(s)". The fourth column excludes early- and hard-hit states, i.e., Washington, New York, and California. The last column excludes tweets from users who are more likely to be Twitter bots, defined as those who tweeted the c-word for more than five times (99 percentile) between November 2019 and April 2020. All regressions control for county fixed effects and year-month fixed effects. Standard errors are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

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Table A5: Examples of President Trump's Tweets about China or COVID-19

Category	Post	Date
Only China	"Years from now, when we look back at this day, nobody's going to remember nancy's cheap theatrics, they will remember though how president trump brought the Chinese to the bargaining table and delivered achievements few ever thought were possible." @ingrahamangle @foxnews	1/17/20
Only China	The Wall Street Journal editorial board doesn't have a clue on how to fight and win. Their views on tariffs & trade are losers for the U.S., but winners for other countries, including China. if we followed their standards, we'd have no country left. They should love sleepy joe!	4/11/20
Only COVID-19	The coronavirus is very much under control in the USA. we are in contact with everyone and all relevant countries. CDC & World Health have been working hard and very smart. Stock market starting to look very good to me!	2/24/20
Only COVID-19	I am fully prepared to use the full power of the federal government to deal with our current challenge of the coronavirus!	3/11/20
COVID-19 & China	Just received a briefing on the coronavirus in china from all of our great agencies, who are also working closely with china. we will continue to monitor the ongoing developments. we have the best experts anywhere in the world, and they are on top of it 24/7!	1/30/20
COVID-19 & China	I will be having a news conference today to discuss very important news from the FDA concerning the Chinese virus!	3/18/20

Notes: This table presents examples of President Trump's tweets mentioning China or COVID-19. We define a tweet to be related to China if it contains any of "China", "Chinese", "Huawei", or "Xi" and a tweet to be related to COVID-19 if it contains any of "covid", "covid-19", "corona", "coronavirus", "virus", "epidemic", or "pandemic".

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The gendered division of paid and domestic work under lockdown[1]

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COVID-19 has uprooted many aspects of parents' daily routines, from their jobs to their childcare arrangements. In this paper, we provide a novel description of how parents in England living in two-parent opposite-gender families are spending their time under lockdown. We find that mothers' paid work has taken a larger hit than that of fathers', on both the extensive and intensive margins. We find that mothers are spending substantially longer in childcare and housework than their partners and that they are spending a larger fraction of their paid work hours having to juggle work and childcare. Gender differences in the allocation of domestic work cannot be straightforwardly explained by gender differences in employment rates or earnings. Very large gender asymmetries emerge when one partner has stopped working for pay during the crisis: mothers who have stopped working for pay do far more domestic work than fathers in the equivalent situation do.

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1. Introduction

The COVID-19 crisis has caused drastic changes to the work and domestic lives of many families around the world. In England, millions of adults have lost work either temporarily or permanently, and many more are predicted to follow. Others are newly working from home, while key workers are experiencing increased demand for work outside the home that carries high health risks. Parents are facing especially challenging circumstances as schools and childcare facilities closed down and they were left with the full responsibility of caring for and educating their children from home.

In the early days of the crisis many hypothesised that COVID-19's effects on work, both paid and domestic, may differ starkly by gender in ways that earlier economic downturns did not (Alon et al. 2020, Hupkau and Petrongolo 2020). However, the direction of these effects is still ambiguous. For instance, back in February the locked-down sectors of the economy disproportionately employed women, putting their jobs at particularly high risk (Joyce and Xu 2020). On the other hand, women were also more likely than men to be key workers or to work in occupations that can be done from home, two traits that contribute to keeping their jobs safe (Blundell et al. 2020). Among parents, mothers are traditionally the main providers of childcare and accumulate a disproportionate amount of housework (Gimenez-Nadal and Sevilla, 2012). It seems natural to assume that they will shoulder most of the additional domestic responsibilities created by the pandemic crisis. But if fathers do take on some of the additional domestic responsibilities, even if not to the same extent as mothers, it may help accelerate changes in norms and attitudes towards more balanced gender roles.

This paper is one of the first to shed light on these effects. We use newly collected data to describe, during the initial stages of COVID-19, how the crisis is affecting mothers and fathers in two-parent opposite-gender families. We describe how the labour market outcomes of mothers and fathers are responding to the crisis as well as how parents are dividing their time between childcare, housework and paid work during the lockdown. Where possible, we use the 2014/15 UK Time Use Survey to provide comparable pre-crisis estimates. We go onto examine gender asymmetries in responses to the crisis, using the shock to examine whether gender gaps in the allocation of domestic and paid work responsibilities can be explained by comparative advantage in the labour market. To investigate this hypothesis we study heterogeneity in the division of household responsibilities by both partners' labour-market circumstances, both in terms of the relative earnings of partners prior to the crisis and in terms of shocks related to COVID-19.[1]

We find that hours of paid work have fallen dramatically during the lockdown period for both mothers and fathers. The average parent in our sample (including those not working for pay) is now working for pay during just three hours a day; in 2014/15 the comparable figure was 6 ½ hours. However, mothers' paid work has shrunk proportionally more than fathers', both in terms of working status and hours of work among those actively in work. In 2014/15, mothers were in paid work at 80% of the rate of fathers; the comparable figure has now dropped to 70%. Mothers in paid work used to work an average of 73% of the hours that fathers worked; this has fallen to 68%. Moreover, the quality of time at work matters for productivity and learning, which in turn may impact future earnings and career progression. Multi-tasking and interruptions are key deterrents of productivity during time at work. Indeed recent evidence suggests that task juggling can result in losses of productivity and earnings (Adams-Prassl 2020; Coviello et al. 2014). To gain insight into how the crisis is affecting the productivity of parents at work,

[1] Single parents face different challenges around how to meet, often on their own, the increased childcare and housework responsibilities the crisis has created. Studying single parents raises specific issues that we do not address in this report.

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we measure how much uninterrupted paid work they do. We find that mothers and fathers doing paid work used to be interrupted during the same proportion of their work hours before the crisis; now mothers are interrupted over 50% more often.

This adds up to a particularly bleak picture of how mothers' work has held up. Overall, in 2014/15, the average mother (including those who did not work for pay) was doing nearly 60% of the number of uninterrupted work hours that the average father did; now she is doing only 35%. Past research shows that the time women take off when having a child, and the reduction in hours once they return to work, have long-term effects, reducing their future hourly wages (Blundell et al. 2016). There is a risk, therefore, that the differences we find in how the work hours of fathers and mothers are being affected by this crisis will contribute to accentuating gender gaps in career progression and earnings.

The gender differences in paid work during this crisis are counterbalanced by unequal gender responses in domestic responsibilities to the large shock to childcare provision due to school and childcare closures. Mothers are doing a greater share of housework and childcare than fathers are, coming to around 2 hours more per day of each.[2] However, these gaps between mothers and fathers time-use are not straightforwardly explained by mothers' lower employment rates or lower earnings. Indeed, gender gaps in time use remain even when comparing mothers and fathers currently working for pay, or mothers and fathers not currently in paid work.

We exploit the variation across couples in terms of asymmetric labour market shocks to check whether the division of domestic work are driven by relative opportunity costs of partners as economic household models would predict (Chiappori 1988; Chiappori 1992; Becker 1965). If specialization in the family is a response to the economic incentives that couples face, then we would expect that fathers assume the primary role at home in couples where the mother is the main earner or where only her job remains active.

We examine whether this is the case in two ways. First, by comparing the division of domestic and paid work in families where either the mother or the father are the primary earners prior to the crisis and both remain in work during lockdown; and second, by looking at the allocation of domestic work between partners when one partner stopped working, depending on the gender of that partner. We find that mothers still do more childcare and the same amount of housework as their partner even when they were the primary earner in the family prior to the crisis. Moreover, mothers who have stopped working for pay during lockdown while their partner continues to work do twice as much childcare and housework as their partner. But in families where the father has stopped working, the parents share childcare and housework equally, while the mother also does an average of 5 hours of paid work a day. We conclude that evidence from this shock does not support the hypothesis that comparative advantage in the labour market explains why mothers do so much more domestic chores than fathers.

While the average gender-disparity in domestic work remains large, we find that fathers' participation in childcare has seen a huge proportional increase from its pre-crisis levels. Whereas, on an average school day in 2014/15, the average father in two-parent opposite-gender households did some childcare during 4 hours of the day, this has doubled under lockdown to 8 hours. To what extent this increase

[2] Our results are consistent with what Adams-Prassl et al. 2020a and Sevilla and Smith (2020) found for the UK, and with similar estimates for Spain by Farre and Gonzalez (2020) and for Italy by Del Boca et al. (2020).

persists as lockdown comes to an end is perhaps the biggest unknown in what the long-run effects of COVID-19 on gender equality in the labour market will be.

Our paper contributes to the recent literature using real-time data to document that women do more childcare and housework than men during the COVID19 pandemic. Adams-Prassl et al. (2020a) asked men and women to report hours spent looking after children and home-schooling during lockdown in the UK. They find that women do approximately an hour and a half more childcare per workday than men, but there is no analysis of the relationship with employment. Sevilla and Smith (forthcoming) directly compare the allocation of childcare within the same household before and after lockdown, and show that women who do a greater share of home childcare pre-COVID-19 are more likely not to be working during COVID-19. Farre and Gonzalez (2020) use a self-selected sample of Spanish households to show that there has been a shift to a more equal distribution of housework (driven mainly by men taking responsibility for shopping) and childcare. Daniela Del Boca, Noemi Oggero, Paola Profeta, Mariacristina Rossi (2020) use data on a representative sample of 800 Italian working women collected before and during the emergency to compare the number of hours spent at work, on housework and childcare before the emergency (April and July 2019) to the hours spent during the first three months of the emergency (April 2020). They find that most of the additional responsibilities have fallen to women, though childcare activities are shared more equally than housework. Compared to previous studies, we analyse time- use data for each hour slot in the day and find that women are doing childcare during more hours of the day than men (during ten of the hour-long slots compared to eight). We also look at how childcare relates to employment and find that men's childcare is more sensitive to their employment.

The paper proceeds as follows. In the next section, we discuss our survey, sample and methods of analysis. In section 3 we provide descriptives of parents' paid work before moving onto descriptives of timeuse in section 4. In section 5, we examine the extent to which the patterns we find can be straightforwardly explained by gender differences in employment rates and pre-crisis earnings. Section 6 concludes.

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2. Sample, Survey and Analysis

Sample

We surveyed 4,915 parents in England who lived with their children between 29 April and 15 May 2020. In particular, to be eligible for inclusion, parents had to be living with (at least one) child in one of eight different school years.[3] These school years corresponded (roughly) to having a child aged between 4 and 15.

Our sample is limited to opposite-gender two-parent households, of which we have 3,591 in the data. While this group include the majority of parents, this work is not necessarily representative of how parents as a whole are experiencing lockdown. The analysis does not include single parents, who make up 14.8% of families in England.[4] Single parents are likely to face particular challenges due to even more-exacerbated time pressures (Cattan et al. 2020). Since most single-parent households are headed by women, this is particularly important for how the crisis will affect mothers and fathers differently. Likewise, the analysis does not include households with two parents of the same gender, who typically divide up responsibilities differently from opposite-gender parents (Andresen and Nix 2019). Both groups merit specific and careful analysis.[5]

Survey

Participants were recruited through a well-reputed online survey company and received a small payment in compensation for their time. We ensured that respondents were diverse in terms of their gender, education, region, marital status, work status and the job they did.

The main aim of our survey was to collect detailed information on how families and children spend their time on a term-time weekday. We asked the surveyed parent and their partner to fill in an online time-use diary, telling us what activities they did during each hour of the day. We also asked the surveyed parent to fill in a similar diary about their child's time use (selecting one child at random in multi-child families), and asked who the child was with during each time slot. Finally, we collected information about the types of home learning activities children are doing, what resources have been provided by the school and what resources are available at home for learning.

In order to keep the survey a manageable length for families, we asked about time use in one-hour slots. Since these are wider than the 10-minute intervals used in the most detailed time-use surveys, such as the 2015 UK Time Use Survey, we cannot say precisely how long respondents spent on a particular activity; respondents could report multiple activities during the hour, so the apparent number of hours

3 We interviewed parents with children entering Reception next year and those with children in school in Reception and in Years 1, 4, 5, 8, 9 and 10.

4 https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2019.

5 While the size of this data set is sufficient to carry out a detailed analysis of how opposite-gender two-parent households (the majority group) are experiencing the crisis, the size limits our ability to conduct specific analysis of these two important groups that addresses the particular challenges each may be facing. As larger data sets collected during the crisis are released (for example, the Understanding Society panel), more analysis of these groups will be possible.

might overstate how long the respondent spent on the activities in that category. Instead, we comment on the number of one-hour slots during which doing at least some of a particular activity is reported.

Analysis

While we comment at points on the ways in which our data appear consistent, or inconsistent, with theoretical ideas and past empirical evidence on household organisation, all analysis we present in this paper is descriptive. We present average time use across mothers and fathers and, at various points, also split by other dimensions of heterogeneity (for example, past relative earnings or which partner experienced job loss during the crisis).

Table 1 presents basic descriptives of the prior economic situation of the families in our sample. To examine the representativeness of our sample across these characteristics, we constructed a sample of respondents from the nationally representative 2019 Labour Force Survey (LFS) who were roughly equivalent to our population of interest: parents with at least one child between the ages of 2 and 15.[6] Columns 1 and 2 of Table 1 show means for this nationally representative sample and for our sample. We see that our sample systematically contains larger proportions of higher earners and more-educated individuals than does the LFS. Importantly, we also see that our unweighted sample contains a higher proportion of individuals who work in industries that have been locked down during the crisis.

Therefore, so that our analysis is representative of the situation in England as a whole, we reweight our sample by key characteristics to ensure that it better matches the distribution of characteristics observed in the LFS. In particular, we reweight on: family structure, women's education, men's education, prior (pre-pandemic) employment, women's 2019 pre-tax earnings, men's 2019 pre-tax earnings, women's industry (particularly whether they work in an industry where more than 50% of jobs have been locked down), men's industry (ditto), women's occupation (particularly whether working from home is possible), men's occupation (ditto), and geographic region.[7] To do this, we pool our data with the LFS sample and use regression analysis to calculate appropriate weights. We truncate our weights at the 10th and 90th percentiles to prevent our analysis being overly sensitive to a few observations.

Column 3 of the table shows means for the reweighted sample. We see that the average characteristics of this reweighted sample are now very similar to the nationally representative LFS sample. Reassuringly, the reweighted sample also matches various moments well that we didn't directly reweight on.

6 The LFS only has information on children's ages in groups, meaning that we were not able to select households with children of the exact ages that would make them eligible for our survey.

7 The share of jobs in an industry subject to the lockdown and the share of jobs in each occupation that can be done from home are calculated using the methods set out in Costa-Dias et al. (2020)

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Table 1. Means for our survey sample (weighted and unweighted) compared with nationally representative LFS sample

	(1) Comparable LFS sample	(2) Our sample, unweighted	(3) Our sample, reweighted
Characteristics reweighted on			
Women's education			
GCSEs or less	0.367	0.256	0.336
A levels	0.249	0.276	0.256
University degree	0.384	0.469	0.408
Men's education			
GCSEs or less	0.416	0.299	0.377
A levels	0.229	0.238	0.237
University degree	0.354	0.463	0.386
Prior employment			
Women's pre-crisis employment	0.745	0.732	0.753
Men's pre-crisis employment	0.935	0.879	0.917
Women's pre-crisis earnings			
£0–£9,999	0.476	0.303	0.448
£10,000–£24,999	0.285	0.422	0.300
£25,000–£39,999	0.151	0.131	0.149
£40,000+	0.089	0.144	0.103
Men's pre-crisis earnings			
£0–£9,999	0.131	0.090	0.142
£10,000–£24,999	0.206	0.330	0.214
£25,000–£39,999	0.301	0.255	0.303
£40,000–£59,999	0.188	0.166	0.186
£60,000+	0.174	0.159	0.154
Pre-crisis industry			
Proportion working in industry where 50%+ of jobs have been locked down			
Women	0.231	0.322	0.260
Men	0.264	0.325	0.286
Pre-crisis occupation			
Proportion working in occupation where home working is possible in 0–15% of jobs			
Women	0.327	0.313	0.322
Men	0.362	0.346	0.355
Proportion working in occupation where home working is possible in 15.1–75% of jobs			
Women	0.237	0.210	0.213
Men	0.192	0.270	0.209

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	(1) Comparable LFS sample	(2) Our sample, unweighted	(3) Our sample, reweighted
Proportion working in occupation where home working is possible in 75.1–100% of jobs			
Women	0.436	0.477	0.465
Men	0.445	0.385	0.436
Region			
Greater London	0.118	0.174	0.120
South East	0.235	0.152	0.214
South West	0.097	0.103	0.103
West Midlands	0.107	0.112	0.108
North West	0.136	0.143	0.142
North East	0.061	0.071	0.065
Yorkshire and the Humber	0.113	0.096	0.103
East Midlands	0.092	0.077	0.094
East of England	0.041	0.073	0.049
Characteristics not reweighted on			
Education			
Neither partner university	0.470	0.394	0.467
One partner university	0.265	0.255	0.247
Both partners university	0.265	0.350	0.286
Employment			
Neither partner employed	0.028	0.060	0.039
One partner employed	0.235	0.270	0.259
Both partners employed	0.737	0.670	0.702

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3. Parents' paid work under lockdown

We begin by examining some basic descriptives of parents' paid work by gender during the lockdown. COVID-19 has brought an unprecedented disruption to working patterns, changing who is in paid work and where, when and how they are working. Of the parents in our (reweighted) sample who were doing some paid work during February 2020, only 54% were still engaging in paid work at the time of the survey. 13% were no longer working for pay due to having lost their job permanently (through being laid off, being fired or quitting), while another 32% of parents were no longer working for pay due to having been furloughed through the UK government's Coronavirus Job Retention Scheme.

So far, there are no conclusive statistics on the rate of furloughing or of job loss and the statistics that do exist vary widely. Official estimates for the UK suggest that 23% of those who were working for pay (employed or self-employed) before the crisis had been furloughed by mid May.[8] However, a recent online survey of the labour market suggested a much higher figure of 43%.b In all, the proportion of parents in opposite-gender partnerships who were previously working that we estimate to have stopped working due to having been furloughed (32%) lies between official figures and those from recent labour market surveys.

Official information about how many people have lost their job is more scarce.[9] Data scarcity, differences in reference periods and the fact that we look at all those who have stopped working for pay (due to being laid off, being fired or having quit) whereas the government figures that are available so far only relate to those claiming benefits due to unemployment (a narrower group) make it difficult to make comparisons with official figures at this stage. Our estimate of the proportion of parents no longer working for pay (13% of those who were previously working) is similar to, but slightly lower than, in a recent labour market survey which estimated a figure of 15% (Adams-Prassl et al. 2020).

Importantly, our estimates of the prevalence of both furlough and stopping work for other reasons are not directly comparable to either official statistics or recent labour market surveys: we focus on opposite-gender, dual-parent households with dependent children in England, rather than all workers in the UK. This could be particularly important since parents are able to ask to be furloughed because of

[8] 1 Official estimates report that 7.5 million (employee) jobs had been furloughed by 12 May (https://www.gov.uk/government/news/chancellor-extends-furlough-scheme-until-october). This compares with Office for National Statistics (ONS) estimates, based on the Labour Force Survey, that there were 33.1 million in paid work in the UK between December 2019 and February 2020 (ONS Dataset EMP01 SA, release date 19 May 2020).

[9] A huge increase in the volume of claims made for benefits related to unemployment and financial hardship indicate the unprecedented scale of the financial challenges facing households. During the first eight weeks after social distancing was announced (on 16 March), there were 2.6 million individual 'declarations' from people applying for universal credit benefits.c Not all these claims will, however, relate to new job loss. The government estimates that as of 9 April, three weeks into social distancing, 856,000 more people than one month earlier were claiming benefits principally for the reason of unemployment;d these numbers are likely to increase substantially as they are updated to cover a greater period of the lockdown. They are also likely to underestimate the true extent of job losses as not all job losses will have resulted in new benefit claims: some newly unemployed workers will already have been claiming universal credit so will not have needed to make a new claim, others will not have met the eligibility criteria, while still more will have been entitled to claim but will not have actually done so. The difference in reference period (our data capture those who have stopped working for pay up until mid May, a month later than the official estimates of new benefit claims for the principal reason of unemployment) makes it difficult to compare our estimates with these official statistics.

c Department for Work and Pensions, 'Universal Credit declarations (claims) and advances: management information', released 19 May 2020, https://www.gov.uk/government/publications/universal-credit-declarations-claims-and-advances-management-information#history.

d Office for National Statistics, 'Employment in the UK: May 2020', released 19 May 2020, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/may2020.

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pandemic-related caring responsibilities, including childcare while schools are closed. Since our figures apply only to parents with dependent children, they are less useful as indicators of the health (or lack thereof) of the UK labour market as a whole. However, they do clearly indicate that parents with dependent children have seen enormous disruption to their working patterns.

While it is early to say whether our figures on job loss and furlough among parents are precise estimates of what is happening in the wider economy, in this report we focus on the *differences* in employment and time use between fathers and mothers and across families, which are likely to be less sensitive to potential sampling bias.

Differences by parents' gender

We find important differences in the rates of job loss and of furloughing between mothers and fathers. We see in Figure 1 that, among parents who were working in February 2020, mothers are indeed 9 percentage points more likely to have stopped working for pay than fathers. 16% of mothers are no longer doing paid work due to having lost their work permanently (whether they were laid off, were fired or quit), compared with 11% of fathers. Mothers are also somewhat more likely to not be doing paid work due to having been furloughed through the Coronavirus Job Retention Scheme (34%, compared with 30% of fathers). These effects compound the already unequal employment rates of mothers and fathers, which in our data were respectively 75% and 92% in February 2020 (very close to the 75% and 93% in nationally representative data for April to June 2019).[10] So, while prior to the crisis mothers were in paid work at 80% of the rate that fathers were, now they are in paid work at only 70% of the rate.

These differences may arise through one of two channels, or a combination of the two. First, mothers are more likely than fathers to work in the sectors that are taking the biggest hit from the lockdown (Alon et al. 2020; Joyce and Xu 2020). This aspect is different from in previous recessions, in which male-dominated sectors suffered the most (Doepke and Tertilt 2016).

Second, the COVID-19 crisis has been distinguished by the sudden, near-total loss of access to schools and childcare, leaving parents with enormous additional responsibilities for childcare and education. Since mothers already spent more time on childcare and other unpaid work (Cattan et al. 2020), and since in many couples the woman is the lower earner, it is possible that these additional responsibilities are being disproportionately shouldered by mothers.

[10] See ONS, 'Families and the labour market, UK: 2019', https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/familiesandthelabourmarketengland/2019. These employment rates are also consistent with findings from other surveys recently collected for the UK (e.g. (Adams-Prassl et al. 2020; Sevilla and Smith 2020))

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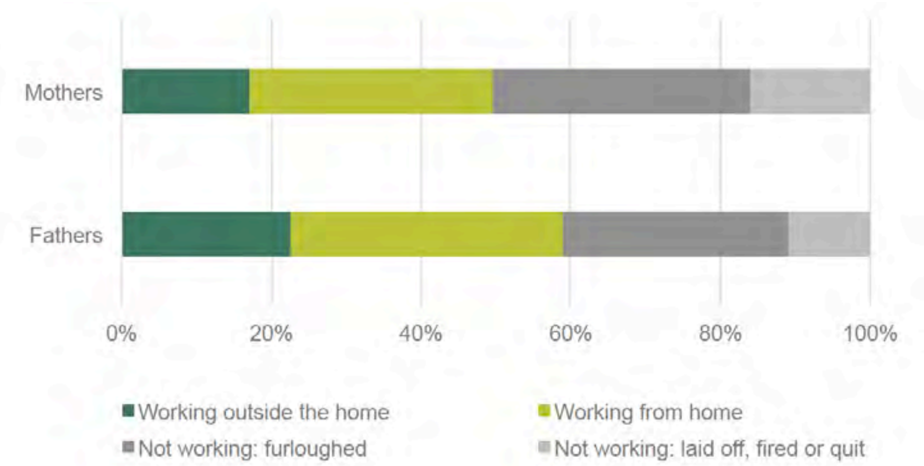
Figure 1. Current engagement in paid work by gender for parents who were in paid work in February 2020



If those who have stopped paid work during the crisis find it difficult to return in the short term, either because low labour demand coupled with high overall levels of unemployment makes it hard to find a job or because their other commitments remain incompatible with paid work, these initial inequalities could persist beyond this crisis through the loss of skills and labour market attachment leading to long-term increases in gender inequalities.

Differences by parents' education qualifications

The lockdown has also opened up inequalities between education groups, as Figure 2 highlights. Amongst both mothers and fathers, individuals with fewer qualifications are more likely to have stopped paid work since the start of the crisis. As has been discussed elsewhere (Costa-Dias et al. 2020), this may well be because more-skilled jobs can be done from home more easily. For example, over three-quarters of university-educated parents in our data who are currently working are working from home, compared with well under half of those with GCSE qualifications or below.

The gender inequalities in who has stopped working are clear within all three education groups: mothers are always more likely to have stopped working than fathers, independent of their qualifications. Strikingly, the gender gap is similar at the top and the bottom of the distribution of education: among degree-educated parents, mothers are 9.2 percentage points more likely to have stopped work, while the gap is 8.8 percentage points among those educated to GCSE level or below. The gap for the group with A-level qualifications is around two-thirds as big again.

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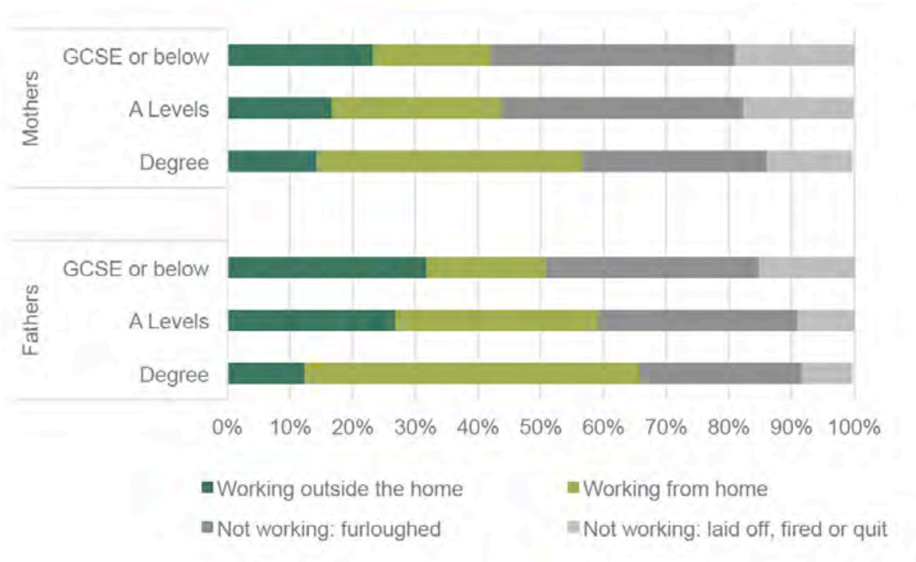
Figure 2. Current work status by gender and education for parents who were in paid work in February 2020



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4. Time Use under Lockdown

Changes in employment patterns are not the only way in which the lockdown is impacting how families spend their time; most children now rely on their parents as their sole childcare and chief education providers. In this section, we document how mothers and fathers are spending their time during lockdown and who is shouldering these additional responsibilities.

In our survey, we asked the main respondent what activities they, their partner and one of their children were doing during each hour of the previous weekday (the survey was paused over weekends and Bank Holidays). The respondent could include more than one activity in each hour slot. For parents, the activities we asked about were paid work, housework, leisure, exercise, personal care, 'active' childcare (such as playing with a child or doing educational activities), 'passive' childcare (keeping an eye on a child), caring for others (not children) and sleep.[11] In this analysis, we combine active and passive childcare into one childcare category, we combine 'exercise' and 'leisure' to create one exercise category and we drop 'caring for others' due to the rarity with which this activity was selected. For children, in addition to age-appropriate activities, we asked who was supervising them during each hour and we use this information to cross-check the hours in which parents were doing passive childcare. This leaves us with six different categories of activities during waking hours. In this section, we describe how, on average, all mothers and fathers (regardless of whether they worked prior to the crisis and whether they are working now) have been spending their time.

How are mothers and fathers spending their weekdays?

For each hour of the day, Figure 3 shows the share of mothers and fathers taking part in each of these six categories of activity. In some cases, Figure 3 shows few differences between men and women: their sleeping patterns, time spent on personal care and leisure time look nearly identical.

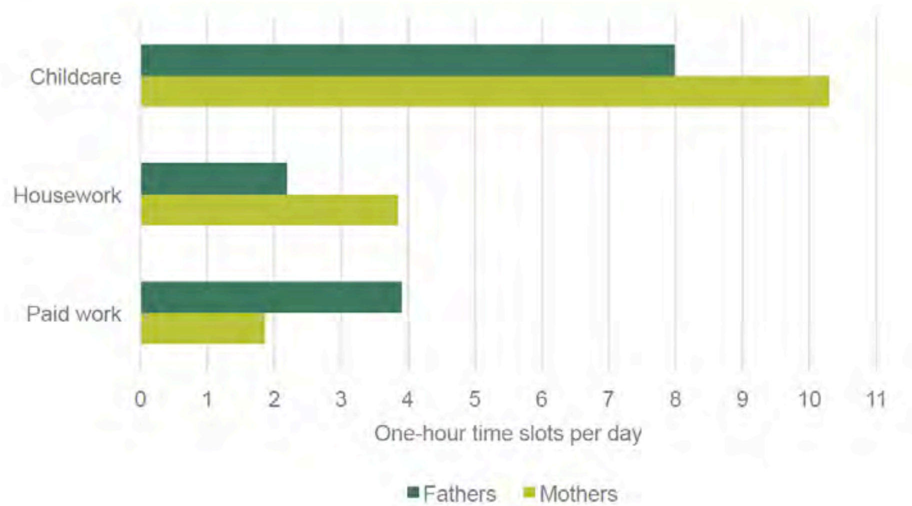
But there are stark differences in time spent on paid work, housework and childcare. At all points in the day, more men than women are doing paid work. For example, while around a fifth of mothers report doing paid work between noon and 1pm, nearly two-fifths of fathers say they are working then. The reverse is true for housework, with more women doing housework during every hour of the day. In childcare too, the gender difference is striking, particularly during core working hours; at noon, for example, around 70% of mothers were doing childcare compared with 50% of fathers.

These differences mean that mothers report spending at least some of their time on housework and childcare in more hour-long slots during the day than their partners do. Figure 4 summarises these findings, showing the total number of one-hour slots in which mothers and fathers report doing childcare, housework and paid work.

[11] In addition to respondents' reports of passive childcare done by them and their partner, we also include hours in which the respondent reported through the child time-use diary that they or their partner was supervising their child.

Figure 3. Mothers' and fathers' time use over the course of the day

Figure 4. Total one-hour time slots reported by mothers and fathers



Averaging across those currently doing paid work and those who are not, Figure 4 shows that, on average, fathers report doing some paid work in four one-hour slots, two more than the average for mothers. On the other hand, fathers report doing housework in just over two time slots, compared with nearly four for mothers. There is a similar story for childcare, where mothers report doing childcare in over ten one-hour slots and fathers do so in eight. Of course, one reason for these gender differences is that – as Section 2 shows – men are more likely to remain in paid work during the crisis and, indeed, are more likely to have been working for pay, particularly in full-time work, prior to the crisis. We return to this in further detail below.

Gender differences in childcare

The differences in time spent on childcare, shown in Figure 4, are stark: on average, mothers are engaged in some childcare – whether active or passive – in over 25% more hour-long slots than fathers. But even for fathers, childcare is the activity that is most frequently reported during waking hours (see Figure 3).[12] This means that parents, especially mothers, are doing some childcare throughout the great majority of their day.

To put these patterns into context, we now look at how these figures compare with the amount of childcare that parents were doing prior to the crisis, using data from the UK Time Use Survey (UKTUS), a nationally representative time-use survey carried out in 2014/15.[13]

Figure 5 shows that, on an average school day in 2014/15, fathers were engaged in childcare during 4.2 one-hour slots and mothers during 6.7 slots; the 8.0 and 10.3 one-hour slots in which, on average, fathers and mothers report doing childcare over the last few weeks are thus very substantial increases. The increase is particularly large for fathers, who have nearly doubled the number of slots in which they engage in childcare. Such a sudden and significant change may have longer-run effects on how parents share childcare going forward, even after lockdown, and on how employers view male employees' childcare responsibilities.

Of course, not all childcare requires the same level of effort from the parent; it could be much easier to combine cooking with keeping an eye on a child while they watch TV than it is to combine writing work reports with playing Lego. Figure 5 therefore also breaks our measure of childcare into 'active' and 'passive' care. It shows that more than half (56% for mothers and 61% for fathers) of the time spent looking after children is taken up with 'passive childcare' – keeping an eye on the children or watching TV together, for example – rather than 'active childcare', such as doing schoolwork or playing together.

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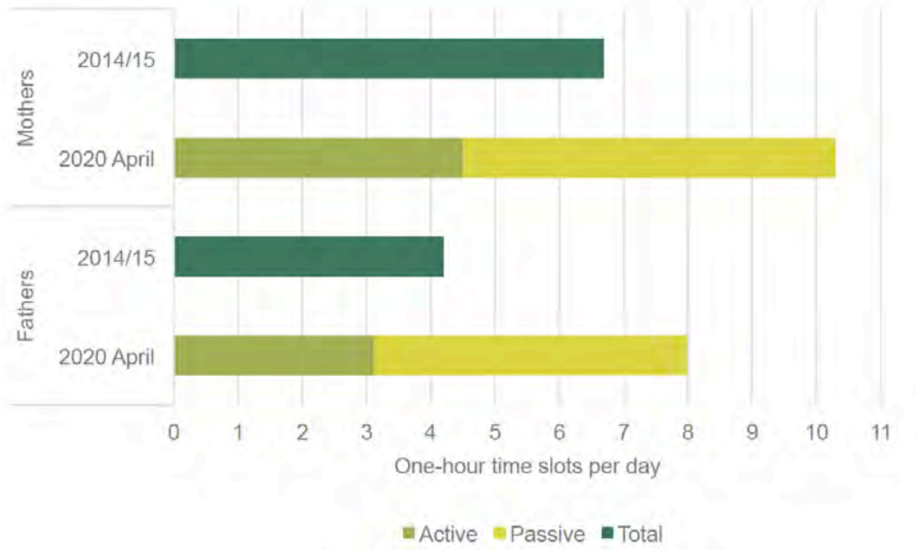
[12] This is consistent with other recent surveys which also find large differences in the time spent on childcare by mothers and fathers during the current crisis (e.g. Adams-Prassl et al. 2020; Sevilla and Smith 2020)

[13] We run this analysis on a subsample of households with children of similar ages to those in our survey (focusing on children from age 8, when child time-use diaries are first available, to age 15). We also recode data from the UKTUS to make them as comparable as possible to ours by recoding the survey's 10-minute intervals into hour-long intervals and recoding whether the respondent did any childcare during that hour. Our measure of doing childcare in the UKTUS is based on cross-checking the reports of when children say they were with parents against their parents' diaries.

Figure 5. Active versus passive childcare and comparison with pre-lockdown time use



Note: 2014/15 figures use the UK Time Use Survey. This data set contains activity information down to 10-minute slots of the day. We create a data set from this that indicates whether a parent did any childcare within a given hour, to best mimic the methodology in our survey.

Quantity versus quality of work time

The amount of paid work that parents can do depends not just on how long they spend working, but also on how productive they are during that time. Indeed, previous research has shown that the total amount of working time and the total amount of focused, uninterrupted working time are both important determinants of workers' productivity and learning (Blundell et al. 2016; Coviello et al. 2015; Coviello et al. 2014; Adams-Prassl 2020).

However, for parents working from home, working time – and especially focused working time – can be hard to come by. Parents, who are now largely responsible for both childcare and education around the clock, are contending with more demands from their families on their time. And childcare, particularly for younger children, is often not an activity that can be rigorously scheduled in focused blocks of time.

In this section, we explore what the lockdown has meant for parents' working patterns. Since we asked respondents to list *all* of the activities they did in each one-hour slot, our data give us a clear picture of the extent to which parents' hours of paid work are being shared with – or interrupted by – other responsibilities. To understand how this crisis is changing the quantity of working time, we compare current figures with what similar parents used to do before the lockdown using the UK Time Use Survey.

Figure 6 illustrates how much working patterns have changed for fathers and mothers. The top panel shows the average number of hour-long slots dedicated to paid work before and during the crisis, for all mothers and all fathers taken together. Overall, we find that fathers are doing paid work in fewer than half the number of hours that average fathers used to work before the crisis. For mothers, the drop

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is even more staggering; they are currently working in less than two-fifths of the number of hours that similar mothers reported prior to the lockdown. In all, while in 2014/15 mothers who were doing paid work were working 73% of the number of hours of fathers in paid work, now mothers are working only 68% of fathers' hours.

Of course, these figures are partly driven by the large changes in employment status that we reported in Section 2. Panel B in Figure 6 shows how working hours among the subgroup of parents who are working for pay during the lockdown period compared with pre-lockdown figures for working parents. It shows that substantial gender differences persist: while the working hours of fathers dropped by about 16%, those of mothers dropped by 22%.

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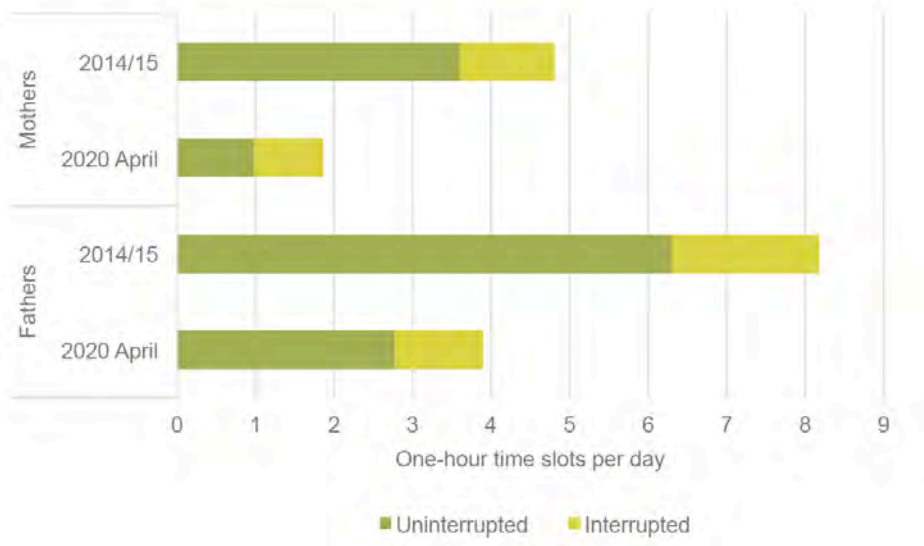
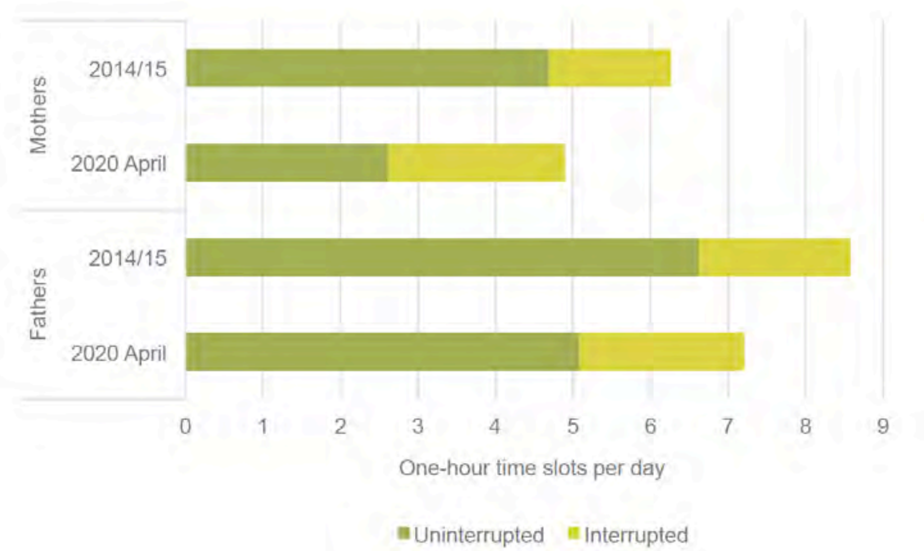
Figure 6. Working hours before and during the lockdown

Panel A. Average working hours: all parents



Panel B. Average working hours: working parents



Note: 2014/15 figures use the UK Time Use Survey. This data set contains data down to 10-minute slots of the day. We create a data set from this that indicates whether a parent did any paid work within a given hour, to best mimic the methodology in our survey.

Figure 6 also shows the amount of parents' paid work hours that are multitasking (or are interrupted), defined as doing at least one work and one non-work activity during the hour-long slot. We see that, before the crisis, parents typically did non-work activities during a quarter of the hours in which they were also doing paid work. Such hours most typically occurred at the start and end of their workdays,

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as they transitioned to and from work.[14] We see that now, overall, parents who are currently working for pay (Figure 6B) have a higher number of interrupted hours, both in absolute terms and as a fraction of their total work hours. The nature of the interruptions is also different; during the lockdown, in roughly 90% of interrupted work hours the parent is also doing childcare alongside his or her paid work. Working time before the crisis was mostly spent in the workplace, where interruptions are likely to be less frequent and less disturbing for the workflow. The increase in interruptions is therefore unsurprising given many parents' transition to doing their job from home with children out of school. The reduction in the proportion of hours that parents work uninterrupted implies that the drop in the *amount* of work that parents are able to do may be even more pronounced than suggested by the drop in working hours. Our data confirm that indeed multitasking is less frequent among those parents working outside the home, in which case it happens in 18% of work hours, compared with 49% for those working from home.

Moreover, the extent of multitasking during work time is more prevalent among women than men. While 70% of fathers' work hours are spent exclusively doing work, this is the case for only 53% of mothers' work hours.[15] In other words, mothers are being interrupted during 57% more of their paid work hours than fathers. This was not the case before the crisis: then, mothers and fathers were interrupted during the same proportion of their work hours. Combined with the gaps in hours spent doing paid work, this amounts to the average father who is currently working for pay having nearly twice as many uninterrupted work hours as the average mother who is currently working for pay (5.1 hours versus 2.6 hours). This is a bigger gap in uninterrupted hours than we saw before the crisis (6.6 hours for fathers versus 4.7 hours for mothers). Combined too with the fact that mothers are more likely to have stopped working for pay since the lockdown and that they were already less likely to be doing so before the crisis, mothers overall (including those not working for pay at all) are working just over a third of the number of uninterrupted hours that fathers are.

Taken together, we find that not only are mothers less likely to work during the lockdown, but also, even if they are working, they spend fewer hours on paid work and the time they do spend working is likely to be less productive than fathers' work time because of interruptions. Lower productivity during the time mothers spend on paid work – and being paid – could itself impact their career prospects, making them seem less committed to their jobs or less able to cope with their workloads than their male colleagues.

[14] Commuting to and from paid work is included in our definition of hours spent doing some paid work.

[15] These findings are unlikely to be driven by differences in reporting behaviour between men and women (e.g. women being more likely to tick multiple boxes). Our analysis includes both the main respondent's and his/her partner's time use. Since our main respondents are a mix of men and women, we have some mothers responding about fathers and some fathers responding about mothers. We did not find systematic differences in gender gaps for reported time use by gender of the main respondent.

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5. What drives differences in how mothers and fathers spend their time?

So far, we have seen that mothers and fathers are spending their time very differently in the lockdown. While men have significantly increased the time they spend on childcare, it is still mothers who are taking on the bulk of childcare and housework responsibilities, often at the same time as they complete other tasks. By contrast, fathers are doing much more paid work than mothers during the lockdown. These results suggest that the adults in two-parent families are continuing – or intensifying – the specialisation they had already developed before the pandemic, with one partner focusing more on paid work while the other takes more responsibility for unpaid work at home.

Notably, this specialisation has been incentivised by policy during the pandemic: the Coronavirus Job Retention Scheme means that couples where one parent stops doing paid work entirely and is furloughed, while the other continues to work their regular hours, are financially much better off than those where both partners reduce their working hours to accommodate their new domestic responsibilities. But noting that there are incentives in favour of specialisation within couples does not answer why, on average, specialisation during the lockdown seems to split along gender lines, with mothers spending more time on domestic responsibilities while fathers do more paid work. There could be a number of reasons for this gendered division of labour, including:

- **Employment rates:** As we have shown, fathers are more likely to be in paid employment than mothers. This was already true before the crisis – 75% of mothers were working between April and June 2019, compared with 93% of fathers[16] – but the differences are now even more pronounced.
- **Hourly earnings:** On average, fathers earn more than mothers; before the crisis, mothers whose first child was 5 years old earned more than 15% less per hour than fathers with a first child the same age, and the gender wage gap continued to grow as the child got older (Costa Dias et al. 2018). This means that an extra hour that a father spends doing paid work is, on average, more financially valuable for the household.
- **Productivity in domestic work:** Similarly, if women are more capable or productive at housework or childcare – for example, because they did more of it before the crisis and so are more experienced – the household might benefit more from an extra hour of a mother's domestic work than it would from a father's.
- **Preferences:** The way in which partners share responsibility for childcare and housework could also be influenced by partners' preferences, habits or beliefs about who 'should' take responsibility for these activities.

These are, of course, not the only reasons that could affect how mothers and fathers choose to divide their tasks; other influences, such as different accommodations from employers, could also play a role. Disentangling all of the different factors at play, and the extent to which each could influence how couples divide their responsibilities, is a complicated question and outside the scope of this paper. But

[16] ONS, 'Families and the labour market, UK: 2019', https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/familiesandthelabourmarketengland/2019 (accessed 21 May 2020).

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in this section, we explore what our descriptives can suggest about the extent to which some of these causes appear to be at play in driving the gendered division of labour during lockdown.

Are gender gaps explained by mothers being less likely to be employed?

Even prior to the current crisis, mothers were less likely to be in paid work than fathers. On top of that, in this report we document that the lockdown has caused mothers to stop working for pay at higher rates than fathers. For efficiency and financial reasons, a spouse who is not working for pay may accumulate most of the domestic responsibilities within the family. Therefore, one explanation for the gender gaps we see in childcare and housework is simply that mothers are more likely to be not currently doing paid work.

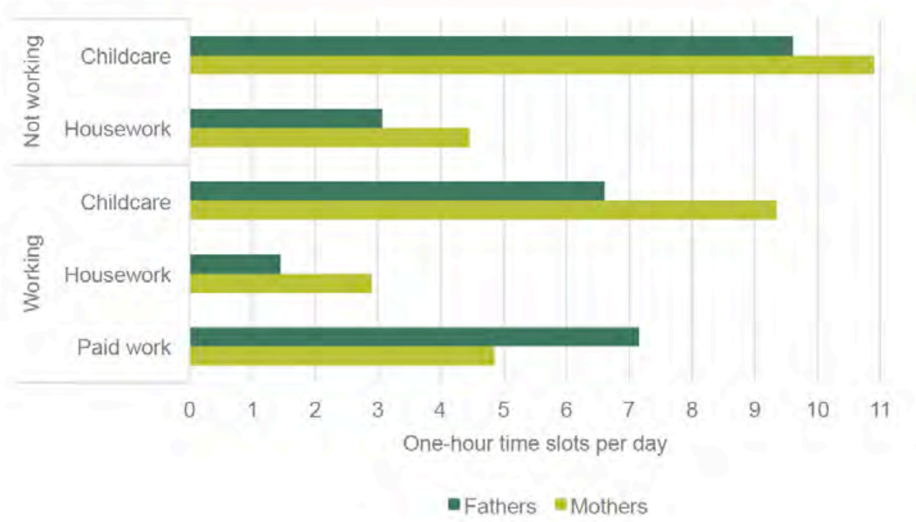
If this explanation were sufficient to explain the gender gaps we see, we would expect that mothers who are currently not doing paid work spend their time in the same ways as fathers who are not doing paid work. Panel A of Figure 7 shows that this is not the case. It graphs the number of one-hour slots in which parents report doing paid work, housework, and childcare (of any type), splitting between those who are currently working for pay and those – including furloughed employees – who are not. Panel B compares those who report they are working from home and those who report working outside of the home.

In Figure 7A, we see large gender gaps even between mothers who are working for pay and fathers who are working for pay, and between mothers who are not currently working for pay and fathers who are not currently working for pay. Mothers spend more time than fathers on housework and childcare, regardless of working status. This tells us that the overall gender differences we observe in time spent on domestic activities are not entirely driven by fewer mothers currently doing paid work. Indeed, mothers who are working for pay spend roughly the same amount of time on these activities as do fathers who are not working for pay.

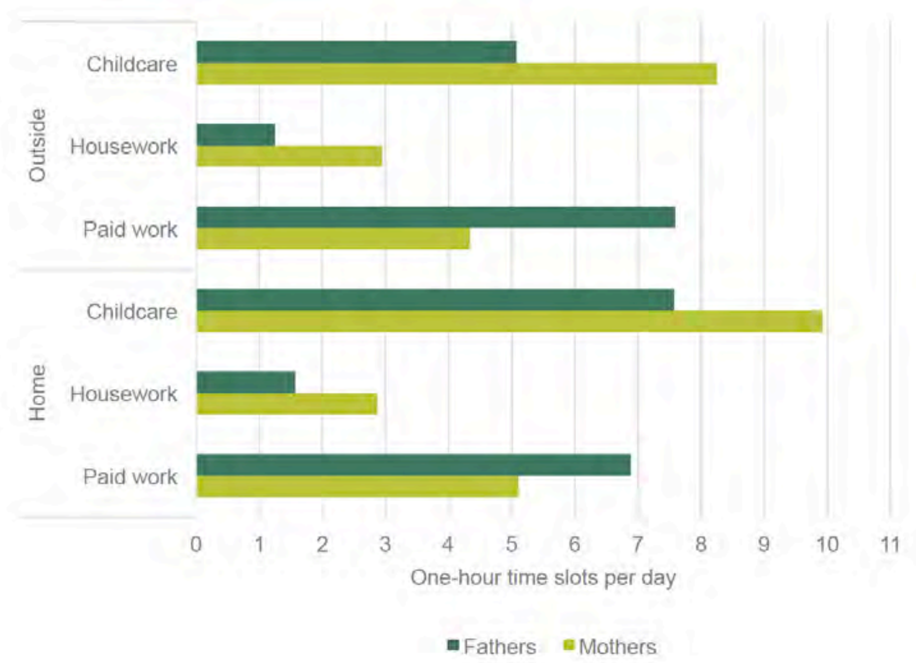
Fathers' time use is particularly sensitive to whether or not they are in paid work: fathers who are not working for pay report spending more than twice as many time slots on housework as those who are, and three more one-hour time slots on childcare. Interestingly, the amount of time that mothers spend on childcare is far less responsive to whether or not they work for pay. Indeed, mothers who are not working for pay do childcare in only one-and-a-half more one-hour time slots than those who are. Altogether this means that mothers who are working for pay have an especially heavy load. While they do 2.3 fewer one-hour time slots in paid work than working fathers, they more than compensate for the difference by putting in an additional 2.7 one-hour time slots of childcare and 1.5 one-hour time slots of housework compared with fathers in paid work.

Figure 7. Time use by current work status

Panel A. By working status



Panel B. Among those working, by whether works at home or outside the home



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The large differences in time use we see between working mothers and fathers could be driven by the type of paid work different genders are doing, which may or may not be compatible with more time for domestic responsibilities. In particular, work outside the home is better insulated from domestic responsibilities during working hours and, after factoring in commuting time, it may also leave fewer hours available for these activities.[17] To shed some light on the extent to which gender differences in domestic responsibilities among working parents can be explained by the nature of their jobs, we split time use by whether working parents work from home or outside of the home. Although both mothers and fathers do more childcare if they are working from home, Figure 7B shows that there are gender gaps both between mothers and fathers who work from home (with mothers doing childcare during 2.4 more hours than men) and between parents working outside the home (where the gap is even larger, at 3.2 one-hour slots).

Are gender gaps explained by mothers having lower earnings?

Before the pandemic, mothers earned less per hour on average than fathers. There is evidence that they were more willing to sacrifice higher earnings in favour of, for example, more flexible working or a shorter commute (Joyce and Norris Keiller 2018; Mas and Pallais 2017). This means that, in strict economic terms, families on average benefit financially more from an extra hour of paid work done by a man, even if it means his partner has to reduce her paid working hours to pick up more of the responsibilities at home. We look now at whether the lower average earnings of mothers relative to fathers can explain the overall gender gaps we see.

If this were the main explanation for the overall gender gaps, we would expect to see that parents behave *symmetrically*. That is to say, we would expect that couples usually prioritise the (paid) work of the higher-earning parent, regardless of whether that parent is the mother or the father. This would imply that, on average, higher-earning partners do the same amount of childcare, housework and paid work whether they are male or female, and lower-earning fathers do the same amount as lower-earning mothers.

Again, this is not what we find. Figure 8 shows how partners who are both currently in paid work are organising their time depending on who earned more before the crisis. It shows clearly that couples where the father earned more do not organise their time in the opposite way to which couples where the mother earned more do. Indeed, it shows that regardless of who was the higher earner in the couple, the father always does more uninterrupted work (2.8 hours if he earned more and 0.6 hours if the mother earned more). Likewise, even when the mother earned more than her partner, she does 1.6 more hours of childcare and about the same amount of housework.

[17] Commuting to and from paid work is included in our definition of hours spent doing some paid work.

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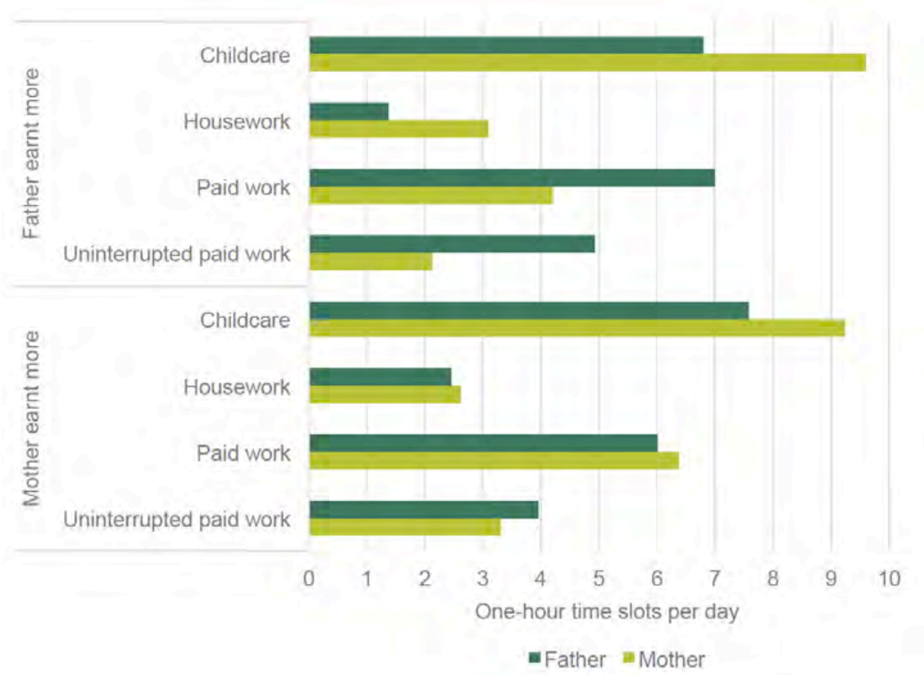
Figure 8. Time use by pre-crisis relative earnings



Note: Earnings are 2019 pre-tax earnings for both partners. Sample includes only couples where both are currently working.

Do gender gaps remain when we remove paid work from the picture?

The evidence above suggests that neither employment rates nor relative earnings can fully explain the differences in how mothers and fathers are spending their time in lockdown. This suggests that other considerations drive how parents share responsibilities. One possible factor is parents' preferences, habits or beliefs about the best way to allocate responsibilities for paid and unpaid work. The dramatic changes in parents' work arrangements during the crisis provide a particularly interesting way of examining whether this is the case.

We take families where both partners were in paid work before the crisis and look at what happens when mothers stop working and when fathers stop working. Comparing what happens when the father versus the mother stops work allows us to see whether there are factors other than economic incentives at play in how parents divide up responsibilities. If the drivers of the division of responsibilities were purely economic, we would expect parents to behave *symmetrically* when either partner stops working: that when the mother stops working but the father continues, the mother does most of the domestic work and leaves her partner to focus on paid work, and vice versa.

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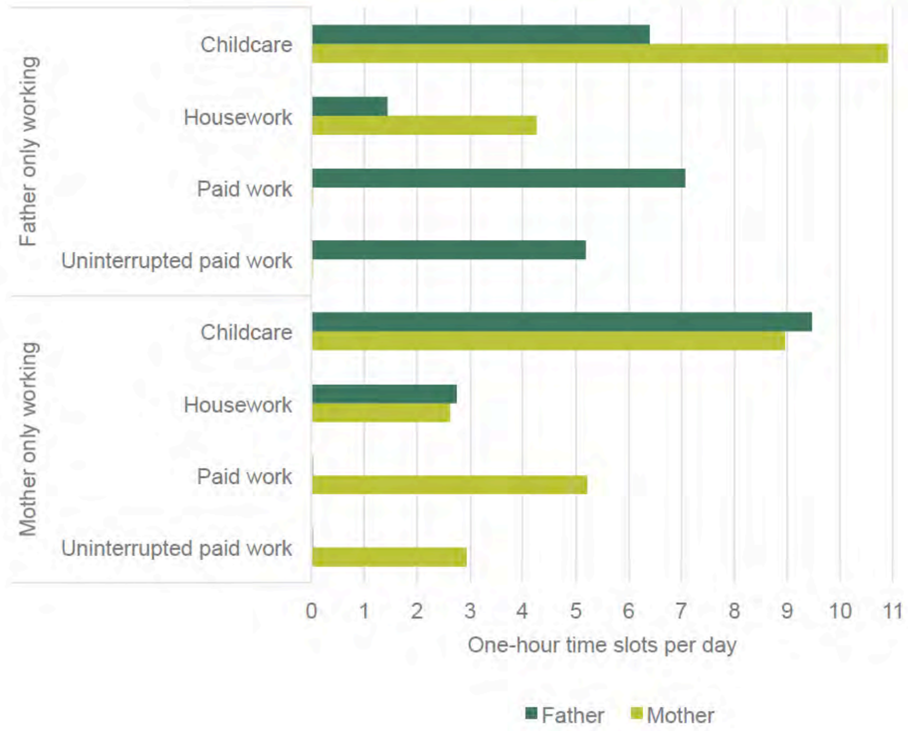
Figure 9. Time use by who is still working for couples who were both in paid work in February



But, in practice, we find that the division of responsibilities depending on which parent has stopped paid work looks very *asymmetric*. Figure 9 shows the total number of one-hour slots in which mothers and fathers do childcare, housework, paid work and uninterrupted paid work for families in which either the mother or the father has stopped working for pay since the lockdown.[18] Mothers who stop working take on domestic responsibilities for almost twice as many hours as their partners (over 4 additional one-hour slots of childcare and nearly 3 additional slots of housework). In these families, fathers do paid work for an average of 7 one-hour slots during the day, with most of this time being uninterrupted work time.

But we see quite a different picture in families where fathers stop working. In these families, mothers and fathers divide domestic responsibilities (for both childcare and housework) roughly equally, *despite* the fact that the mother is also working during an average of 5.2 one-hour slots. The result is that mothers who continue to work for pay do so while also taking on half the domestic responsibilities.

Despite the especially heavy load of mothers who are the only parent working for pay, fathers in these families do take as large a share of domestic responsibilities as their partners, spending 9.5 hour-long slots on childcare and 2.7 on housework. Previous research has shown that men who take on more domestic responsibilities temporarily – for example, doing more of the childcare when offered a more

18 To reduce differences between families where only the father or only the mother works, we restrict the analysis to families where both parents were working in February. This reduces confounding effects from families where spouses were already specialising in home or paid work prior to the lockdown, and which may well be less affected by the crisis if the job of the working partner remains active.

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generous paternity leave – often, but not always (Ekberg et al. 2013), continue to contribute more to childcare responsibilities going forward (Tamm 2019; Farré and González 2019). This suggests that the temporary changes that the pandemic and the lockdown have forced on families could have longer-lasting impacts on how partners see their roles in the family and organise their work and childcare going forward.

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6. Conclusion

The COVID-19 pandemic is disrupting parents' working lives across the board. Many parents have lost their jobs, temporarily or permanently; most are having to contend with vastly increased responsibilities for education and childcare, as well as housework. At the same time, parents who are still working are more often than not doing it from home, meaning that family and work responsibilities are now co-existing to a much greater extent than before in the same place and at the same time.

These changes could have substantial effects on gender differences in how couples approach paid work and family responsibilities. It is well known that, prior to the pandemic, women were less likely than men to be in paid work; even among workers in similar roles, there is evidence of a persistent gender gap in hourly wages, with women being paid less, particularly after workers become parents. On the flip side, women shouldered a greater share of the responsibility for housework and for childcare.

The COVID-19 pandemic affects these inequalities in several ways. We find that – unlike in previous recessions – mothers are more likely than fathers to lose their job (temporarily or permanently) during the crisis. Among those who are still working for pay, mothers spend less time on paid work throughout the day, and more of that working time is split between paid work and other activities, principally childcare. We find that the relative differences between mothers' and fathers' work patterns have increased since 2014/15 in all three dimensions: being in paid work at all, the hours spent on paid work, and the likelihood of being interrupted during work hours.

While mothers are still disproportionately responsible for the – much increased – time spent on childcare and housework, there is some evidence that fathers are also dedicating significant amounts of their time to family responsibilities. This is particularly true for couples where the father has lost his job while the mother has kept hers; in these families, fathers are now shouldering slightly more than half of the burden of childcare and housework.

However, absent the extreme shock of one parent losing his or her job, there is much less evidence that the gender gaps that we document are driven solely by families' focusing on immediate financial considerations. We find significant gender gaps even between fathers and mothers who are not currently working and, within a couple, the division of labour during the crisis looks strikingly similar whether a mother earned more or less than her partner before the pandemic. While such patterns in the way parents share responsibilities may have predated the crisis, the vast size of the labour market shocks that many have faced and the increased need for parents to provide childcare may exacerbate the effects that unequal sharing have on mothers' careers.

This research raises at least two crucial questions. First, what will be the impact of the crisis on women's experience of the labour market? Will women whose careers have taken a hit during the crisis – whether because of childcare responsibilities or simply because they work in a more exposed sector – be able to recover from this in the medium term? Will the effects of the crisis halt or even partly reverse the progress that has been made in closing the gender wage gap?

The second question is how experiences during the crisis will reshape the attitudes that mothers, fathers and employers hold towards the division of labour. Recent evidence from paternity leave policies aimed at increases fathers' childcare time is mixed. Farré and González (2019), Patnaik (2019), and Tamm (2019) all show that paternity leave leads a persistent increase in fathers' involvement in childcare in

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the case of Spain, Canada, and Germany respectively. However, Ekberg et al. (2013) do not find an effect of "daddy months" in Sweden in father's likelihood to take medical leave to care for children. The lockdown as a result of COVID-19 is an even bigger shock to family dynamics than paternity leave reforms. If this shock has reshaped attitudes towards gender and work, and if these changed attitudes in turn prompt lasting change in families and workplaces, that could be one silver lining to what has so far been a very dark cloud.

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Covid Economics **Issue 39, 23 July 2020**

Epidemics and increasing returns to scale on social distancing

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It is shown that the standard Susceptible Infectious Recovered model of an epidemic implies that there for a large set of epidemic parameter values there will be increasing returns to scale if the objective is to limit the economic cost of infection. The explanation is that if an epidemic has a high basic reproduction number, a given amount of social distancing will not have much effect. The same amount may however be very effective if the reproduction number is lower (but still larger than one).

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Introduction.

There is a considerable literature on the economic management of epidemics. Historically this literature has to a considerable extent been mostly, but not exclusively, concerned with vaccination. As is to be expected, results will depend on the biological characteristics of the pathogen at hand. A very important distinction is between endemic diseases and transient epidemics. Endemic diseases, although subject to episodic spikes, require a different policy perspective than transient epidemics, see Goldman and Lightwood (2002), Barrett and Hoel (2006) for discussions of endemic diseases. Here the focus is on transient epidemics such as the common flu and (hopefully) Covid-19. Several articles analyze the management of transient epidemics by utilizing the well established Susceptible-Infectious-Recovered (SIR) model, developed by McKendrick and Kermack (1927), see e.g. Morton and Wickwire (1974), Francis (1997) (2004) and Nævdal (2012). Several papers have examined the effect of policy interventions. E.g has Brito et al. (1991) and Geoffard and Philipson (1996) examined vaccination policies. Gersovitz and Hammer (2004) examined the case of several instruments. Nævdal (2012) identified the possibility of increasing returns to scale on pre outbreak vaccination efforts. For some parameter values and stocks of unvaccinated individuals in the population it turned out that the marginal value of vaccination is an increasing function of the number of vaccinated, i.e. increasing returns to scale. Nævdal (2012) explained this with a "brush fire" effect where a vaccination in a very fast spreading epidemic has little effect unless followed up with more vaccination. Here I show that the same argument applies to social distancing as a policy measure.

The analysis is done with a very simple deterministic model in order to highlight how the epidemic dynamics may imply increasing returns to scale.

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The SIR - model

The model has 3 variables. x is the number of susceptibles, y is the number of sick and z is the number of individuals who are immune rate. It is assumed that the population is a constant n so that $x + y + z = n$. From hereon n is normalized to 1. The infection rate $\dot{y}$ is proportional to the product of the number of infected and the number of susceptibles. An individual can acquire immunity by recovering from the disease. The equations of motion are given by:

$$\dot{x} = -\beta xy \tag{1}$$

$$\dot{y} = \beta xy - \gamma y \tag{2}$$

$$\dot{z} = \gamma y \tag{3}$$

Here β and γ are positive constants. γ has the interpretation that γ^{-1} is the expected duration of the disease for an infected. Thus the duration of the epidemic for an infected individual is exponentially distributed with intensity γ. β is the contact rate and is a product of the transmissibility of the pathogen and the number of interactions an individual has per day. The basis reproductive number R_0 is given by

$$R_0 = \beta\gamma^{-1} \tag{4}$$

This is roughly the number that an infected person will infect in the beginning of the epidemic. In the basic SIR model, this number together with initial values of state variables will determine the path of the epidemic.

Since $\dot{x} + \dot{y} + \dot{z} = 0$ it holds that $x(t) + y(t) + z(t) = x(0) + y(0) + z(0) = 1$ for all t. Also, the system has an infinite number of steady states. Any triple $(x, y, z) = (x^*, 0, z^*)$ such that $x^* + z^* = 1$ is a steady state. There are no steady states with positive values of y.

The initial conditions are $x(0) = 1 - \varepsilon$ and $y(0) = \varepsilon$. From (2) it is immediately clear that the epidemic reaches it's apex, $\max_t y(t)$ when $x = \gamma/\beta = R_0^{-1}$. We can

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derive a single differential equation for y as a function of x. We denote this function $Y(x)$.

$$y = Y\left(x\right) = \frac{\dot{y}}{\dot{x}} = -\frac{\beta xy - \gamma y}{\beta xy} = -1 + \frac{R_0^{-1}}{x}, \; Y\left(1-\varepsilon\right) = \varepsilon \tag{5}$$

Solving (5) yields:

$$Y\left(x\right) = 1 - x + R_0^{-1}\left(\ln\left(x\right) - \ln\left(1-\varepsilon\right)\right) \tag{6}$$

The solution in (6) shows how x and y moves in tandem during an epidemic. Note that as long as ε is small, it has very little impact on the path. In the absence of any interventions the number of individuals who will be susceptible after an epidemic is given by the value x, denoted x_{min} such that:

$$Y\left(x_{\min}\right) = 1 - x_{\min} + R_0^{-1}\left(\ln\left(x_{\min}\right) - \ln\left(1-\varepsilon\right)\right) = 0 \tag{7}$$

We now modify (4) in order to account for social distancing measures. Over a time interval $[0,\ T]$ where T we have that

$$R = R_0 - h \tag{8}$$

Here h is some, possibly constant, function of time over the interval $[0,\ T]$ where $T < \infty$. For $t > T$ we have that $h = 0$. One way of interpreting h is simply as the reduction in the number of potentially infective social interactions per day, scaled to be in the same units as R_0. Thus the definition of social distancing used here is different than that employed by e.g Gollier (2020) where a fraction of the population is in lock down.

It is easy to show that for any $R_0 > 1$ there is an interval of steady states $S = \left[x_{\min}, R_0^{-1}\right]$ that is the set of feasible endpoints for the epidemic. x_{min} represents a worst case scenario where the maximum number of individuals, $1 - x_{min}$, have been infected. With interventions, the medically best possible outcome is that the disease ends with $1 - R_0^{-1}$ having been infected. If we restrict h to constant functions over we can identify x_h which is, roughly, the long run number of people never infected given a constant value of h until T. Whenever $x > R_0^{-1}$, the epidemic will always reappear when h is set equal to 0. x_h is determined by a modification of (7).

$$Y\left(x_h\right) = 1 - x_h + \left(R_0 - h\right)^{-1}\left(\ln\left(x_h\right) - \ln\left(1-\varepsilon\right)\right) = 0 \tag{9}$$

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It is not possible to find an explicit solution that solves (9) for x_h as a function of h.[1] However it is straight forward to plot x_h as a function of h for given values of R_0 and ε. This is done in Figure 1.

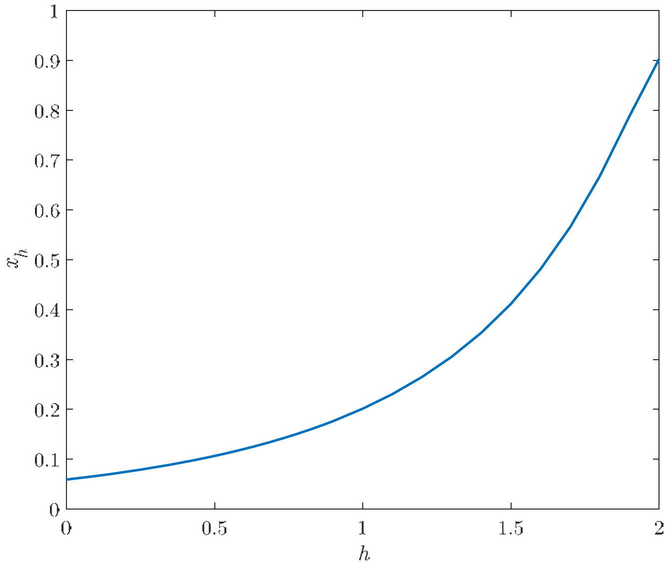

Figure 1. The long run stock of remaining susceptibles, x_h, as a function of social distancing

The important thing to note about the relationship between h and x_h is that x_h is a convex function of h, implying that the higher h, the more effective is a marginal increase in h at reducing the number of infected during the course of an epidemic. This is confirmed in Figure 2 where the time paths of x for an epidemic with $R_0 = 2.5$ is plotted. The effect of setting $h = 0.1$ has a negligible effect. x_0, that is x_h when $h = 0$, is 0.89. $x_{0.1} =$ is 0.88, a reduction of 1 percentage point. However if h is set to 1 and then further increased to 1.1, we have that $x_{1.5} = 0.58$ and $x_{1.1} = 0.51$, a reduction of 7 percentage points.

Herein lie the explanation for increasing returns to scale. When R_0 is large, marginal increases in social distancing simply has very little effect on the outcome of the epidemic. When R_0 is small or substantial social distancing is in

[1] An explicit solution can be found using the Lambert function.

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effect, marginal increases in social distancing has a much larger effect on the epidemic outcome.

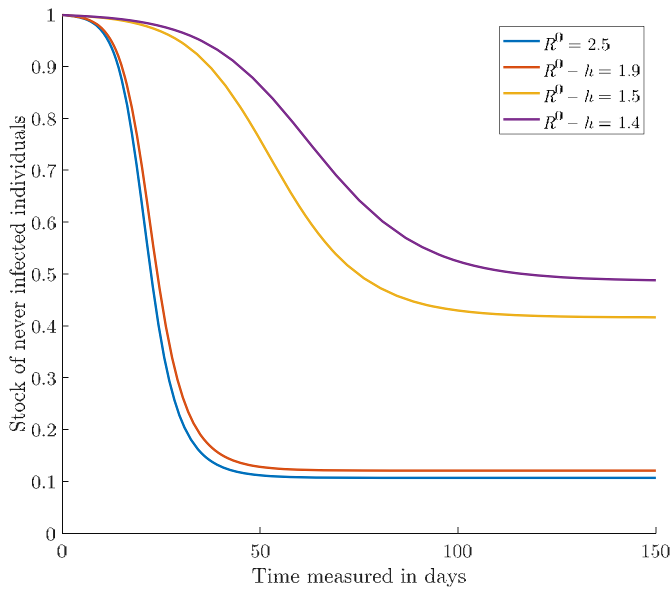

Figure 2. The stock of susceptible individuals over time at different levels of social distancing.

The economic benefits of social distancing

To see how social distancing affects the economic costs of an epidemic we can change the model so that R_0 becomes a function of distancing efforts:

$$\begin{gathered} R_0 = (\beta - h)\gamma^{-1} \\ \downarrow \\ \beta(h) = \gamma R_0 - h \end{gathered} \tag{10}$$

We write β as a function of distancing efforts. Thus the epidemic equations for x and y may be written:

$$\begin{aligned} \dot{x} &= -(\gamma R_0 - h)xy,\ x(0) = 1 - \varepsilon \\ \dot{y} &= (\gamma R_0 - h)xy - \gamma y.\ \ y(0) = \varepsilon \end{aligned} \tag{11}$$

Here h is a measure of social distancing. Then a very simple model of an epidemic is:

$$V\left(h\right)=\int_{0}^{\infty}-wye^{-rt}dt \tag{12}$$

Here wy is the economic surplus lost if y individuals are ill for a unit of time. In the simulation below w is normalized to one. Let us examine the benefits of social distancing without examining the costs by doing a thought experiment. Assume that we fix β so that $h > 0$ for $x \geq x_{crit}$. When x goes below x_{crit} we set $h = 0$. The benefit from such an intervention is shown in Figure 3.

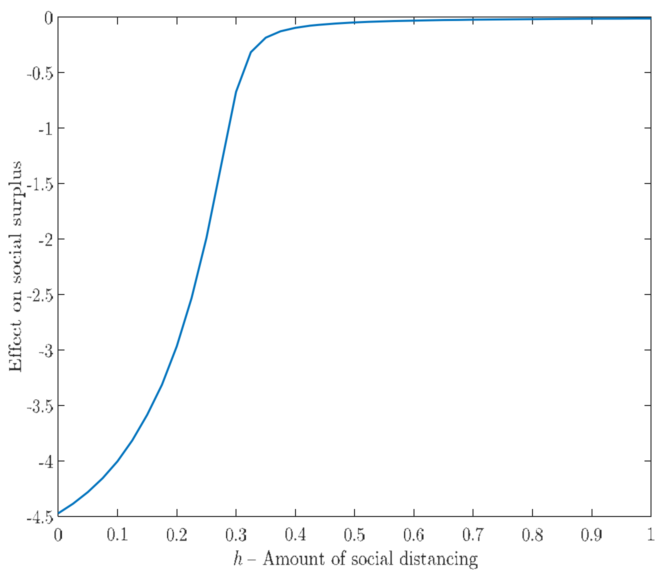

Figure 3. Relationship between the cost of , h. It is clear that the benefits exhibit increasing returns to scale for h in the interval 0 to 0.3. Thereafter there are diminishing returns that quickly go to zero. Here x_{crit} is set to 0.1.

The specification of the epidemic cost is very simple. In particular they are linear with respect to the stock of infected. This is unlikely to be the case when an epidemic is serious with respect to mortality, infectiveness and health outcomes. If the instantaneous marginal cost of y depends on the magnitude of y, this may, paradoxically, imply returns to scale become diminishing. This is in line with Nævdal (2012) who found that more serious epidemics exhibited diminishing returns to scale on vaccination efforts.

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Summary and policy implications

A transient epidemic is in many ways like a brush fire. A high R_0 has the same effect as a severe drought has on brush land. The drier the vegetation, the more vegetation is consumed, the quicker is a specific area consumed and the less is the effect of a bucket of water. This has some implications for economic management. A very dry area may be a lost cause. However, if it pays to throw one bucket of water on the fire it pays even more to throw a second bucket. The same goes for epidemics. There may be increasing returns to scale to social distancing and other efforts to control the epidemic. The results have some very clear policy implications.

1) With increasing returns to scale, a corner solution, i.e. no distancing, may be optimal.
2) *If* it pays to apply social distancing as a policy, then it is often the case that if it pays to do a little it pays even more to do a lot.
3) An issue not covered in the present paper is what happens when individuals respond behaviorally to an epidemic threat by choosing to socially distance themselves, Garibaldi *et al* (2020). Does this negate the need for public intervention? In general, the answer is no as the individual only receives part of the benefits from their own behavior. Additionally, the analysis here indicates that for some parameter values increasing returns to scale implies that individual self distancing may increase the value of public efforts.

It should also be noted that if alternative measures of social distancing are employed, this will affect results. The approach to modeling social distancing employed by Gollier (2020) implies that β becomes a quadratic function of the fraction of people in lockdown. This would likely strengthen the results in the present paper.

The results underscore the need for economic analysis to be founded on a solid understanding of the mathematical dynamics of an epidemic.

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The cost of being unprepared or the benefit of the precautionary principle? Comparing cost-benefit COVID-19 policies and outcomes in Scandinavia

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The Scandinavian countries of Denmark, Iceland, Norway and Sweden have approached the first months of the 2020 novel coronavirus pandemic with a range of economic and health policies that have resulted in disparate outcomes. Though similar in behavioral norms and institutions, Denmark, Iceland and Norway chose a precautionary approach that formally shut down schools and businesses to protect human health, while Sweden took a Business-As-Usual (BAU) approach aimed at maintaining normal economic and social activities. Iceland and Denmark have further invested in testing, tracking and containing the disease. Economic costs of the pandemic and government fiscal and monetary interventions to reduce their impacts have been dramatic and similar across countries, while Sweden has had the most severe loss of life. Using a panel from the four countries since the beginning of the pandemic, we calculate lives saved from stricter interventions by estimating cases and deaths as functions of behavior and government

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interventions with a bioeconomic model, then estimating the additional lives lost if these interventions did not occur. Comparison of the countries reveals three important lessons for both policies aimed at the pandemic and broader goals with high uncertainty levels: (1) the precautionary approach can be lowest cost, while still expensive; (2) detection and monitoring (e.g. testing and tracking) are integral to a successful precautionary approach; and (3) expecting tradeoffs between economic activity and health creates a false dichotomy – they are complements not substitutes. Pandemic policy should focus on minimizing expected costs and damages rather than attempting to exchange health and safety for economic well-being.

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1. Introduction

This paper uses data for the Scandinavian countries to roughly estimate the net expected benefits of the policies in place across the region to address the novel coronavirus pandemic, and tradeoffs amongst the different policies in place. With extremely high levels of uncertainty, the policy differentials are coming to represent potential under-intervention (Sweden), potential over-intervention (Denmark and Norway), and the estimated benefits of increased information and testing (Iceland and Denmark). With similar cultures and institutions but differing current approaches to the pandemic, the Scandinavian countries provide an opportunity to investigate how policy differences might be expected to affect the economic and social outcomes from the virus in the short and longer run.

Recall that initial arguments for the shutdown of economic activities focused on 'flattening the curve.' This was intended to alleviate critical anticipated shortages in protective gear (PPE) and hospital beds, equipment and staff, and to buy time to remedy a lack of ability to quickly test, trace, and isolate. The losses from months of dramatically reduced economic activities have been significant and immediate, and not without controversy. The Danish Prime Minister, Mette Frederiksen, has had to defend her government's "extreme precaution" policy, under which the Health Authorities were told to ignore 'proportionality' concerns in regulations for the sake of public health and safety (Ritzau, 2020a), where proportionality refers to the normal way in which Danish regulations must consider the full consequences of government action rather than only health or economy, for example.

In contrast, perceived preparedness, in terms of adequate investment in scientific knowledge, facilities, testing and tracking, and gear, may have minimized some economic losses by keeping social and economic activities more open. This openness has also not been uncontroversial. Sweden has experienced significantly higher infection and death rates, which they have defended as a 'sustainable' long run investment in overall societal well-being due to the expectation that it will be a long time before a vaccine or cure can be ready (Ritzau, 2020b). This 'sustainability' is more in line with the Danish business-as-usual (BAU) than proportionality would have been. Thus, the two countries' responses represent a precautionary principle approach (Denmark) vs. a BAU risk management approach that focuses more on the known-unknowns (Sweden) and health advice rather than behavioral mandates.

For Iceland, Norway, and Denmark, we calculate estimates for lives saved for the first months of the pandemic from stricter measures relative to the Swedish experience. We contextualize this analysis with greater understanding of behavioral changes tracked with Google Mobility data and of preparedness perceptions with data on hospital capacities. We also track expected economic losses in GDP for 2020 as forecasted at different points in the pandemic, contextualized with information on government interventions to understand how expectations and costs have unfolded as consequences become evident over time. We find evidence that the precautionary principle approach has had greater payoffs than BAU risk management and suasion alone.

2. Background and Literature

At the four-month mark, there has been a turning point in strategies and a measurable divergence of outcomes that justifies evaluation of these early decisions, despite high remaining levels of uncertainty. The uncertainties are great for both epidemiological and economic consequences of the decisions. Global insurance markets, for example, remain uncertain how to handle the changes, with a large outstanding legal question regarding the extent of liability for business disruptions in a global pandemic (Chester et al, 2020). Stock markets have crashed and recovered, with high volatility remaining. There is some evidence that ESG stocks - those investing according to Environmental, Social and Governance principles - have fared better than the broader market (Albuquerque et al, 2020), supporting our understanding that choices aimed at resilience and precaution that avoid external damages can pay off. The long-term effects of the disease, particularly in younger people, remain unknown while continuing investigations provide a wide range of concerns, also promoting an interest in avoiding long term downside risks.

Sweden's position as a policy outlier due to its refusal to issue lockdown orders has garnered significant research and lay interest. Born, Dietrich and Mueller (2020) and Cho (2020) each create a counterfactual "Sweden" out of composites of other European countries to analyze the effects of the non-pharmaceutical interventions available to Sweden but unused; they find opposing results. Born et al (2020), published with data for only the first month of the crisis, suggest that lockdowns would not have given Sweden any significant additional benefit. Soo (2020), with later data available, finds the opposite. Sweden's government and epidemiological team have argued from the start that there is a need for long term strategy (Prime Minister's Office, 2020), and assessments moving forward may indeed reflect a back-and-forth in measures of success over the next year or longer in the search for a vaccine or cure. However, the significant re-openings of Denmark, Iceland and Norway suggest that there have been important

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opportunities to reduce the impacts which Sweden lost in the early days of the pandemic. Sweden itself has determined, as of July 8th, that some policy revision may be needed (Ministry of Health and Social Affairs, 2020a) and has also launched an investigation into the early handling of the pandemic (Ministry of Health and Social Affairs, 2020b), though the investigation's results are not expected until the end of February 2022.

The pandemic seems to have eased significantly, at least temporarily, in Denmark, Norway and Iceland. A slow restarting of economic activities begun mid-April has been gaining momentum. This has occurred so far without significant increases in cases or deaths; combined COVID-19 deaths by June 30, 2020 for the three countries number 865 (Table 1) and new cases per 100,000 residents per week are now below 5 in all three countries (Table 1). On June 15th these three countries plus Germany began allowing mostly unrestricted travel again, and further unrestricted EU travel became possible July 1st. Sweden, on the other hand, with whom full open borders will not recommence for the time being, has had the highest national rate of new cases per capita amongst Northern, Southern and Western European countries since week 22 (May 24-30).

Table 1: COVID-19 Disease statistics for Scandinavian Countries through July 1, 2020.

Country	Confirmed Cases (01/07/20)	Attributed Deaths (01/07/20)	Cumulative deaths per 100,000 residents (01/07/20)	Cumulative Cases per 100,000 residents (01/07/20)	Cases per 100,000 residents, week 11	Cases per 100,000 residents, peak (week)	Cases per 100,000 residents, week 26	Cumulative Tests per 100,000 residents (01/07/20)*
Denmark	12,768	605	10.445	220.434	13.51	35.67 (15)	4.9	18,661
Iceland	1,842	10	2.93	539.78	21.24	138.04 (13)	3.81	18,503
Norway	8,865	250	4.611	163.523	9.59	34.73 (13)	1.86	6,039
Sweden	68,451	5,333	52.806	677.782	6.3	73.53 (26)	73.53	5,151

*latest testing data from Sweden is 28/06/2020; latest testing data from Iceland is 13/06/2020.
Sources: worldometers.info (tests per 100,000 inhabitants) and European Center for Disease Prevention and Control (remainder)

2.1. Effects of intervention on epidemiological outcomes for COVID-19

Epidemiological-economic modeling for COVID-19 is proceeding rapidly. Most of these models currently rely on a parameterized S(E)IR (Susceptible-Exposed-Infected-Recovered/Removed) model in a dynamic optimization framework (Eichenbaum et al, 2020; Flaxman et al, 2020; Thunstrom et al, 2020; Greenstone and Nigam, 2020). The models have varying degrees of detail for both economic and demographic-epidemiological parameters, but few have so far included human behavioral responses directly in the assessments of economic costs and benefits. Moving

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forward, more emphasis is likely to be placed on such behavioral responses as we come to better understand the impacts of decentralized decision-making under social-distancing (Cornell Atkinson Center for Sustainability, 2020) and the role of super-spreaders (e.g. Sneppen & Simonsen, 2020). For our purposes, we use Google Mobility Data to explore behavioral changes. Furthermore, high levels of trust in Scandinavia (Andersen, 2017) may minimize any distortions of modeling without formal accounting for behavioral responses, which we must do to include Iceland. This is because most citizens readily follow the advice of government and medical professionals; this assumption is confirmed for the pandemic with the Google Mobility Data (see section 3.4).

We have examined in close detail the Imperial College London epidemiological method described in Flaxman et al, (2020) and find that even the state-of-the-art epidemiological modeling is fraught with overly simplified assumptions of both the transmission of the disease and the efficacy of policy. These simplifications generate great uncertainty in the unchecked potential of this pandemic and have lent themselves to generating large estimates of the magnitudes of savings. We have run their shared program code with updated country-specific data and the addition of Iceland through June 3rd, 2020 to discover that their model, while replicable, produces unreasonable results when just a few weeks are added to the analysis and also does a poor job of explaining Iceland's pandemic experience. In short, with their model, without lockdown interventions, more Europeans would have COVID-19 by this time than exist.[1] Their estimates that suggest there were millions of lives saved in 11 European countries by early May, generated by the assumption that the disease would have spread unchecked at high reproduction rates (~3.8 for the Scandinavian countries) are not convincing for the longer term. Our model uses the Swedish case as the counterfactual, thus avoiding the need to make heroic assumptions about deaths avoided as the pandemic has unfolded.

2.2. Effects of intervention on economic outcomes for COVID-19

Like Flaxman et al (2020), economists' research on the net benefits of social distancing has produced large estimates of benefits. Thunstrom et al. (2020) and Greenstone and Nigam (2020) both found that in the US case, social distancing measures should save the US economy over $5 trillion in losses, mainly due to avoided loss of life from 'flattening the curve' and overwhelming scarce medical resources. Eichenbaum et al (2020) dive further into the US economy with a more

[1] We are not alone in noticing the significant limitations of this model, as the comments on the Nature website pertaining to it attest.

thoroughly defined SIR-model coupled to a macroeconomic model with both aggregate demand and supply effects. They also found 'doing nothing' to induce social distancing should result in tens of trillions of dollars in net losses to the US.

These papers, released at the beginning of the pandemic in the US, in March 2020, focus mainly on the statistical value of saved lives (VSL). Their mean estimates of economic damages are now lower than current estimates of the magnitude or duration of the economic consequences for the U.S., where about 40 million people have filed for unemployment benefits in the last 2.5 months.[2] Recent estimates from the Congressional Budget Office (CBO) place the expected reduction of GDP in the US in double digits for 2020, and requiring a decade to recover to 2019 levels (CBO, 2020). Furthermore, as US workers often receive health care benefits through their place of employment, additional health risks may be accruing from the unemployment, compounding the problem. Government schemes to support workers have been both unprecedented in magnitude and insufficient to cover the losses Americans face (Parrott et al, 2020). At the same time, over 140,000 persons have died from the coronavirus in the US, providing a rough estimate of 1.3 trillion US dollars in losses at a current VSL of $9.3 million (Eichenbaum et al, 2020). Epidemiologists have now estimated that these US figures could have been 40% lower if social distancing mandates had taken effect one week earlier in March (Pei et al, 2020). With numbers of US cases rising dramatically again, the call for new social distancing requirements and lockdowns is growing, including from the director of the National Institutes of Allergy and Infectious Diseases, Dr. Anthony Fauci (Linebaugh and Knutson, 2020). The significant economic costs that have already been paid will have been almost complete losses if greater control is not established over the pandemic. This is an important lesson that the Scandinavian experience highlights in cross-section rather than time series. Swedish economic gains appear to be virtually non-existent compared to the other Scandinavian countries; there has been little if any positive tradeoff in purely economic gains.

Furthermore, since labor and health markets in Scandinavia operate differently from the US, with e.g. national health care and flexicurity (Barth et al, 2014), and government interventions have funded schemes to keep workers employed, the overall economic consequences in the region have been borne more broadly by government spending and borrowing than by individuals; this may defer more costs to future years but has maintained considerable economic continuity in spite of social distancing-imposed closures and restrictions. Neither the economic nor

[2] This likely does not include significant numbers of e.g. informal workers in tourism who are not eligible for unemployment.

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epidemiological outcomes in Scandinavia have been as dire as in the US. These are broader lessons to preparedness and resilience.

Economic forecasts have varied within and across locations, reflecting unprecedented uncertainty about the local and global effects of COVID-19 interventions. The breadth of estimates, also in comparison to the beginning of the year and in the weeks following the WHO's first public notification of the COVID-19 disease spreading in Wuhan Province, China, on January 12th, is shown in Figure 1 (See Appendix 1 for summary and sources). In January 2020, all four countries were expecting modest growth between 1-2%, with consensus across a variety of sources. Since new estimates started to surface from mid-March, all countries are predicting declines in GDP for the year, but there remains little certainty about the magnitude of those declines. Between the BAU forecasts at the beginning of the year and the spring estimates, all countries experienced their first COVID-19 cases (dash-dotted lines), and all had issued varying degrees of restrictions on movement and recommendations for social distancing.

Table 2: Restrictions and Social Distancing Policies

	Denmark	Iceland	Norway	Sweden
Border Closures	3/13 -6/27*	3/16-6/15*	3/12-8/20*	3/18-6/15**
Testing for visitors	Yes	Yes	No	No
Mobile Contact Tracing App Start	6/18	4/1	4/18***	4/29
Event Prohibitions	Yes	Yes	Yes	Yes
Max. number (most restrictive)	10	10	5	50
Max. number (July 10)	50	500	50	50
Start Date	3/13	3/16	3/12	4/29
School Closures				
Primary (gr K-5)	3/11-4/15	3/16 - 5/4**	3/12 - 4/27	none
Middle (gr 6-10)	3/11- 5/18	3-16 - 5/4**	3/12 - 5/11	none
Gymnasium (gr 11-13)	3/11-6/8	3/16 - 5/4*	3/12 - 5/11	3/17-6/15**
Universities	3/11-6/22*	3/16 - 5/4*	3/12 - 6/15	3/17-6/15**
Business restrictions:				
Health and Personal Care	3/13-4/15	3/16 - 5/4*	3/12-4/27*	independent
Retailers	3/13 - 5/11**	3/16 - 5/25*,**	3/12-4/27*,**	independent
Restaurants	3/13-5/18**	3/16-5/25*,**	3/12-5/11**	independent^
Cultural activities	3/13-5/27	3/16 - 5/4	3/12-6/15	independent

*partial lifting
**partial openings throughout
*** App use banned June 15 citing privacy concerns
^ distancing regulations and liabilities changed in SE July 1, increasing requirements

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The timeline in Figure 1 and dates summarized in Table 2 mark the periods during which the major restrictions and behavioral advice were announced and implemented by each country as the period between solid lines for each country (Denmark in red, Norway in gray, Iceland in blue, and Sweden in yellow). As is well known, Sweden has had the least direct economic interventions. The country also took the greatest amount of time to issue recommendations and to implement the few restrictions on some gathering sizes and some school closures, with first recommendations as early as March 11th and the closure of gymnasiums (high schools) on March 27th. Denmark announced dramatic restrictions, also on March 11th, but these would come into effect by March 13th, including travel restrictions to and from other countries. Norway's restrictions were announced a day later, with immediate effect, though there were a few additional days before the travel restrictions commenced. Iceland, which had a jump on testing that began at the end of January, took longer than Denmark or Norway to implement fewer overall restrictions. Denmark and Norway used the lockdown period to increase testing capacities. While gradual openings started before the full effect of increased testing capabilities came online in early May, most testing and tracking implementations were in place before students older than about 11 returned to schools, and adults to work, from mid-May.

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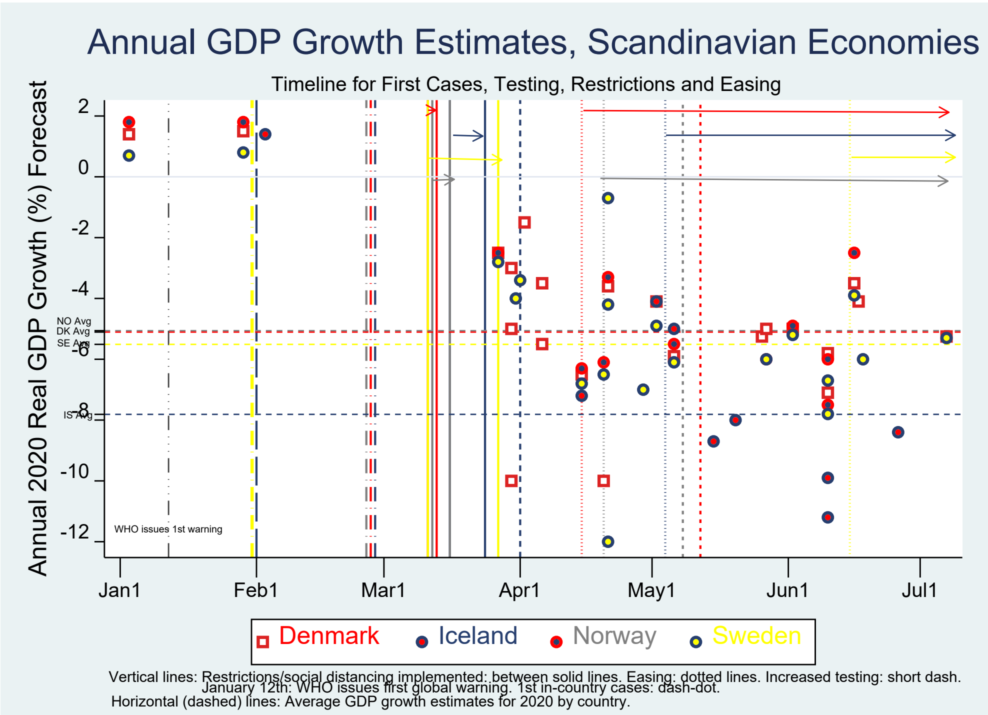

Figure 1: Estimates of GDP growth in 2020 over time

The figure includes the average forecasts for GDP losses in 2020: Denmark and Norway at 5.1% of 2019 GDP, Iceland at 7.8% of 2019 GDP, and Sweden at 5.5%. The Icelandic economy is highly dependent on foreign tourism, accounting in large part for its higher expected losses. Sweden's openness has not protected the forecasts for economic growth.

3. Model and Data

3.1. Model

We first model how many cases a country will have at a given time, as a function of their current caseload and the non-pharmaceutical interventions and behavior. We do this using a logistic growth SEIR approach, so that:

New cases = fn (total cases, country specific non-pharmaceutical interventions, carrying capacity, behavioral responses)

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We then model the probability that these cases translate to deaths per 1000 people for each country. The mortality rates may differ due to formal interventions promoting social distancing, knowledge of illness (testing), and by fixed effects including hospital capacities, so that:

New deaths per 1000 people = fn(previous case rates, previous testing rates, country specific non-pharmaceutical interventions and hospital capacities, behavioral responses)

We use these models and panel data from March through early July 2020 pertaining to cases, deaths, testing and hospital capacities, mobility patterns and country-specific non-pharmaceutical interventions to estimate expected cases and deaths for each country. With these sets of estimates, we cast conditions in Denmark, Norway and Iceland to Swedish conditions to estimate how many cases and deaths have been avoided through stricter social distancing requirements.

3.2. Pandemic Preparedness

In 2019, for the first time a Global Health Security Index ranked countries for their pandemic preparedness (GHX Index, 2019). The index considers 34 indicators aimed at comparing prevention, detection, response, health, norms and risk preparedness for pandemics. Table 3 shows how the four Scandinavian countries ranked, as well as their scores.

Table 3: Pandemic preparedness figures

	Denmark	Iceland	Norway	Sweden
GHS Index Score (out of 100)	70.4	46.3	64.6	72.1
GHS ranking (out of 195 countries)	8	58	16	7
Hospital beds per thousand people	2.5	2.91	3.6	2.22

The index correctly assessed that no country was particularly well prepared for a pandemic. It also suggests Sweden and Denmark were viewed as relatively more prepared for the pandemic than most other countries, including Iceland and Norway. The breadth of the preparedness index did not enter the political debate regarding whether to shut down or not, however; this focused almost entirely on the number of ICUs and respirators.

The overall Swedish and Danish preparedness indicated by the index is not well-reflected in hospital beds per 1000 people (Table 3). Sweden had the lowest number, at 2.22 per 1000 people,

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while Norway had the most, at 3.6 per 1000 people. As mentioned, the focus of most social distancing policies was to flatten the curve in order to not exceed the capacity of the health care system. One of the most critical aspects is the availability of intensive care units (ICUs). Figure 2 shows the total capacity of directly available ICUs as estimated by the different authorities in Denmark, Norway and Sweden, as well as the number of people occupying these units.[3] Sweden has had a larger number of people in intensive care (IC), and actually has exceeded their direct capacity, whereas Denmark and Norway have not come close to capacity.

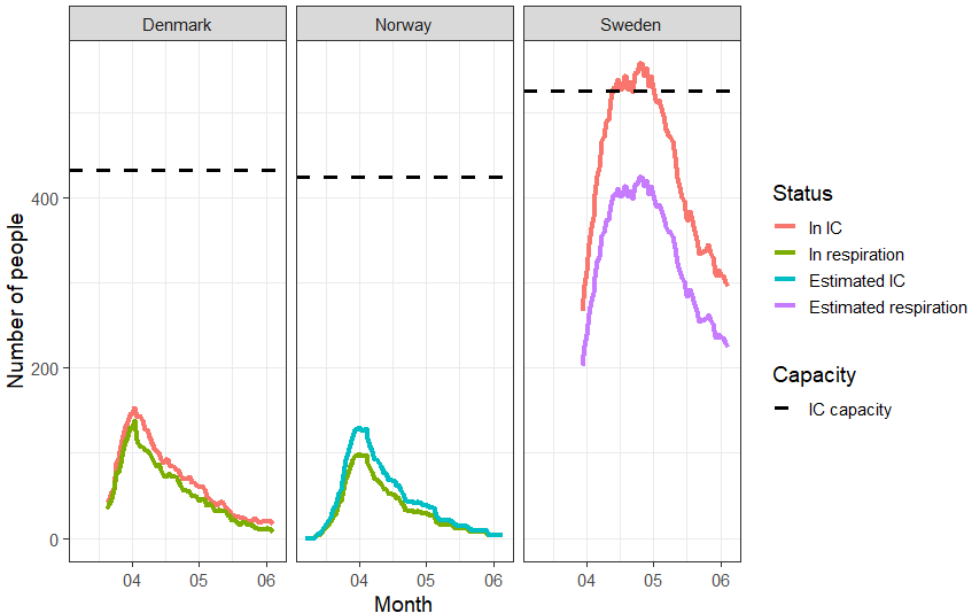

Figure 2: Number of people in intensive care (IC) and in respiration. For Norway and Sweden respectively the number of people in IC and in respiration were not directly available; they have been estimated based on the mean percentage difference in Denmark. Supporting data in Appendix 2. Sources: Danish IC and respiration: Statistikbanken, capacity: Sundhedsstyrelsen, Norwegian data: Helsedirektorat, Swedish IC data: Svenska Intensivvårdsregistret, Swedish capacity: Sjödin et al., 2020.

Given that these are absolute numbers it is not surprising that Sweden has a larger number of people in IC than Denmark and Norway, as Sweden's population is roughly twice as large as that of Denmark or Norway. However, the absolute IC peak in Sweden is 3.6 times the number in Denmark, so even after accounting for differences in population the number of people in IC is

[3] Figures for Iceland could not be located, but capacity has not been exceeded.

significantly higher. Also, the duration of the peak seems to be longer in Sweden. Despite the continuing climb in deaths in Sweden, IC and ventilator use have declined into July.

3.3. Policy Interventions

In this section, we compile the economic and non-pharmaceutical measures taken in the four countries as recorded by the IMF (IMF, 2020a). These show that all four countries have taken extensive monetary and fiscal policy measures (Tables 4 and 5 and Figure 5) to counter the economic effects of the virus, and again that Sweden has not had reduced costs in this dimension.

3.3.1. Non-Pharmaceutical Interventions

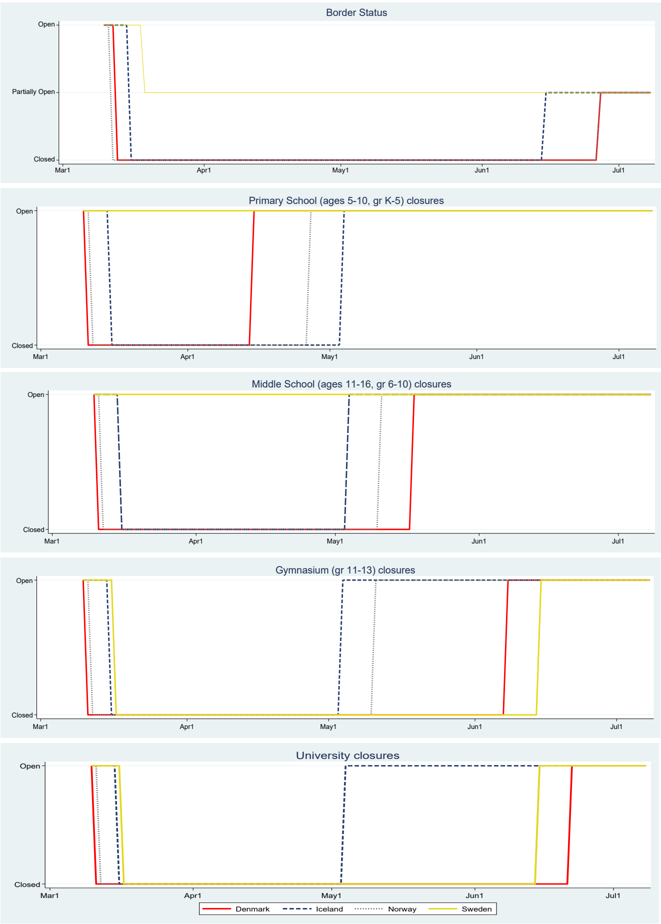

Figure 3: Border and School Closings Since March 10, 2020.

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3.3.1.1. Closures (Lockdowns)

Sweden kept borders and schools more open, as visible in Figure 3. Given that we have learned that children do not exhibit illnesses as frequently or as intensely from COVID-19 infection (Lee et al, 2020) and may not transmit the virus as easily, or at least are no more likely as adults to transmit it (Rajmil, 2020), and there were no significant spikes after primary schools reopened, it is possible that by not closing primary schools, the main impact has been that parents did not stay home with them. The school closures may well have enforced adult distancing more than directly influenced the reduction in spread through their actions.

3.3.1.2. Testing

The testing strategies of the countries provide the detection and monitoring necessary to complete management of the pandemic at low levels of spread and to maintain the benefits of the precautionary approach. They have been quite different from one another (Figure 4). Iceland was quick to scale up testing, and the country was able to use a broad testing strategy to effectively identify and isolate cases quickly; deaths on the island nation have been limited to 10. Additionally, the information from Icelandic testing has informed the world about the high levels of asymptotic carriers and the spread of the disease (Gudbjartsson et al, 2020), creating significant positive externalities for the world's battle against the virus. In Denmark, Novo Nordisk has contributed financial and technical support worth tens of millions of dollars to increase testing (Novo Nordisk Fonden, 2020). This investment has significantly increased testing capacities in the country; testing has gone from requiring significant symptoms and a doctor's approval to access for anyone to schedule an appointment for themselves, including at mobile sites in vacation communities. Both Iceland and Denmark are now offering testing for arrivals at airports. While Norway has not increased the rate of testing to the extent Denmark has, they have increased testing and access to testing over time as well. The Swedes are not yet testing at levels that catch significant numbers of asymptotic or mild cases, which is reducing the ability to contain and track the disease.

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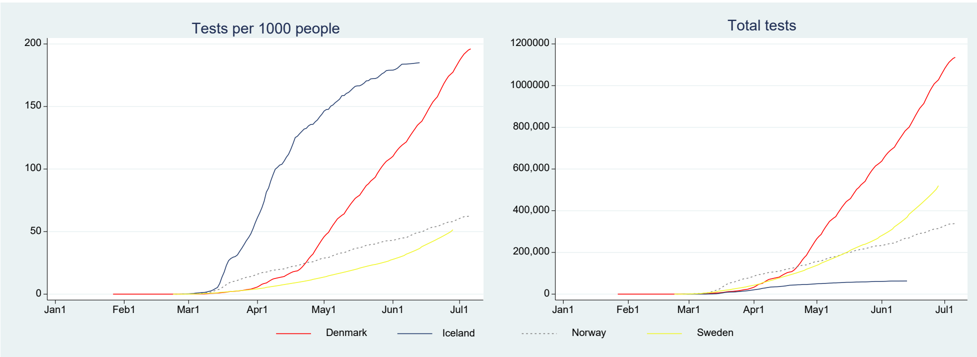

Figure 4: Per Capita and Total Testing Data for COVID-19

3.3.2. Fiscal Policy Interventions

Table 4 and Figure 5 summarize fiscal policy intervention efforts. All Scandinavian governments have implemented significant fiscal stimulus and support, totaling around 10% of the countries' 2019 GDPs. All four countries have made some form of security for wages, through which they support employers who keep workers on the payroll even when they must stay home or there is no work for them. Gaps in the programs have resulted in increased unemployment, but the increases in unemployment are significantly lower than in other countries. IMF estimates for 2020 unemployment, alongside 2019 values, are also shown in Figure 5; estimated unemployment impacts are significant despite these interventions, with Denmark and Sweden expecting to perform better than Iceland and Norway in this dimension.

Table 4: Fiscal Interventions to Counter Economic Losses from the COVID-19 Pandemic

Fiscal Intervention	Denmark	Iceland	Norway	Sweden
Discretionary spending (currency)	131.4b (DKK)	2.04 b (USD)	162.1b (NOK)	544b - 832b* (SEK)
Discretionary spending (%2019 GDP)	5.70%	10%	5.50%	10.8-16.6%*
Automatic stabilizers, expected (%2019 GDP)	5.10%	unk.	2.83%	
Wage securities** (partial)	Yes, ~75%	Yes, ~75%	Yes, ~80%	Yes, ~75%
Reduced VAT	No	No	Yes	Deferred payment

*discretionary and automatic not separated

** Arrangements differ between countries and wage structures

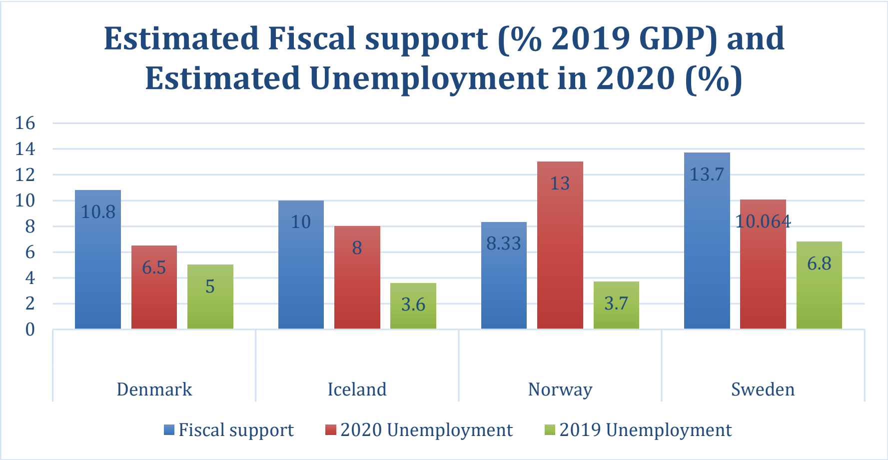

Figure 5: Estimated Fiscal Policy Support as percentage of 2019 GDP and Estimated 2020 Unemployment (IMF World Economic Outlook estimates, April 2020).

3.3.3. Monetary Policy Interventions

Monetary policy options have been limited due in large part to historically low, even negative, interest rates. Table 5 summarizes the interventions taken, which have included opening and/or expanding swap lines with the European Central Bank, the Federal Reserve, and other national European central banks and a number of special loan conditions aimed at supporting businesses.

Table 5: Monetary Policy Intervention Summary

	Denmark	Iceland	Norway	Sweden
Policy Rate	Increased 15 bps to -0.6%	Cut 175 bps to 1%	Cut 150 bps to 0%	Cut 55 bps to 0.2%
Swap lines	Yes	Yes	Yes	Yes
Special loans/ conditions	Yes	Yes	Yes	Yes
Exchange rate	Peg to Euro maintained	Flexible, 2 large (opposite) interventions	Flexible, continuous evaluation	Flexible, no interventions

3.4. Behavioral Responses

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In considering Sweden as our baseline, it is important to identify what social distancing without government mandated lockdowns looks like in terms of behavior, versus a more complete lockdown.

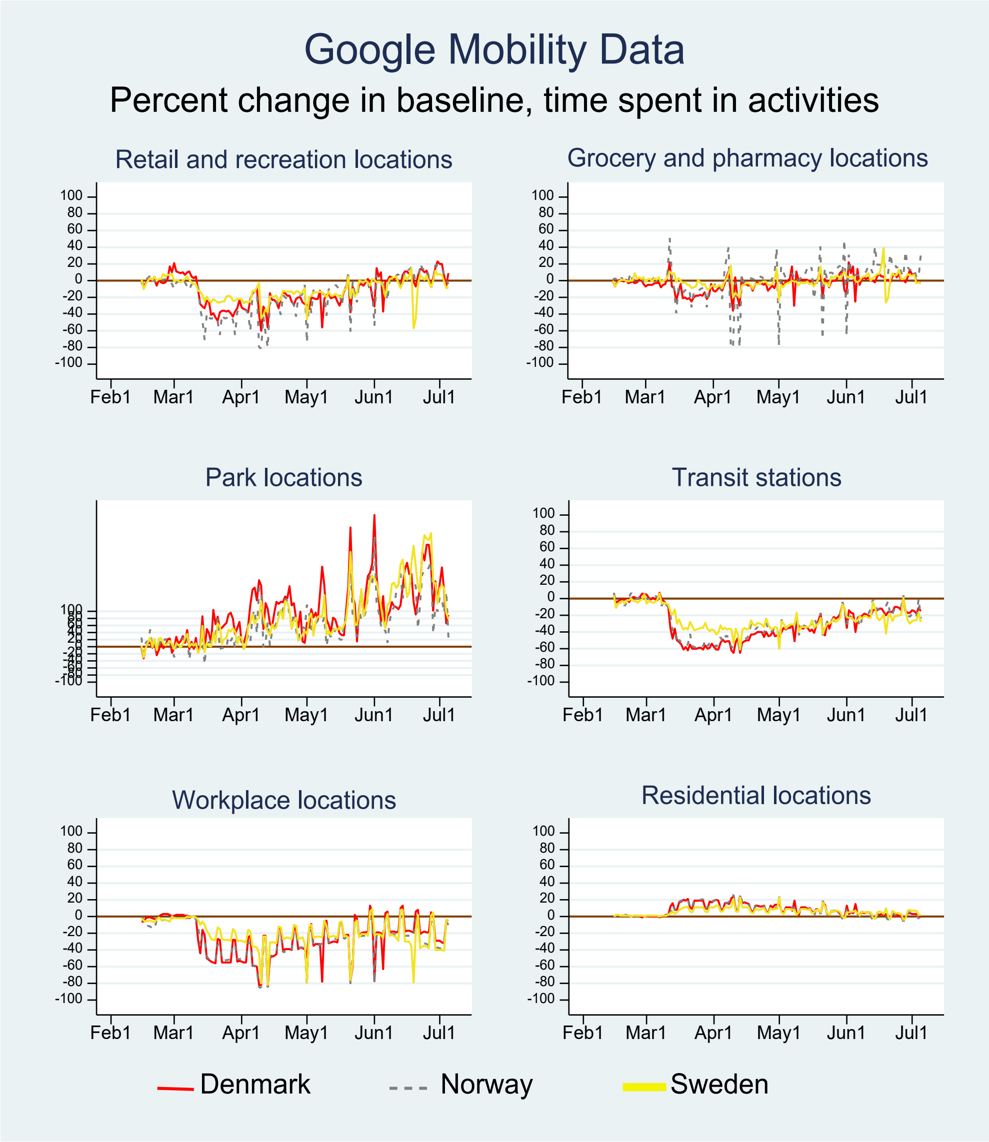

Figure 6: Google Mobility Data for Feb 15-July 5, Denmark, Norway, and Sweden.

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In an effort to understand the human dynamics of the COVID-19 pandemic and response, Google has collated information from web browser use on the daily percent changes from baseline in daily visits to six types of places where visitor patterns are thought to have been impacted from COVID-19 and our responses. From Feb. 15, 2020 on, the company has used location data from web browsers to show how visits to retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential locations have changed relative to an initial baseline. The baseline is "the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020" (Google LLC, 2020). The data may have selection issues relating to, among other things, seasonal changes and/or which users allow their location data to be tracked, so the results should be taken as indicative rather than definitive. There is no data available for Iceland.

One can see in Figure 6 that while the patterns for Scandinavians are very similar, the Swedes behaved differently from the Danes and Norwegians during the more stringent Danish and Norwegian restrictions, and less so before and after these periods. Swedes are changing their behaviors to reduce risks, but these changes are less intense than for Norway and Denmark; relatively, they are staying home less (*residential locations*), they are going to work more (*workplace locations*), and they have not reduced their use of public transport nearly to the same extent (*transit stations*). As the restrictions in Norway and Denmark ease, behaviors have converged again, supporting our assessment that now is a good point in time to analyze the different policies.

4. Results

4.1. Predicting New Cases

We use a random effects model for the panel composed of the 4 Scandinavian countries and a timeline from the early cases at the end of February to the beginning of July to predict new cases with two model specifications. Specification (I) relies on the bio-economic structure of a density-dependent (logistic) growth function with non-pharmaceutical interventions that slow the growth rate (spread) of the virus while specification (II) adds behavioral information on where Scandinavians have spent their time. Specification II comes at the expense of the Icelandic case, for which there is no Google Mobility data. Results for Specifications (I) and (II) are visualized in Figure 7, while parameters and diagnostics are in Appendix 3. Both specifications have high econometric fit. The visualization in Figure 7 makes clear that the addition of the mobility data is valuable, particularly in the continuing evolution of the Swedish experience. The peaks of new cases in Denmark, Norway, and Iceland are smoothed. This is likely due to the lack of spatial

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differentiation; a model that separated urban and rural cases, for example, should better predict the peaks.

From the regression results, we are also able to calculate a base reproduction rate (R_0) estimate of between 2.9 and 3.0. This is in line with lower- to mid- rates used or found in most models to date, which Alimohamadi et al. (2020) estimate through meta-analysis to have a mean of 3.32 (2.81-3.82).

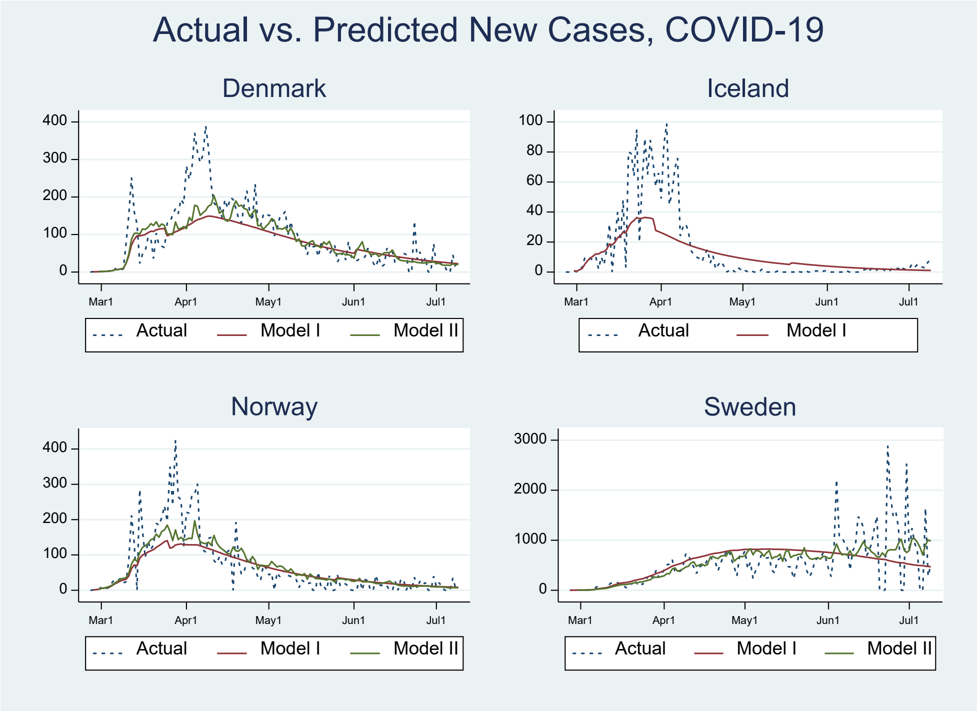

Figure 7: Actual vs. Predicted New Cases of COVID-19 in 4 Scandinavian countries over time, Feb. 26-Jul 5, 2020.

Both specifications include the closure of Middle Schools (ages 10-16, grades 6-10) lagged by two weeks for the intended effects to show. This measure is used as the most indicative of the impacts of highly collinear lockdown activities in the three countries (evidenced in Figure 1 and Table 2); by the time these students go back to school in May, the Google Mobility differences between the countries with closures and Sweden have shrunk back significantly (Figure 6). While the coefficients are negative, they are not significant. This may be due to collinearity problems with interacted timeline terms, which reflect how the virus's rate of growth has slowed much more in Denmark, Norway, and Iceland over time. It may, however, reflect the importance of behavior relative to mandate.

Density dependence is not yet a significant factor; this is expected as the infection rates remain very low compared to the overall population. Again, a more spatially granulated model, or one further into the future, might find that the virus is running out of space to spread in some communities.

4.2. Predicting Deaths from Cases

Countries may also differ in their ability to prevent cases from becoming deaths. We again construct two specifications with AR-1 processes for predicting new deaths per 1000 people using our panel data[4], with similar reasoning to the above. Specification (Id) includes Iceland and uses only lagged cases per 1000 people, tests per 1000 people, school closing and hospital capacities (fixed effect) to predict new deaths, while specification (IId) excludes Iceland but includes behavioral information from Google Mobility data. Again, both specifications have good fits. The regression results are in Appendix 4.

In all specifications, the lagged total case rates are unsurprisingly significant factors. Furthermore, higher testing rates (lagged) indicate significantly lower death rates. This suggests that people are able and willing to act on the information contained in testing in ways that reduce deaths. Indeed, Iceland's early and aggressive testing and Denmark's dramatic increases in testing (recall Figure 4) are quite different policies from Sweden's poor testing performance. Testing aggressively, a parallel to monitoring and early detection of environmental and health problems more broadly, should be recognized as a vital component of the precautionary principle.

Additionally, in both cases, lagged middle school closures do have significant negative coefficients. This suggests that closing schools and/or correlated mandates to stay home have helped keep increasing cases from translating to increasing deaths, even if they did not significantly contribute to reducing cases. There may be many reasons for this, which this analysis cannot fully address, but may include significantly reduced activity outside the home by all family members if children are at home. This is aided by the supportive Scandinavian approach to work-life balance, which for example even in non-coronavirus times, facilitates parents' ability to stay home for the first days of a child's illness, and provides other short and long term leaves for illness

[4] AR processes are anticipated in the time series due to the progressive nature of the virus, and AR-1 is confirmed by a Wooldridge test for serial correlation using xtserial following Wooldridge (2002) and Drukker (2003).

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of oneself and one's family members (Øresunddirekt, 2020a; Øresunddirekt, 2020b; NAV, 2020, Nordic Co-operation, 2020).

As shown in the previous section, Sweden has exceeded its hospital capacities, while the other countries have not come close. Higher hospital capacities, which in this case are ordered fixed effects (recall Table 3), do coincide with lower rates of conversion from cases to deaths in both specifications; this undoubtedly reflects not only relative hospital capacities but other fixed effects between the countries.

Unlike the estimation of new cases, behavioral information adds little in terms of significant results. This is not surprising given the lack of knowledge about how to treat the virus, so that it must generally run its natural course once contracted.

4.3. Avoided Cases and Deaths in Denmark, Iceland and Norway.

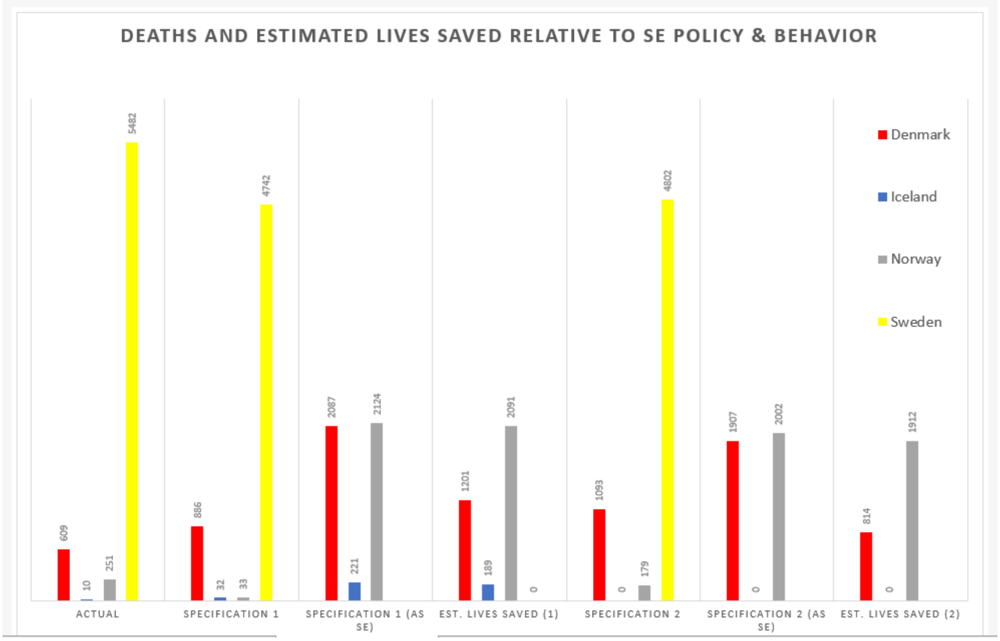

Figure 8: Actual and estimated deaths and estimated lives saved in DK, IS, and NO relative to SE behavior

Figure 9 shows the actual and estimated total deaths in the four countries for the two model specifications, alongside estimated deaths if Denmark, Iceland and Norway had policies and behaviors that replicated Sweden's (data in tabular form in Appendix 5). Estimated lives saved for DK, IS, and NO combined under Specification (I) are 3,481, while for Specification (II), with DK and NO only, the total is 2,726. The models somewhat overestimate deaths in Denmark and Iceland but underestimate them in Norway and Sweden.

4.4. Estimated Damages

4.4.1. Estimated Value of Statistical Lives Saved (VSL)

We have two sets of estimates of value of statistical lives that parameterize the expected gains from social distancing and lockdown. Viscusi (2017) provides the income adjusted VSL figures in Table 6.

Table 6: US-based and Own-Country VSL figures

Country	VSL (Viscusi 2017, 2015 USD)	VSL (Natl. Figs. in 2015 USD) (1)
Denmark	10.073 m	5.097 m
Iceland	8.600 m	No national estimate
Norway	16.127 m	4.75 m
Sweden	9.965 m	3.99 m

(1) National figures converted to USD using 2019 exchange rate (IRS) average (and deflated to 2015 with GDP deflator from measuringworth.com:
DK: 34 m DKK (2019), finance ministry (fm.dk)
IS: no estimate
NO: 34.940 NOK (2019) TØI rapport 1704/2019
SE: 40.5 M SEK (2019), Trafikverket

4.4.2. Range of Estimated Losses

We calculate a range of estimated losses in billions of 2019 USD. For the low end, we assume that government expenditures are covered with future growth and do not include them. We also use the lower value estimates for VSL and the lowest estimates for GDP losses. The mean estimates also ignore government expenditures, but they include the higher VSL figures and the mean estimates for GDP losses. For the high end, we include government expenditures as well as use the higher VSL figures and the worst-case GDP loss scenarios. Figure 10 shows that Iceland faces the lowest expected total losses. At the mean, this translates to $5,781 per capita (Table 7). This is higher than the Danish and Norwegian per capita losses, which are $4,124 and $4,541 respectively. Sweden outpaces all three countries with a mean per capita loss estimate of

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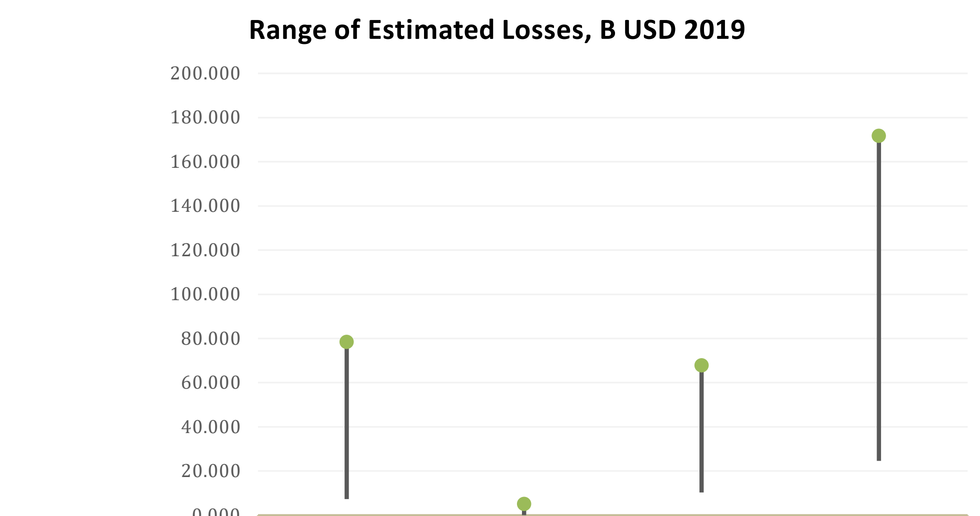
$8,300. At the top end, the per capita figures are $12,524 (NO), $13,559 (DK), $15,279 (IS), and $17,004 (SE). Supporting calculations for estimates of lives saved are in Appendix 5.



	Denmark	Iceland	Norway	Sweden
Estimated Losses, mean	23.886	1.973	24.618	83.824
Estimated Losses, low	8.325	0.992	11.276	25.589
Estimated Losses, high	78.535	5.214	67.896	171.730

Figure 9: Estimated losses (B USD) to Scandinavian countries through June 2020.

Table 7: Per capita estimated losses (USD) to Scandinavian countries through June 2020

	Denmark	Iceland	Norway	Sweden
Mean Per Capita Losses	4,124	5,781	4,541	8,300
Low Per Capita Losses	1,437	2,906	2,079	2,533
High Per Capita Losses	13,559	15,279	12,524	17,004

Finally, we estimate the VSL attributable to the precautionary approach that drove lockdown mandates. We find that the Danish savings relative to a Swedish approach range from 4.149 billion USD to 12.098 billion USD, Icelandic savings relative to a Swedish approach are estimated at 1.625 billion USD, and Norwegian savings range from 9.082 billion USD to 33.722 billion USD. The per capita values are shown in Table 8, alongside the breakdowns of these ranges.

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Estimated per capita savings from the precautionary approach in lives saved are of approximately the same magnitude as or larger than the damages incurred in these countries. The benefits to date of stricter restrictions have been substantial.

Table 8: VSL of Lives Saved by Precautionary Approach

VSL Values for Lives Saved by Precautionary Approaches relative to SE, through June 2020			
	DK	IS	NO
Precautionary Approach Value in Avoided Deaths (I), US, B USD	12.097673	1.6254	33.72156
Precautionary Approach Value in Avoided Deaths (II), US B USD	8.199422		30.83482
Precautionary Approach Value in Avoided Deaths (I), Own, B USD	6.121497		9.93225
Precautionary Approach Value in Avoided Deaths (II), Own, B USD	4.148958		9.082
Per capita low estimates (USD)	716		1675
Per capita high estimates (USD)	2089	4763	6220

5. Discussion

5.1. Issues of Incidence and Insurance

In considering the net costs and damages of the pandemic, we have not considered incidence in any detail. Government support in all four countries has postponed and distributed costs of unemployment, and long run impacts are difficult to assess at this time.

For businesses, the burden of incidence remains unclear, and depends on how insurance claims and legal controversies are resolved. As insurance is a key tool for risk management, it is useful to understand how the pandemic is affecting the industry in Scandinavia. Overall, the influence in the insurance sector is diverse and depends on the carrier's exposure in various insurance lines. The lines of insurance that are suffering the most significant losses in Scandinavia so far seem to be those that are negatively influenced by the forced stop in activities, e.g., travel insurance, event cancellation insurance, etc. On the other hand, some have been positively influenced by a stop. Most clearly this is being seen in private property claims and motor claims. Burglaries have been declining in private homes, and other claims are also expected to decrease as well, as homes have been watched over 24/7. Motor claims have significantly decreased as a consequence of people traveling less.

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As the crisis was not perceived by most individual decision-makers to be a likely threat before it occurred, many insurance policies have failed to include appropriate coverage for the actual impacts. Where it has been included in the apparent scope of coverage, several currently contested legal factors affect eligibility for insurance compensation. For example, the government's instructions are seen to affect the eligibility for compensation. Lack of precision in the lockdown strategy can cause clients to fail to qualify for compensation, which has been an effect of the more open instructions in Sweden.

The rapid change in the risk landscape has made it difficult to foresee the short- and long-term economic effects in the insurance market. Future data will provide a better understanding of how different lockdown strategies have affected the insurance market and how the market will mitigate future pandemic crises in the world and/or distribute the costs across those affected.

The virus itself has to date overwhelmingly affected elderly individuals in the Scandinavian countries, particularly elderly individuals in elder care homes. In addition to the interest in weighing the meaning of this uneven distribution, this suggests that an age-structured SEIR model may be appropriate for future work. Sweden, in one of its few strict restrictions finally banned most visits to elder care facilities, has admitted that it should have done more, earlier, to reduce contact between elderly populations and others (The Local, 2020) and would likely have reduced deaths in so doing.

5.2. Substitution and Income effects

Much has been made of the improvements in air quality from reduced travel during the pandemic, with e.g. claims of up to 30% reductions in pollution in some locations with the strictest lockdowns (Muhammad et al, 2020). To the extent these gains are real, they are not expected to last, unless the break in activity produces other substitutions. A cursory examination of the data for major Scandinavian cities (Appendix 6) suggests possibilities worthy of further investigation. In particular, while nitrous oxides, the main regional pollutants from transportation vehicles, are lower during the main 'lockdown' months of March and April 2020 vs. 2019, for Denmark, Norway and Sweden, they are also lower for other months versus 2019 as well. Scandinavian countries, particularly Norway, have already invested significantly in urban air quality as they have become some of the richest countries in the world. Oil prices have declined, reducing Norwegian wealth and increasing the opportunity costs of transitioning to more fuel-efficient transport. If, as can be expected, these effects and the broader economic losses of the pandemic divert efforts from both private and public long-term plans to improve environmental quality, this will add to the overall losses generated by the pandemic.

6. Conclusions

For Denmark, Iceland, and Norway, precautionary principle approaches that include successful testing and tracing strategies have paid off to date. They have saved lives estimated to be worth up to 47.4 billion USD, with no measurable tradeoff in economic consequences compared to Sweden. We use a bio-economic model of growth in the disease and augment it with behavioral information from Google Mobility data. The model predicts cases and deaths from COVID-19 well and confirms R_0's for Scandinavian countries of ~3, as found by others. Both government mandates and individual changes in behaviors reduce the reproduction rate over time; countries with more strict mandates have seen fewer deaths than those without.

The comparison of the Scandinavian countries' early experience with the novel coronavirus in the first half of 2020 provides an opportunity to evaluate precautionary approaches to BAU risk management. The results emphasize that the idea of a clean tradeoff between economic and health outcomes is a false dichotomy. The problem is rather a joint cost and damage minimizing exercise, with inseparable interactions.

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Appendix 1: Summary of GDP Growth estimates

Real GDP 2020 Annual Growth Rate Estimates since Feb 15.

Country	Mean	Std. Dev.	Min	Max	# Estimates	Sources
Denmark	-5.1	2.2	-10	-1.5	20	Danish Economic Council, Danish National Bank, DanskeBank, Nordea, Focus Economics, SEB, IMF, EC, OECD, Reuters Poll
Iceland	-7.8	2.4	-11.2	-4.1	8	Central Bank of Iceland, Landsbankinn, Focus Economics, IMF, EC, OECD, Statistics Iceland
Norway	-5.1	1.7	-7.5	-2.5	10	DanskeBank, Nordea, Focus Economics, SEB, IMF, EC, OECD, Reuters Poll
Sweden	-5.5	2.4	-12	-0.7	18	National Institute for Economic Research (SE), DanskeBank, Nordea, Focus Economics, SEB, IMF, EC, OECD, Reuters Poll, Statista

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Appendix 2: Supporting data from hospitalizations

Norwegian data does not identify daily totals of patients. Instead, Figure A2.1 shows the cumulative total IC hospitalizations for COVID-19 alongside the new admittances each day. The numbers are in line with Figure 2.

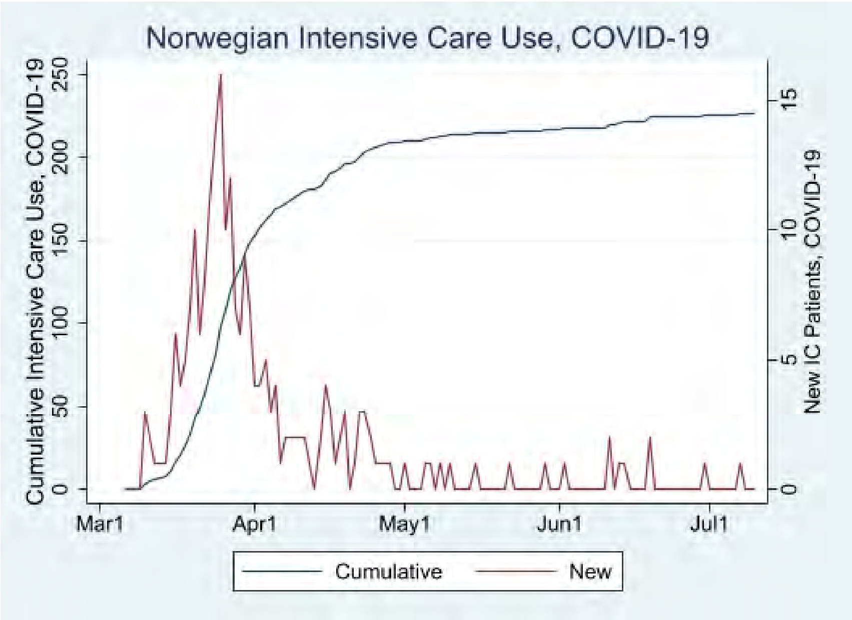

Figure A2.1: Norwegian intensive care use, COVID-19.

Swedish data identifies procedures but not days on ventilator. Ventilator procedures do appear a relatively stable share of IC days. New Swedish IC use has not increased as cases and deaths have grown in late June and July.

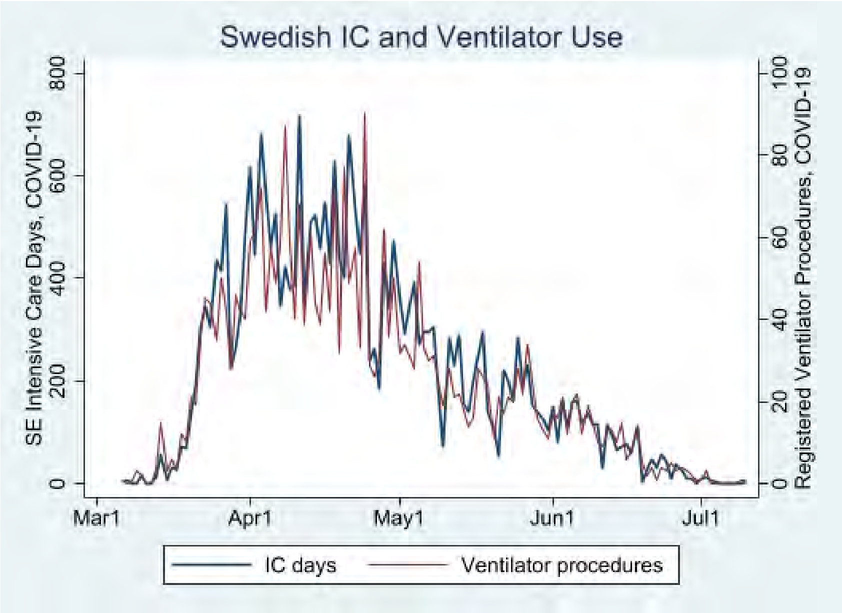

Figure A2.2: Swedish intensive care and ventilator use.

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Appendix 3: Regression Results for Predicting New Cases

Dependent variable: New cases (ln)	Panel regression		
time unit: daily	RE model, Robust std. err.		
panel: Denmark, Iceland‡, Norway, Sweden	P-values in parentheses		
		Specification	
Variable		I	II
Total Cases (ln)		0.817	0.879
		(0.000)	(0.000)
Middle schools (age 10-16) closed,		-0.222	-0.352
14 day lag		(0.458)	(0.209)
Denmark*Days from first case		-0.028	-0.041
		(0.000)	(0.000)
Norway*Days from first case		-0.034	-0.046
		(0.000)	(0.000)
Iceland*Days from first case		-0.034	
		(0.002)	
Sweden*Days from first case		-0.006	-0.021
		(0.348)	(0.000)
			-
Density measure (ln)		219.84	24.592
		(0.295)	(0.742)
Percent change in transit station frequency,			-0.005
14 day lag			(0.573)
Percent change in residential frequency,			-0.021
14 day lag			(0.215)
Percent change in retail frequency,			-0.002
14 day lag			(0.000)
Percent change in grocery frequency,			0.004
14 day lag			(0.002)
Percent change in parks frequency,			0.002
14 day lag			(0.000)
Percent change in work frequency,			-0.006
14 day lag			(0.844)
Constant		-0.409	-0.469
		(0.000)	(0.000)
R-sq (within)		0.773	0.827
R-sq (between)		0.998	0.999
R-sq (overall)		0.874	0.884
N.Obs.		456	358
N.Groups		4	3
sigma_u		0	0
sigma_e		0.0669	0.545
rho		0	0
Estimated R_0		**2.927**	**3.034**

‡ Google Mobility data is not available for Iceland

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Appendix 4: Regression Results for Predicting Mortality Rates

Dependent variable: new deaths per 1000 ppl	Panel Data Regression	
time unit: daily	RE model with AR(1)	
panel: Denmark, Iceland‡, Norway, Sweden	P-values in parentheses	
	Specification	
Variable	Id	IId
Total cases per 1000 ppl, 14 day lag (ln)	0.0016	0.0017
	(0.000)	(0.000)
Total tests, 14 day lag*	-0.0018	-0.0018
	(0.000)	(0.000)
Middle schools closed (ages 10-16), 14 day lag	-0.0006	
	(0.084)	
Hospital beds per 1000 ppl**	-0.0013	-0.0014
	(0.004)	(0.005)
Percent change in transit station frequency, 14 day lag		2.54*10^-5
		(0.388)
Percent change in residential frequency, 14 day lag		9.12*10^-5
		(0.225)
Percent change in retail frequency, 14 day lag		-2.53E-05
		(0.161)
Percent change in grocery frequency, 14 day lag		1.71*10^-5
		(0.190)
Percent change in parks frequency, 14 day lag		1.82*10^-6
		(0.633)
Percent change in work frequency, 14 day lag		2.66*10^-5
		(0.219)
Constant	0.011	0.011
	(0.000)	(0.000)
R-sq (within)	0.123	0.09
R-sq (between)	0.933	0.9262
R-sq (overall)	0.402	0.378
	78.26	53.18
Wald chi^2	(0.000)	(0.000)
N.Obs.	470	364
N.Groups	4	3
rho (AR)	0.483	0.530
sigma_u	0.0002	3.142
sigma_e	0.002	20.844
rho	0.016	0.022

*test data for Sweden is smoothed over weekly observations
** fixed by country. See Table 3.
‡ Google Mobility data is not available for Iceland

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Appendix 5: Estimated Deaths and Lives Saved

Deaths	Denmark	Iceland	Norway	Sweden
Actual	609	10	251	5482
Specification 1	886	32	33	4742
Specification 2	1093	n.a.	179	4802
Specification 1 (as SE)	2087	221	2124	
Est. Lives Saved (1)	1201	189	2091	
Specification 2 (as SE)	1907	n.a.	2002	
Est. Lives Saved (2)	814	n.a.	1912	

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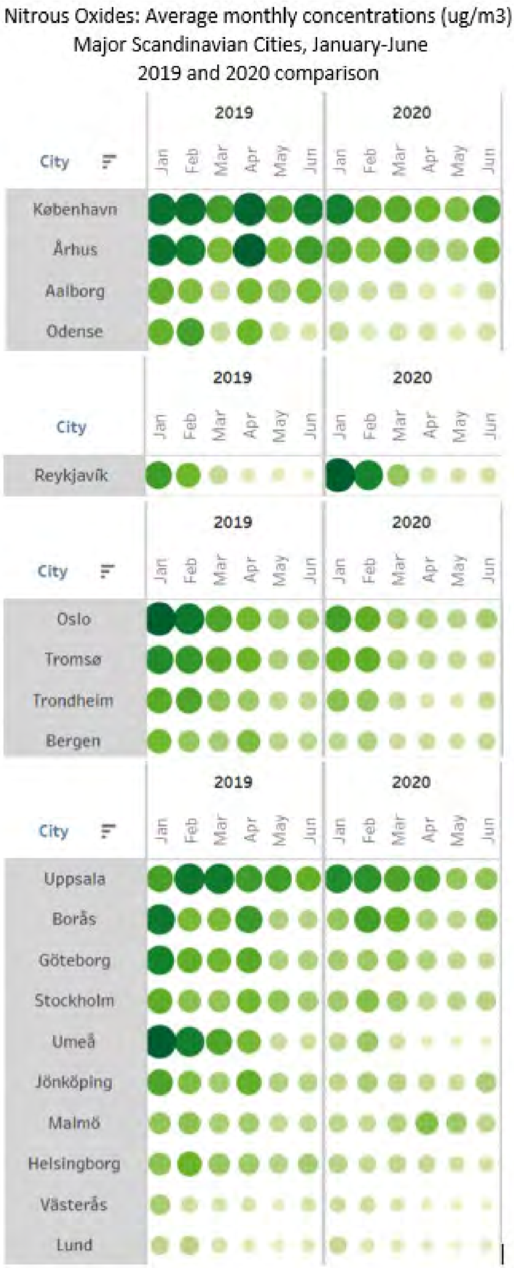
Appendix 6: Air Quality, Scandinavian Cities



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Coronagraben: Culture and social distancing in times of COVID-19

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Social distancing measures have been introduced in many countries in response to the COVID-19 pandemic. The rate of compliance to these measures has varied substantially. We study how cultural differences can explain this variance using data on mobility in Swiss cantons between January and May 2020. We find that mobility declined after the outbreak but significantly less in the German-speaking region. Contrary to the evidence in the literature, we find that within the Swiss context, higher generalized trust in others is strongly associated with lower reductions in individual mobility. Additionally, support for a limited role of the state in matters of welfare is also found to be negatively associated with mobility reduction. We attribute our results to a combination of these cultural traits having altered the trade-off between the chance of contracting the virus and the costs associated with significant alterations of daily activities.

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1 Introduction

After the initial outbreak in Wuhan in early January 2020, COVID-19 quickly spread across all regions of the world, achieving a pandemic status. Flattening the contagion curve has rapidly become a priority in many countries in an attempt to reduce the load on the healthcare system and the overall mortality rate. A two-months strict lockdown was introduced in the Chinese province of Hubei on January 23, and Western democracies followed suit enacting shelter-in place and social distancing measures and large cut backs on production activities. Many countries have also tried to reduce interpersonal contact and mobility through massive "stay at home" media campaigns aimed at altering citizens habits. While the health measures enacted have been, by and large, homogeneous across countries, compliance to these rules varied widely with the local context. In the absence of perfect enforcement capacity by the states, cultural attitudes and behavioral norms, which typically vary from country to country, can make an important difference and explain deviations in voluntary compliance. This is all the more true when it comes to individual mobility decisions, which entails a delicate trade-off between the chance of contracting (or diffusing) a disease and the economic (and individual well being) costs associated to significant alterations of daily activities.

There are major cultural differences, for example, in the physical distance that people keep when interacting with others, with Southern Europeans preferring closer interpersonal distance than Northern Europeans and Northern Americans (Remland et al. (1995); Sorokowska et al. (2017)). Since social contact patterns are a crucial factor behind the spread of the disease, the benefit of abiding to strict social distancing rules and reducing mobility will be higher in societies accustomed to close interactions (Prem et al. (2017); Oksanen et al. (2020)). Can there be a role for cultural biases in the spread of pandemics? We study how cultural values may play a role in the evolution of individual mobility under COVID-19 measures. Our work contributes to a growing body of studies linking cultural variables, social distancing, and the spread of COVID-19 (Durante et al. (2020); Barrios et al. (2020); Borgonovi and Andrieu (2020); Brodeur et al. (2020); Egorov et al. (2020); Bargain and Aminjonov (2020)). Building on these papers, we investigate various dimensions of culture and focus our analysis on Switzerland, which provides a unique case study due to its native language groups which are shared by the adjoining countries and the distinct linguistic geographical areas with deep historical roots. These areas are associated with specific cultural traits and an example that highlights this is the colloquial name for the border between the French and German speaking region, called Röstigraben. *Rösti* refers to a hashed potato dish which originated in the canton of Bern and is typical of Swiss German cuisine, and *Graben* is a trench or division. The intensity of the COVID-19 pandemic has varied substantially between the Swiss regions and the divide around the spread of the virus has been defined by some observers as a *Coronagraben*, in reference to the cultural border. We discuss this in further detail in section 2.

We add to the existing literature by focusing on a set of cultural dimensions and mechanisms that might have shaped the actual adherence to social distancing in Switzerland. More precisely, first we examine the relationship between average distance travelled in a day and language as a proxy for culture. Then to further investigate the role of specific cultural dimensions, we examine the relationship between daily mobility and a set of specific cultural traits associated with the linguistic background - trust, altruistic beliefs, political leaning and preferences for re-distributive policies. We measure these values and attitudes using European Social Survey and Swiss Household Panel,. To capture the adherence to social distancing, we rely on phone location tracking records of 3000 individuals, collected by Intervista AG on behalf of the Swiss Federal Statistical Office (FSO). Our analysis focuses on two important dates. The first is February 25, when the first COVID-19 case was reported in Switzerland, marking the beginning of the outbreak in the country. The second is March 16, when the Swiss government declared an “extraordinary situation”, instituting a ban on all private and public events and closing places such as restaurants and bars. The period between these two dates would be indicative of voluntary compliance to social distancing while the period post March 16 would be indicative of adherence to official measures. In our empirical model, we include canton and daily fixed effects and also control for time-varying number of COVID-19 cases reported and fatalities at the canton level. Our specification also includes the interaction of a rich set of baseline geographic, demographic, and socio-economic cantonal controls with time dummies. This accounts for difference in mobility levels across cantons and the the common evolution of mobility in all cantons in any give day. Additionally it accurately captures the effect of culture by controlling for factors that maybe correlated with it and may affect changes in mobility. Lastly to ensure the effect we are capturing is from our stated cultural dimensions and not other elements

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of social capital, we also control for average time spent watching, reading or listening to news and for trust in institutions.

Using this approach, we find surprising results showing that cantons in the German linguistic region, which are also characterized by higher levels of generalized trust towards others and more altruistic beliefs, reduced their mobility significantly less than the French speaking cantons. Therefore, within the Swiss context, high interpersonal trust is strongly associated with lower reductions in individual mobility. These findings are at odds with Durante et al. (2020) and Brodeur et al. (2020), who document a significantly higher decline in mobility in areas with higher civic capital and trust. We attribute these results to the specific way in which these cultural traits alter the trade-off behind individual decision on mobility. Reducing mobility becomes less relevant as an instrument to reduce the probability of contracting (or diffusing) the disease if one believes that other individuals in society will respect, among other things, physical distance and other infection prevention and control norms (IPC), thus making mobility reduction less relevant. In a sense, physical distancing replaces social distancing. Additionally it is important to note that German speaking cantons are also relatively right leaning on the political scale, support a limited role of the state in maters of welfare and greatly value individual freedom. Therefore in these cantons, reducing individual mobility due to government imposition could be perceived as a sacrifice of a taller order than in more collectivist regions. We also find preliminary evidence of a possible mechanism driving these results: a combination of higher interpersonal trust and conservative political attitude that may have shaped the lower reduction in mobility for the German speaking cantons. Overall, our results show that the costs and benefits associated with compliance changes with culture and suggests that contextual conditions, shaped by the culture of reference, are key in determining how traits such as interpersonal trust, preference for re-distributive policies and political attitudes, mediate the social distancing process. The paper closest to ours is Mazzonna (2020), who uses a different set of mobility data for Switzerland and sheds light on the mobility differences across the German and Latin (French and Italian) speaking regions in Switzerland. While Mazzonna (2020) looks at differences across the linguistic regions and the role of elderly demographic, our paper decomposes the effect of culture by highlighting the specific cultural values and beliefs that may explain these differences and also explores the underlying mechanism. Both the papers can be seen

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as complimentary in emphasizing the role of culture and the main results are consistent with one another.

The remainder of the paper is organized as follows. Section 2 presents our conceptual framework, discusses the cultural differences in Switzerland and gives a background on the COVID-19 emergency in the country. Section 3 describes the data used for our analysis and Section 4 presents our empirical and identification strategy. Section 5 discusses the results while Section 6 concludes.

2 Culture and its dimensions

We first clarify what we mean by *culture*. We follow the definition proposed by Guiso et al. (2006), where *culture* is defined as a set of "customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation". We focus on language as a proxy for culture and further look at two specific dimensions or traits of culture and explain their place in the context of Switzerland:

Language: There is a large literature linking culture and language. This literature essentially builds on *The Sapir–Whorf hypothesis* also known as the linguistic relativity hypothesis, which highlights how the language one speaks influences the way one perceives the world. This hypothesis is a culmination of several early contributions in anthropology that explored this link, spanning from van Humboldt (1836) to Mandelbaum (1951), Whorf (1956), Sapir (1968) and Boas (1982) whose work on cultural relativism further highlighted that language and culture were interdependent. Several studies, across various disciplines, have shown that an examination of cultural groups can be engaged by language since it has an impact on identity, values, attitudes and behaviour (Heslop et al. (1998); Schulz et al. (2006); Laesser et al. (2014)). More recently works of economists such as Bisin and Verdier (2011) and Ginsburgh and Weber (2020) show that the notion of a common native language is inextricably linked with cultural proximity. This goes beyond language proficiency and ability to speak and in fact captures the vertical and horizontal transmission of values.

Generalized trust: One of the most commonly defined cultural trait is generalized trust towards

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others, the beliefs held about others' trustworthiness. Alesina and La Ferrara (2002) hypothesize that this belief is a moral or cultural attitude and is positively correlated with individual characteristics such as the level and type of education received and occurrence of recent misfortunes. They also show the importance of community characteristics such as high income inequality which often leads to low interpersonal trust. From the early work of Arrow (1972), who recognized the importance of mutual trust in commercial and noncommercial transactions, the relation between generalized trust and economic development is well established (Algan and Cahuc (2014); Butler et al. (2016)). It is important to note that this differs from the concept of trust in institutions, which may simply be capturing the efficiency or corruption of the government in power.

Preferences for redistribution: Alesina and Giuliano (2011) define preferences for redistribution as a situation in which one agent also cares about the utility of somebody else. They reject the notion of these preferences being unpredictable "social noise" and highlight the role of culture as an important determinant. Different cultures may have distinct approaches in contrasting the merits of equality versus individualism. As shown by Alesina and Giuliano (2015), views on inequality and redistribution emphasize both the *value* and *belief* component of culture. Luttmer and Singhal (2011) highlight the former by showing a significant correlation between second-generation immigrants' redistributive preferences and the average preference in their birth countries. An individual's predisposition to support a welfare state may also be determined by cultural traits such as perception of poverty and fairness. Think of an individual who not only cares about his own income but dislikes inequality due to luck rather than effort and ability. His *belief* that success is primarily determined by luck and personal connections, rather than hard work, will determine his preferences for redistribution and social policies. Furthermore, these cultural values and attitudes are significantly persistent and tend to remain fairly stable over time and generations.

Alesina and Giuliano (2011, 2015) show that these preferences also underlie the formation of political attitudes and are in fact a crucial factor in dividing the political left and the political right. Perception about fairness (work vs. luck) in the income-generating process is key in formation of political attitudes and supporting a welfare state. Luttmer and Singhal (2011) find evidence that cultural influences affect voting behaviour by documenting that immigrants from high-preference

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countries are more likely to vote for more pro - redistribution parties.

2.1 Why Switzerland?

Switzerland provides an excellent case study where language is in fact a very appropriate proxy for culture (Büchi (2001)). Switzerland has twenty-six cantons and four official languages having equal status in law - German, French, Italian and Romansh. According to the 2000 census, German is spoken by 63.7% of the population, French by 20.4%, Italian by 6.5%, and Romansh by 0.5%. Three cantons - Valais, Fribourg, and Berne - are bilingual (French, German); one canton - Graubünden - is officially trilingual (German, Romansh, Italian). From the remaining cantons, seventeen are German speaking, four French speaking and one Italian speaking. Looking at Panel (a) in Figure 1, we observe that there are geographically distinct linguistic regions. These language borders have deep historical roots and with the exception of few minor movements, the early historical development of the German-French and German-Italian language boundaries have been relatively stable since AD 1100 (Sonderegger et al. (1967); Egger and Lassmann (2015); Büchi (2001)). For example, historically the border of the canton Valais traced along the border of the Roman-Catholic Diocese of Sion and most of the canton Graubünden was once part of a Roman province called Raetia, which was established in 15 BC, resulting in multilingualism (Eugster et al. (2017)). These language borders are a measure of cultural values and beliefs manifested by means of differences in native languages. Therefore these explicit language regions can be thought of as pockets of different cultures and the *Röstigraben* exemplifies this fact. The language frontier manifests itself through different preferences in many aspects of everyday life and provides an ideal context to study the effects of culture. There are several works of public economics and trade that have exploited this unique variation in languages within Switzerland (Eugster et al. (2017), Athias and Wicht (2014), Egger and Lassmann (2015) and Eugster and Parchet (2011)).

These distinct language zones also capture the variation in preferences for redistributive and social policies. One can see this in the voting shares of Swiss citizens on several federal popular initiatives.[1] These initiatives tackle various socio-economic issues and are very informative about the attitudes

[1] This is a unique aspect of Swiss democracy which allows citizens to propose changes to the Swiss Federal Constitution. For a popular initiative to succeed, those launching the initiative need to collect 100,000 signatures from people entitled to vote within eighteen months. If Parliament decides that the initiative is valid, it is put to a popular vote.

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and perception of cantons towards matters of welfare and social spending. One issue that has always brought the cultural divide to the forefront is the unemployment insurance (assurance-chômage). In 1997 and 2010, the citizens voted on whether there should be further cuts on the financing of unemployment benefits. The variation in vote share, as seen in Panel (b) of Figure 1, results in a map with demarcations that look strikingly similar to the language borders seen in Panel (a). Despite the thirteen years gap, note the persistence in the preferences across the cultural borders. Thus one can say the Röstigraben is also reflective of the left-leaning voting behavior of the French-speaking part, especially when it comes to social policy issues (Germann et al. (2012)).

2.2 COVID-19 in Switzerland

The first case of COVID-19 in Switzerland was confirmed on February 25 a 70-year-old man tested positive in Ticino, followed by a second case on February 26 in Geneva. Due to its proximity to Lombardia, Ticino took early restrictive measures while the only rule imposed on the remaining cantons was a relatively moderate step taken by the federal government - to raise the alert level to "special situation" by banning events with more than 1,000 people.[2] However, by mid March the country was particularly affected by the epidemic, the increase in confirmed cases accelerated with the reproductive number oscillating between 1.5 and 2 (Sciré et al. (2020)). With more than 2,600 people infected, there was a need to mobilise up to 8,000 members of the military to help contain the rapid spread, representing the largest army mobilisation since the Second World War. The Swiss government also introduced border checks with Germany, France and Austria. This was the turning point for Switzerland and on March 16 the government declared an "extraordinary situation", instituting a ban on all private and public events and closing restaurants, bars, leisure facilities and shops apart from grocery stores and pharmacies. It is important to note that unlike its neighbours, Switzerland did not announce a definite lockdown but encouraged its citizens to follow "social distancing" as part of an information campaign by the Federal Office of Public Health (FOPH). The first phase of relaxing the restrictions began on April 27. Figure A.1 shows the evolution of the total cases reported in Switzerland for three different periods.

The intensity of the health crisis has varied substantially in the country. An invisible border

[2] This included football and ice hockey championships, carnivals in Basel and Lucerne, the Geneva Motor Show and Baselworld watch fair.

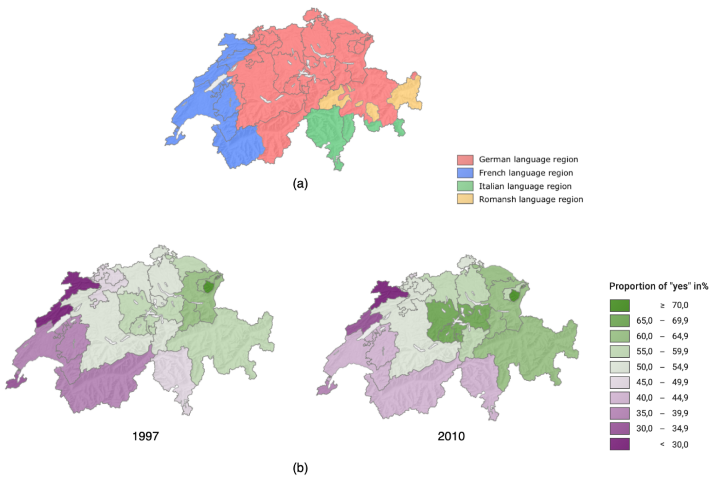

Figure 1: Panel (a) - Language regions of Switzerland. The grey lines are the canton borders. Panel (b) - Percentage of yes votes for the Law on unemployment insurance in 1997 and the revision of this law in 2010. *Source: Swiss Federal Statistical Office (FSO)*

has divided Switzerland during the emergency: the French- and Italian-speaking parts have been significantly more affected than the German-speaking areas, with only few exceptions. The cantons of Geneva, Ticino and Vaud lead by far the ranking of most cases per 10,000 inhabitants, recording values that more than double the majority of German speaking cantons. This linguistic divide around the spread of the virus has been defined by some observers as a *Coronagraben*, in reference to the cultural Röstigraben.

3 Data

Before we proceed to describe the variables we use for our empirical analysis, we address one major limitation. Although it would be ideal to have data at the municipal level and use the multilingual cantons as a way to investigate our research question, unfortunately neither the mobility data nor the statistics related to the pandemic are available for municipalities. All the data described below are at the cantonal level. Therefore we drop five cantons from our sample of twenty-six: Bern, Valais, Fribourg and Graubünden, as they are officially multilingual. Additionally we also drop Ticino because of its proximity to the Italian region of Lombardia which may bias our results. This

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limits our focus to studying the the impact of cultural differences between the French and German speaking cantons.

Social Distancing: We use daily data on individual mobility in each canton between January 1 and April 27, 2020. This has been collected by Intervista AG, a market research institute, on behalf of the Swiss Federal Statistical Office (FSO). It is based on the phone location tracking records of 3,000 individuals, selected according to several criteria, such as sex, age, canton of residence and mobility behavior in accordance with the representative guidelines provided by the FSO. The data consists of average distance travelled each day as well as the radius of daily travel, both measured in kilometres. The former indicates the sum of all journeys made by an individual during a day, by foot or by means of transport such as car, bicycle or public transportation. The daily radius indicates the distance from the overnight accommodation, the night before, to the most distant location reached in one day as the crow flies.

Culture: For the first indicator of culture, language, we associate each canton with a dummy variable equal to one if the official language is German and zero if it is French. This information is available on the official websites of the FSO and of every canton. To measure cultural traits we use two surveys: Swiss Household Panel (SHP)[3] and European Social Survey (ESS).[4]

To assess generalized trust towards others, the survey elicits beliefs by asking - *Would you say that most people can be trusted or that you can't be too careful in dealing with people, if 0 means "Can't be too careful" and 10 means "Most people can be trusted"?* Using the average intensity of trust beliefs we classify cantons as "high trust in others" and "low trust in others". To gauge interpersonal trust we also look at an additional question - *Would you say that most of the time people try to be helpful or that they are mostly looking out for themselves?* Similar to above, the response is on scale from 0 to 10, where 0 means people mostly look out for themselves and 10 means that people mostly try to be helpful. The intended contrast is between self-interest and altruistic helpfulness. We classify cantons as "high altruistic beliefs" and "low altruistic beliefs ".

[3]It is an annual panel study based on a random sample of private households in Switzerland over time. The aim is to observe social change, in particular the dynamics of changing living conditions and representations in the population of Switzerland. We use wave 19 (2017) and wave 20 (2018).

[4]The ESS is a cross-sectional survey administered in a large sample of mostly European nations, containing information on individuals' social values,cultural norms, and behavioral patterns. We use round 8, 2016 for Switzerland.

To capture views on equality and beliefs about preferences for redistribution, the survey asks the respondents to agree or disagree with the statement - *Large differences in people's incomes are acceptable to properly reward differences in talents and efforts.* Using the percentage of respondents who agreed, we classify cantons as "high acceptance of income differences" and "low acceptance of income differences".[5] As discussed in Section 2, cultural perceptions of the role of state are central to formation of political attitudes and ideologies. Utilizing the survey question - *In politics people sometimes talk of "left" and "right". Where would you place yourself on this scale, where 0 means the left and 10 means the right?* - we focus on political positioning along the left-right spectrum and classify cantons as "right leaning" and "left leaning". The cantonal distribution of these measures can be seen in Figure 2.

Other variables: To distinguish the effect of culture from other factors, we include a rich set of economic, demographic and geographic controls at the cantonal level. To capture the quality of the health system and hospital capacity, we use data on the number of hospital beds per 1000 inhabitants. We also control for two measures of vulnerability to the pandemic: the share of population older than 65, representing the at-risk individuals and the tourism statistics which is the total number of arrivals in hotels and health establishments. Our specification also includes population density, area, share of urban and foreign population in the canton, graduation rate in higher education institutions, household disposable income, temperature and GDP per capita. These help control for the fact that they maybe potentially correlated with both mobility and the cultural traits. This information is publicly available on the FSO website. Additionally to control for the severity of COVID-19 at the local level, we control for the total cases reported and fatalities recorded. The data on daily COVID-19 statistics is taken from the website corona-data.ch, which uses official information communicated by the cantons and FOPH.

Finally, to ensure the effect we are capturing is from our stated cultural dimensions and not other elements of social capital we control for average time spent watching, reading or listening to news and for trust in institutions. Although we do not have a variable on physical proximity, we use information on frequency of interpersonal relations, which maybe a likely determinant of mobility.

[5]The survey provides five options: strongly agree, agree, neither agree nor disagree, disagree and strongly disagree. We look at the share of first two responses.

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This information is taken from ESS and SHP. Summary statistics for all variables are reported in Table A1.

4 Empirical strategy

First we estimate the following equation:

$$Y_{ct} = \alpha_c + \theta_t + \beta\ Lang_c \times D_t + \delta \mathbf{X}_{ct} + \epsilon_{ct} \tag{1}$$

Y_{ct} is the average distance travelled in a day t, in a given canton c, measuring individual mobility and adherence to social distancing. $Lang_c$ is a dummy variable which is equal to one if the official language is German and zero if French. D_t is a vector of time dummies indicating the three phases of the pandemic:

- Phase 1: January 1 - February 25 $\longrightarrow$ Pre-outbreak
- Phase 2: February 25 - March 16 $\longrightarrow$ Post-outbreak & Pre - "extraordinary situation"
- Phase 3: March 16 - April 27 $\longrightarrow$ Post - "extraordinary situation"

Our main interest is in the coefficient β on the interaction between $Lang_c$ and D_t. This captures the differential evolution of mobility in areas with different languages, as a proxy for cultural values, over the different phases. Note that Phase 1 is excluded as the reference. $\mathbf{X}_{ct}$ is a vector of controls that includes average monthly temperature and log of total COVID-19 cases and fatalities reported in the canton up until day $t-1$, which captures the degree of exposure and the urgency to comply with social distancing measures. To isolate the effect of the culture and to control for factors that maybe correlated with it and may affect the change in mobility, we include interactions between the phase time dummies and all the economic, geographic and demographic controls described in section 3. Additionally we include daily fixed effects θ_t and canton fixed effects α_c to account for difference in mobility levels across cantons and the the common evolution of mobility in all cantons in any give day. Similar to Durante et al. (2020), the identifying assumption for (1) comes from the fact that after controlling for canton observable and unobservable time invariant characteristics, severity of the pandemic at the cantonal level and daily changes in mobility at the country level,

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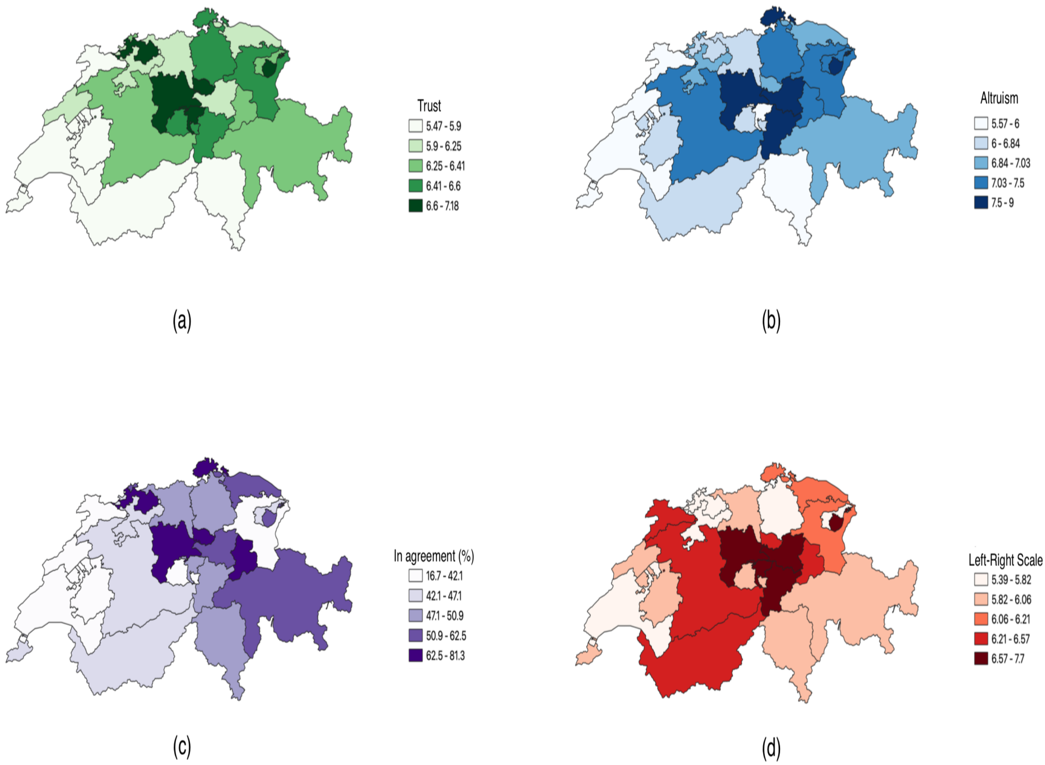

Figure 2: Panel (a),(b) - Distribution of measures of trust. Panel (c),(d) - Preferences for redistribution and political positioning

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the differential change in mobility in German and French speaking cantons is unrelated to factors other than the ones explicitly controlled for.

While equation (1) provides us with the first insight in to the significant mobility differences across the German and French speaking region, to further examine the role of specific *dimensions* of culture, we estimate:

$$Y_{ct} = \alpha_c + \theta_t + \gamma \, Dim_c \times D_t + \delta \mathbf{X}_{ct} + \epsilon_{ct} \tag{2}$$

All the variables in (2) are the same as (1) with the exception of Dim_c which reflects one of the cultural dimensions - generalized trust towards others and preferences for redistribution. As discussed in section 3, Dim_c is a dummy variable taking on one of the four indicators capturing these dimensions and our main coefficient of interest is γ. Finally, to understand the possible mechanism driving our results we estimate a modified version of (2). Instead of looking at one cultural dimension at a time, we introduce a triple interaction between the two dimensions - trust in others and political position on the left-right scale - and the phase time dummies.

$$Y_{ct} = \alpha_c + \theta_t + \phi \, Trust_c \times Political\ Position_c \times D_t + \delta \mathbf{X}_{ct} + \epsilon_{ct} \tag{3}$$

5 Results

Figure 3 shows the relationship between mobility and linguistic regions using the raw data.[6] In the weeks prior to the outbreak, cantons in both linguistic regions displayed more or less similar mobility patterns. Soon after the first case was reported we can observe elements of divergence. Although there is a marked drop in mobility for both areas, there is a clear difference between the two, especially in phase three. After the government declared “extraordinary situation”, in fact, the fall in average distance travelled daily is notably less in German speaking region as compared to the French speaking one. Figure A.2, in the Appendix, shows how the difference, between the two regions evolves over time, and the mean value of the difference for each phase. Note how the average value of the difference becomes positive post-outbreak. This is validated by our results from estimating (1) and the cultural trait indicators provide an explanation as to why we may be

[6]This depiction comprises all the cantons in both the linguistic regions, including the multilingual ones.

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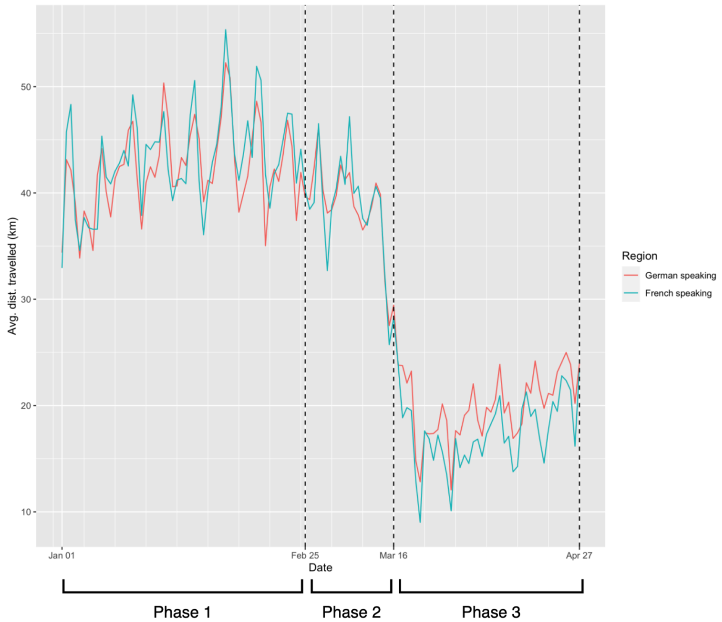

Figure 3: Daily mobility (average distance travelled in a day) across the linguistic regions

observing this behaviour.

Figure 4 shows our main results from (1). We find that during phase two i.e. post-outbreak and pre - "extraordinary situation", the drop in mobility in the German speaking cantons was, on average, around 18 kilometres less than in the French speaking region. The mobility reduction in this phase is indicative of the voluntary compliance of individuals in response to the outbreak. Although this difference reduced in phase three which is post - "extraordinary situation", it continued to remain positive and significant, with German speaking cantons reducing their average mobility by 8 kilometres less than their counterpart. Figure 5 shows average differences in weekly mobility between the two linguistic regions over several phases of the pandemic. The pattern is broadly consistent with that of Figure 3. Prior to the outbreak, there is no significant difference between the German and French speaking cantons but the divergence in mobility patterns becomes significantly positive after the identification of the first COVID-19 case in the country (phase two) and remains significant up until week 13 of phase three.

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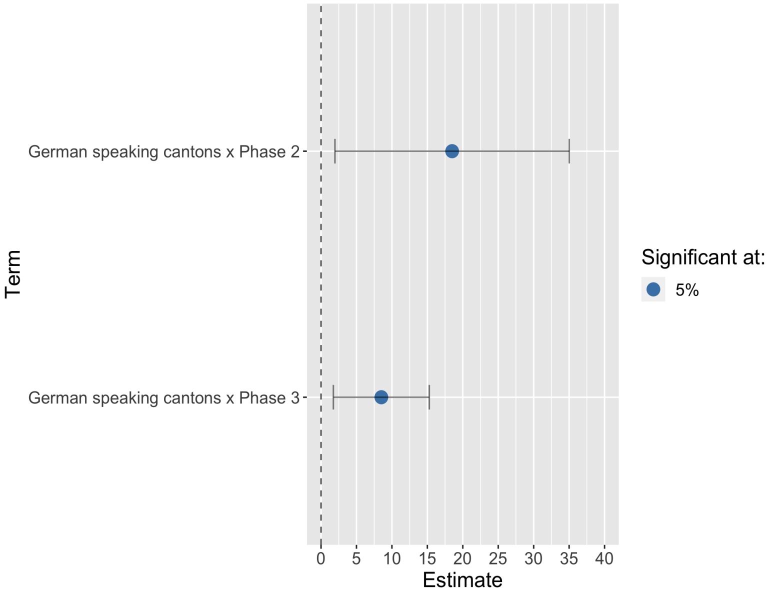

Figure 4: Language as proxy for *culture*. Estimating equation (1) with economic, demographic, geographic and COVID -19 controls. Daily and canton FE. Standard errors are wild bootstrapped and clustered at canton level

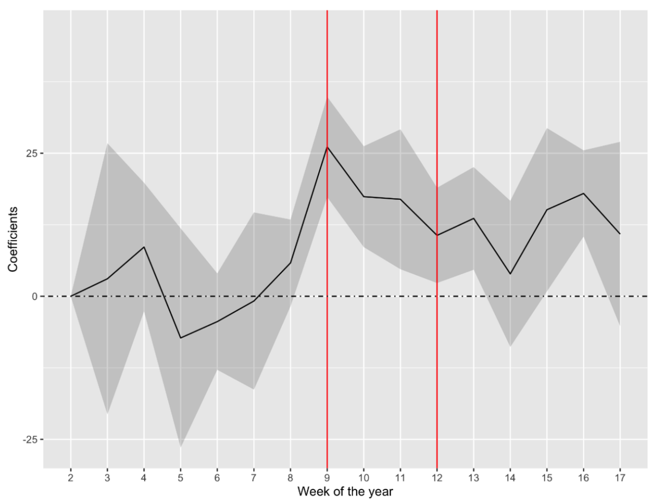

Figure 5: Difference in mobility between German and French speaking cantons. Week 9: 24 February - 1 March. Week 12: 16 March - 22 March. Date of outbreak: 25 February and implementation of federal measures: 16 March

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To further examine which cultural traits may be contributing to this divergence, we estimate (2). Figure 6 depicts the results for the first cultural dimension, generalized trust towards others. We find that after the introduction of federal measures, in cantons with higher trust in others, the mobility decline was around 6 kilometres less than in the low trusting cantons. Similarly, for phase two and three of the pandemic, cantons with higher altruistic beliefs reduced their mobility by 12 and 8 kilometres less than cantons with lower altruistic beliefs. Figure 7 shows the results for the second cultural dimension, preferences for redistribution. Cantons which are more accepting of inequality and position themselves towards the political right, reflecting the diffusion of individualistic attitudes in the society, reduced their mobility significantly less than their counterparts. In the right leaning cantons, for both phase two and three, the mobility reduction was approximately 6 kilometres less than in the left leaning cantons. We show the average differences in weekly mobility for each of these cultural indicators in Figure A.3. In the Appendix, section B, we show further robustness checks.

6 Discussion and mechanisms

Our results show the existence of significant differences concerning the evolution of mobility in the German and French speaking cantons. Cultural values and beliefs may provide an insight into the divergence in mobility patterns between the two linguistic regions. Observe in Figure 2, cantons with higher generalized trust towards others and politically right leaning with stronger stance against re-distributive social policies, tend to broadly fall in the German speaking linguistic region. Individuals living in these cantons may believe that even while travelling, fellow citizens will behave responsibly by following social distancing and hygiene rules, reducing the benefit of limiting individual mobility as meeting strangers and acquaintances involves a relatively lower (perceived) risk of contracting the disease. Additionally, their attitude towards income differences and poverty may reflect their position on the role of state and the fact that the population is likely to be more uncomfortable with public decisions entailing severe limitations of personal liberties to preserve the social welfare. This is also reflected in a recent public survey where a third of Swiss Germans believed that the closing of shops and establishments of personal services was too extreme, against

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18% of Swiss French.[7] It is also of interest to note that many cantons within the German linguistic region are the stronghold of The Swiss People's Party also known as the Democratic Union of the Centre (SVP/UDC), which has consistently won the largest share of votes in the national council since 1999. Ideologically the party stands for the rejection of the expansion of the welfare state, lower taxation and was extremely critical and vocal during the pandemic to reopen the economy.

As discussed in the introduction, a part of our results is at odds with the recent work on civic capital and mobility, and especially the results by Brodeur et al. (2020) who show high-trust American counties decrease their mobility significantly more than low-trust counties post-lockdown. However, our results on political attitudes and the role of state are broadly consistent with the second finding of Brodeur et al. (2020), that counties with relatively more self-declared democrats decrease significantly more their mobility. To understand the possible mechanism driving our results we estimate (3) as displayed in Figure 8. Instead of looking at one cultural dimension at a time, we introduce a triple interaction between the two cultural dimensions - trust in others and political position on the left-right scale - and the phase time dummies. This allows us to gauge the heterogeneity present in our results. Figure 8 shows that, during both phases of the pandemic, the effect of higher trust in others, on average daily mobility, is significant and *positive* for right leaning cantons compared to the left leaning cantons where it is *negative* and significant. This provides some preliminary insight into the the fact that it may have been a combination of higher interpersonal trust and conservative political attitude that shaped the lower reduction in mobility in the German speaking cantons. This emphasizes the fact that the same cultural traits may elicit different responses under a crises situation such as a pandemic and that understanding the country specific context is crucial to policy implementation. It is extremely telling that the Swiss government did not impose any stringent lockdown like several other European countries and even while preparing for a possible second wave the government is against imposing nationwide lockdown restrictions.

[7]This survey was carried out by Sotomo research institute and more information can be found on: https://www.rts.ch/info/suisse/11314737–coronagraben-quand-romands-et-alemaniques-ne-vivent-pas-la-meme-crise.html

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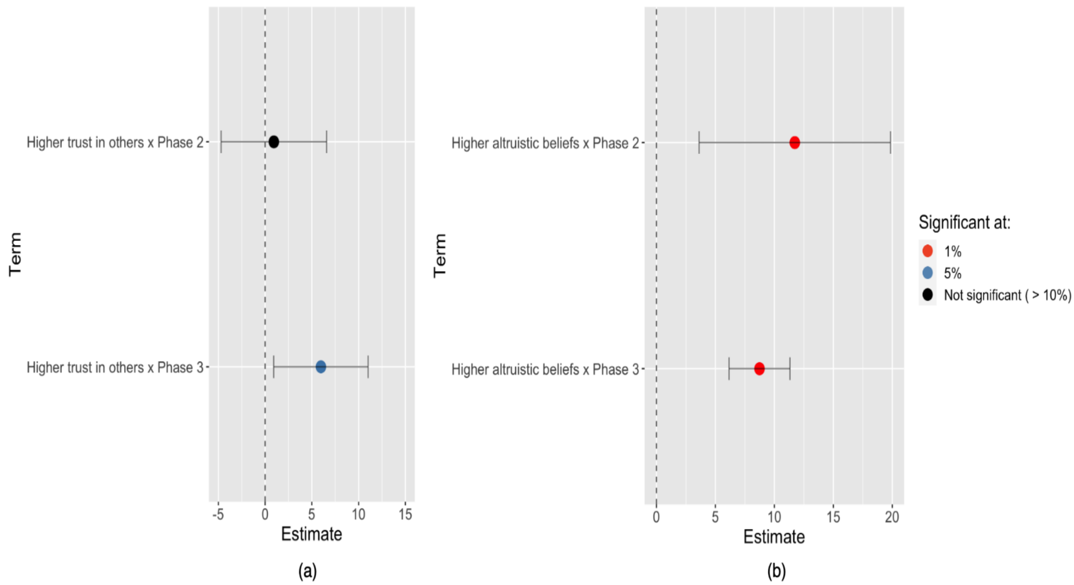

Figure 6: Cultural *dimension*: Generalized trust towards others. Estimating equation (2) with economic, demographic, geographic and COVID -19 controls. Daily and canton FE. Standard errors are wild bootstrapped and clustered at canton level

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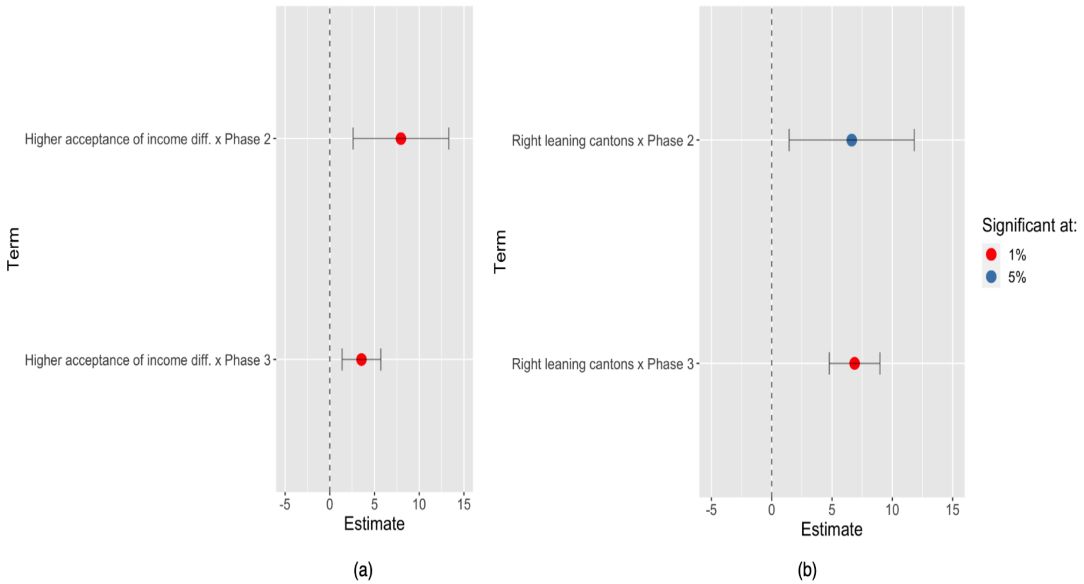

Figure 7: Cultural *dimension*: Preferences for redistribution. Estimating equation (2) with economic, demographic, geographic and COVID -19 controls. Daily and canton FE. Standard errors are wild bootstrapped and clustered at canton level

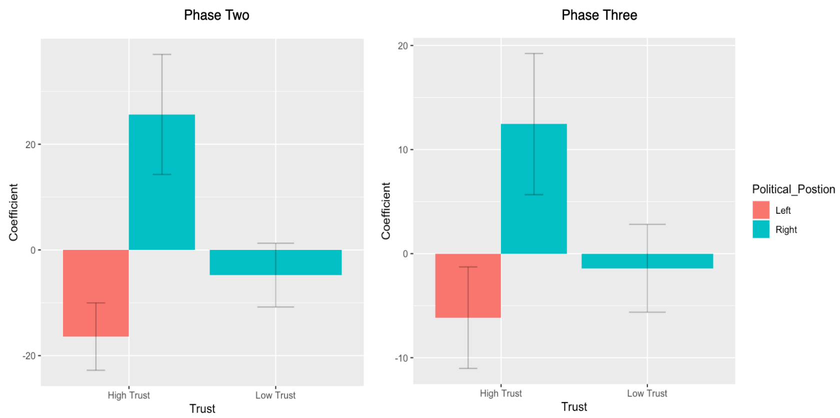

Figure 8: Heterogeneity across the the cultural dimensions. Estimating equation (3) with economic, demographic, geographic and COVID -19 controls. Daily and canton FE. Standard errors are wild bootstrapped and clustered at canton level

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7 Conclusion

Rarely in history have we witnessed such homogeneous policy response to shocks as in the case of the COVID-19 pandemic. In an attempt to contain the spread of the virus and reducing the load on the healthcare system, virtually all countries have adopted restrictive measures aimed at reducing individual mobility and inducing social distancing. Interestingly, however, the rate of compliance to such measures has varied enormously. This paper examines to what extent cultural differences can explain these variations. We focus on a specific set of cultural dimensions that might have shaped the actual adherence to social distancing in Switzerland, a country characterized by cultural differences that vary across its cantons. More precisely, we examine the relationship between average distance travelled in a day and language, trust, altruistic beliefs, political leaning and preferences for re-distributive policies. We document how the Swiss reduced their mobility first as a (voluntary) response to the outbreak in Ticino and Geneva during the last week of February and later in response to the federal measures introduced by the government on March 16. This reduction, however, was lower in German cantons than in French speaking areas of the country. We also document how specific cultural traits, can shape individual mobility decisions. Our results suggest that the perceived costs and benefits of complying to individual mobility restrictions norms change with culture. As a consequence, contextual conditions, shaped by the culture of reference, are of critical importance in determining how traits such as interpersonal trust, preference for re-distributive policies and political attitudes, mediate the social distancing process.

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Appendix

A Figures & Tables

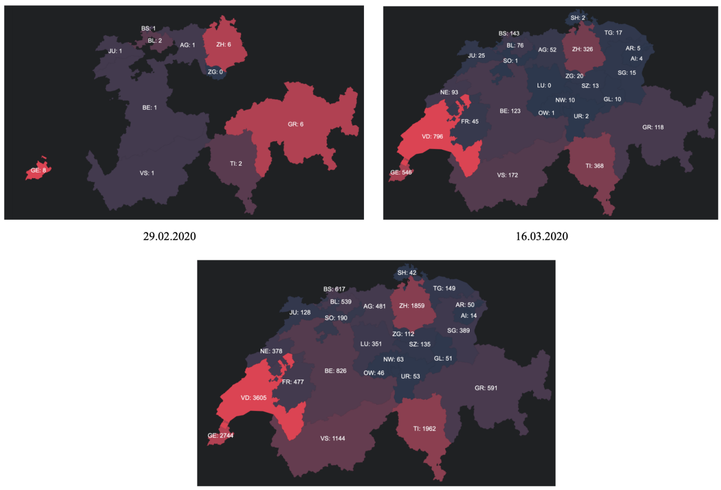

Figure A.1: Evolution of total COVID-19 cases reported

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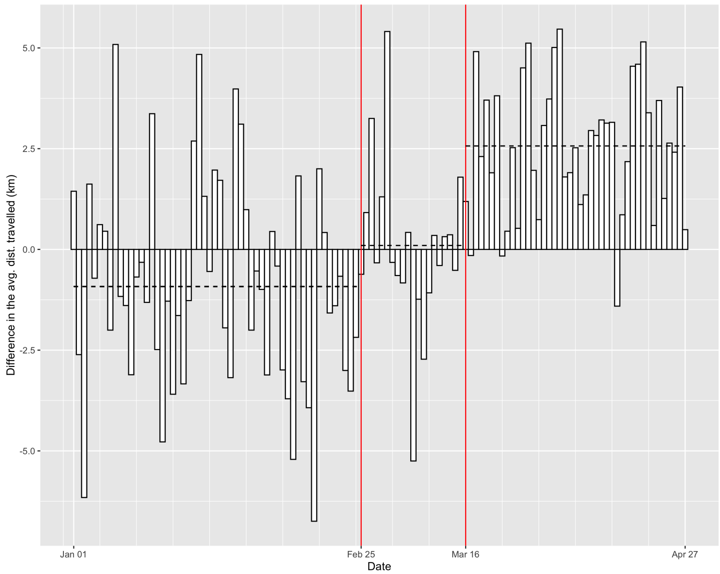

Figure A.2: Difference in mobility. The dashed lines are the period means.

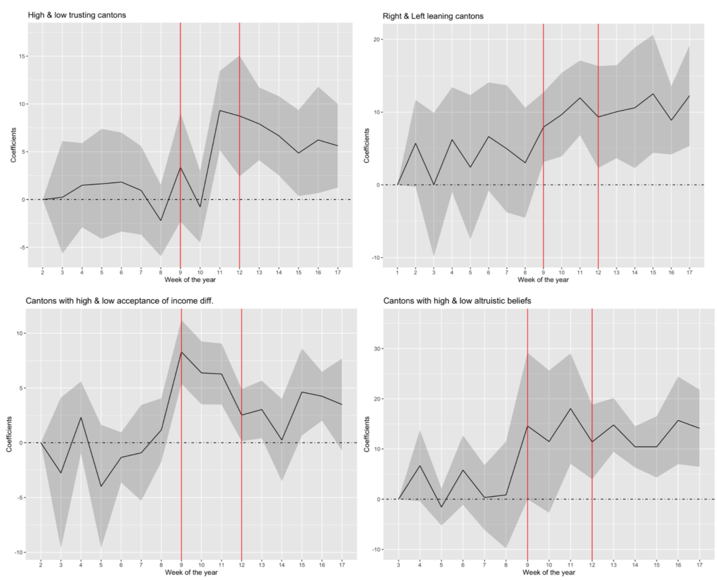

Figure A.3: Average difference in weekly mobility (Average distance travelled daily). Week 9: 24 February - 1 March. Week 12: 16 March - 22 March. Date of outbreak: 25 February and implementation of federal measures: 16 March

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Table A1: Summary Statistics

	N	Mean	St. Dev.	Min	Median	Max
Avg. distance travelled (km)	2,457	33.181	16.348	0.049	32.663	131.405
Daily total reported cases	2,457	242.025	776.836	0	0	5,222
Daily total fatalities	2,457	8.555	35.690	0	0	373
Avg. monthly temperature (°C)	2,457	4.397	4.291	−2.260	5.460	11.790
Urban population (%)	2,457	76.352	25.070	0	85	100
Hospital beds per 1000 inhabitants	2,457	4.148	2.251	1.300	3.800	11.100
Graduation rate in higher education institutions	2,457	27.290	4.148	19.900	26.500	34.300
Foreign nationals (%)	2,457	23.043	7.455	11.300	24.100	40.000
Population density	2,457	611.386	1,124.819	34.500	275.000	5,271.100
Tourism (in 1000)	2,457	544.143	761.769	65	208	3,299
Share of people aged 65 and over (%)	2,457	18.881	1.583	16.400	19.000	21.900
GDP per capita in Swiss francs	2,457	79,695.330	31,751.090	52,468	68,102	185,826
Area in km^2	2,457	881.790	743.746	36.980	790.370	3,212.210
Trust toward others	2,457	6.346	0.407	5.610	6.404	7.179
Trust in institutions	2,457	6.315	0.250	5.885	6.278	6.873
Frequency of interpersonal relations	2,457	0.685	0.102	0.500	0.684	0.870
Altruistic beliefs	2,457	6.926	0.851	5.632	6.981	9.000
Avg. time watching, reading or listening to news	2,457	151.838	126.889	47.143	87.145	530.000
Left - right scale	2,457	6.249	0.570	5.393	6.133	7.700
Share of agreement for statement on income diff. (%)	2,457	51.654	13.860	16.667	50.000	81.250
Household disposable income	2,457	78,897.670	10,175.900	62,001.800	78,291.820	102,216.800

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B Robustness Check

In Figure B.4 we show results from estimating (1) and (2) but using an alternative measure for mobility. Our dependent variable is now average radius of daily travel. Observe, although the difference in reduction of daily mobility between the two linguistic regions is not significantly very different in phase two, it becomes strongly significant in phase three. Post federal measures, the German speaking region reduced their radius of daily travel by 5 kilometres less than the French speaking area. This is also clearly visible in the raw data in Figure B.5, where there is a marked difference in the mobility levels of the two regions after March 16. Consistent with our main results, when comparing regions across different cultural dimensions we observe a similar trend. Cantons having higher trust, altruistic beliefs and conservative political ideologies reduced their radius of daily travel by less when compared to other areas. Figure B.6, similar to Figure 5 and A.3, shows average differences in weekly radius of daily travel between the two regions, over several phases of the pandemic, and confirms that there wasn't a significant difference in the mobility patterns prior to the outbreak. However, post February 25 and the introduction of federal measures, one can observe a significant and positive change.

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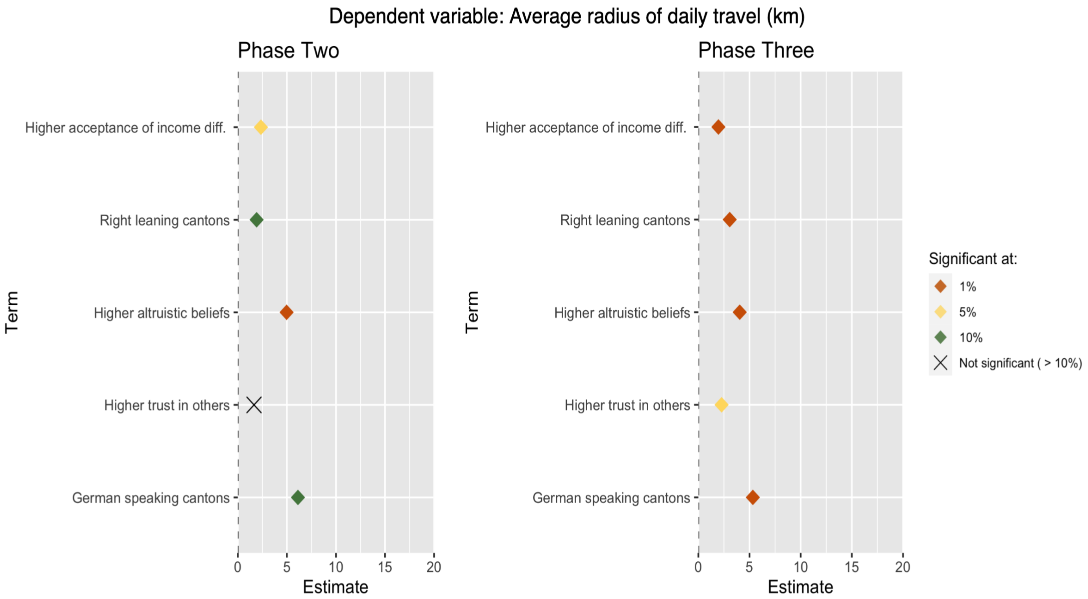

Figure B.4: Economic, Demographic, Geographic and COVID -19 Controls. Daily and Canton FE
Note: Standard errors are wild bootstrapped and clustered at canton level

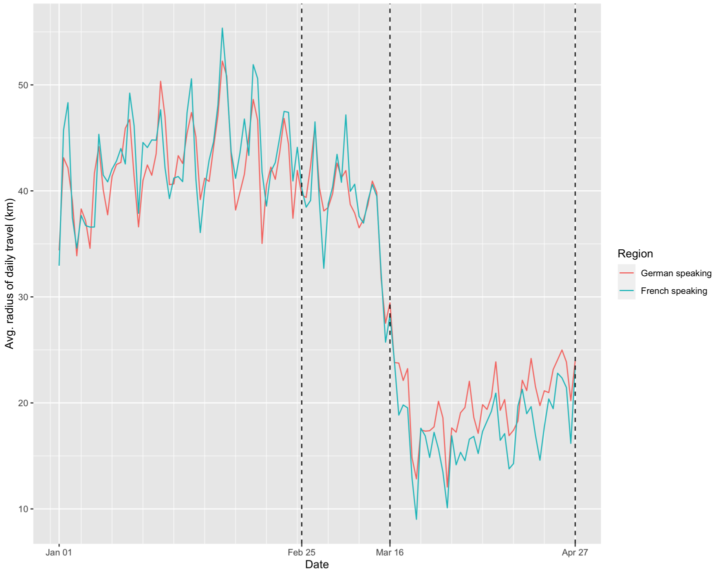

Figure B.5: Daily mobility (average radius of daily travel) across the linguistic regions

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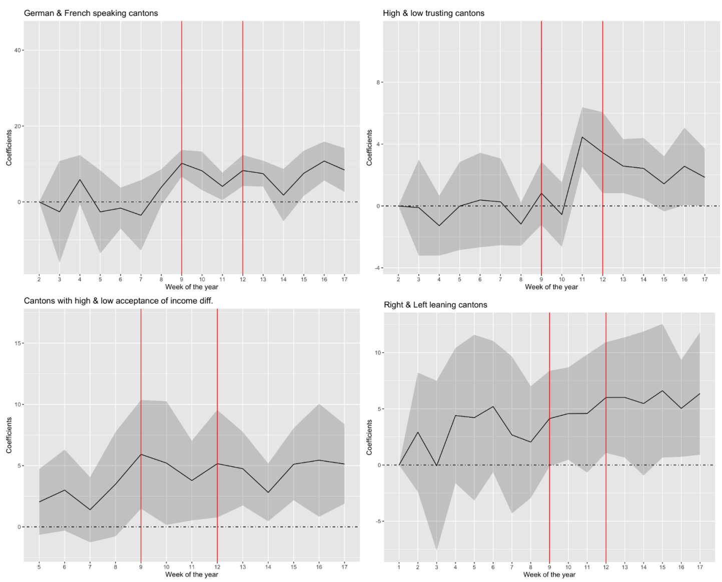

Figure B.6: Average difference in weekly mobility (Average radius of daily travel). Week 9: 24 February - 1 March. Week 12: 16 March - 22 March. Date of outbreak: 25 February and implementation of federal measures: 16 March