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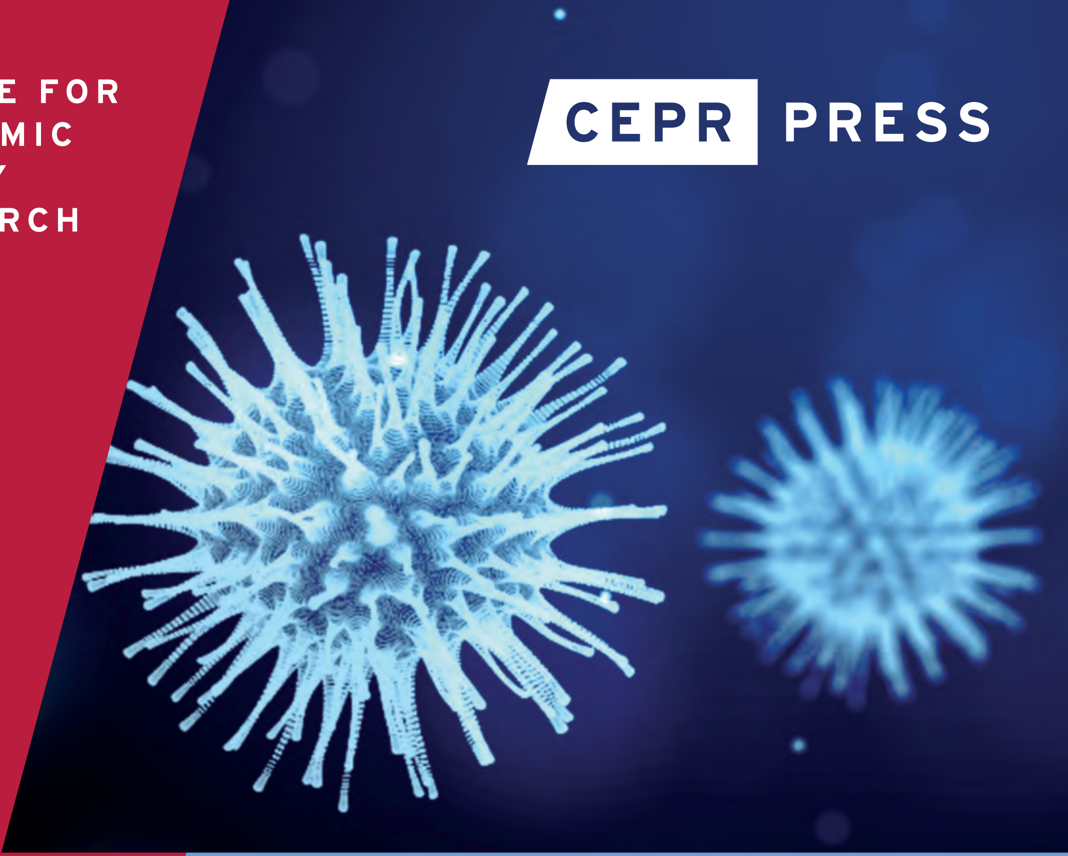

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 22
26 MAY 2020

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

Economic Journal

Economics of Disasters and Climate Change

International Economic Review

Journal of Development Economics

*Journal of Econometrics**

Journal of Economic Growth

Journal of Economic Theory

*Journal of the European Economic Association**

Journal of Finance

Journal of Financial Economics

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*Journal of Labor Economics**

Journal of Monetary Economics

Journal of Public Economics

Journal of Political Economy

Journal of Population Economics

*Quarterly Journal of Economics**

Review of Economics and Statistics

*Review of Economic Studies**

Review of Financial Studies

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

Covid Economics
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Issue 22, 26 May 2020

Contents

Covid Economics **Issue 22, 26 May 2020**

How should policy responses to the Covid-19 pandemic differ in the developing world?[1]

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Date submitted: 22 May 2020; **Date accepted:** 23 May 2020

The COVID-19 pandemic has already led to dramatic policy responses in most advanced economies, and in particular sustained lockdowns matched with sizable transfers to much of the workforce. This paper provides a preliminary quantitative analysis of how aggregate policy responses should differ in developing countries. To do so we build an incomplete-markets macroeconomic model with epidemiological dynamics that features several of the main economic and demographic distinctions between advanced and developing economies relevant for the pandemic. We focus in particular on differences in population structure, fiscal capacity, healthcare capacity, the prevalence of "hand-to-mouth" households, and the size of the informal sector. The model predicts that blanket lockdowns are generally less effective in developing countries at reducing the welfare costs of the pandemic, saving fewer lives per unit of lost GDP. Age-specific lockdown policies, on the other hand, may be even more potent in developing countries, saving more lives per unit of lost output than in advanced economies.

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Covid Economics 22, 26 May 2020: 1-46

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Covid Economics 22, 26 May 2020: 1-46

1. Introduction

Governments in most advanced economies have responded to the COVID-19 pandemic with dramatic and unprecedented policy responses. Huge swaths of the economy have been ordered shut down and millions of workers required to stay home indefinitely. To cushion against the loss of income, governments have sent direct transfers to workers affected by the lockdowns, in addition to making regular social insurance payments. Unemployment benefits, in particular, have reached levels many times larger than at any prior point in history. The total costs of these and other transfers may even reach 10 percent of GDP in some countries.

As COVID-19 made its way to less-developed countries, policy makers there largely followed suit with similarly sweeping lockdowns. Yet it quickly became clear that policy responses in the developing world could not just mimic those of the west. Policy would instead have to be tailored to the dramatically different economic and demographic landscape that characterizes most low-income countries. Governments in these countries lack the fiscal capacity to make substantial transfers to major segments of the population for long periods. Moreover, high levels of poverty mean that many households are effectively living hand-to-mouth, rendering prolonged lockdowns economically infeasible. Large informal sectors make lockdown enforcement much harder, and expanding the tax base nearly impossible. The potential health consequences of the pandemic are also quite distinct from those of the west, which has an older and more susceptible population but substantially more developed healthcare systems.

This paper provides a preliminary quantitative analysis of how policy responses to the COVID-19 pandemic should differ in developing countries. We focus on broad aggregate economic policy, meaning over the extent and duration of lockdowns and transfers, including the extent to which either should be age-specific. We also illustrate how the fiscal and healthcare capacity constraints interact with informality and the younger demographics to inform optimal policy responses relative to advanced economies of the west. The analysis is preliminary largely because the requisite data are not available yet to draw firmer conclusions, though data is being collected in developing nations at an unprecedented rate, which will soon better inform analyses such as the current one.

To study how aggregate policy should differ in developing and advanced economies, this paper follows the newly emerged literature on the macroeconomics of pandemics by combining a workhorse macro model with a variant of the SIR model standard in epidemiology. The model in this paper builds most closely on the framework of Glover, Heathcote, Krueger, and Ríos-Rull (2020), and in particular their tractable model of heterogeneous agents that face income shocks and health risk that varies by age. In addition, our model features fiscal capacity constraints –

Covid Economics 22, 26 May 2020: 1-46

motivated broadly by the work of Besley and Persson (2009), Jensen (2019) and many others – which reduce the ability of governments to tax and transfer resources across households. It adds an "informal sector" as in Ulyssea (2018) and a large development literature, and worker sorting on skill as in Roy (1951) and following the specification of Feng, Lagakos, and Rauch (2018). We allow for hand-to-mouth consumers, which is the emphasis of Kaplan, Moll, and Violante (2020), and healthcare capacity constraints as in the recent macroeconomic literature on the pandemic. We model the epidemiological dynamics in the model using a variant of the SICR model that is standard in the epidemiology literature, combined with economic choices that govern the disease path endogenously, as in the macroeconomic literature on disease transmission (e.g. Greenwood, Kircher, Santos, and Tertilt, 2019; Eichenbaum, Rebelo, and Trabandt, 2020; Guerrieri, Lorenzoni, Straub, and Werning, 2020; Alvarez, Argente, and Lippi, 2020; Chang and Velasco, 2020).

We parameterize the model to match the pre-pandemic stationary distribution of a representative advanced economy, calibrated to match characteristics of countries in the top quartile of the world income distribution. We then compute the model's equilibrium response to the COVID-19 pandemic as a surprise "MIT shock" where a small exogenous fraction of the population becomes infected with the coronavirus, and the disease then makes its way through the populous. We then do the same for an alternative calibration of the model taken to match a representative developing economy, representing averages of the lowest-income quartile of countries. We match in particular the substantially lower population share of the old, the lower fiscal and healthcare capacity, the larger informal sector, and greater proportion of hand-to-mouth households. We then simulate the effects of various types of lockdowns in the advanced and developing economies and compare their impacts on GDP, fatalities, and consumption-equivalent welfare.

The model predicts that blanket lockdowns (affecting the entire population) are not as effective in developing countries as in advanced countries. In particular, blanket lockdowns do less to reduce the welfare costs of the COVID-19 pandemic in developing countries, and save fewer lives per unit of lost GDP. For example, in the developing economy, a medium length blanket lockdown lasting 28 weeks saves around 70 lives per hundred thousand at the cost of a 7 percent decline in GDP. Thus, for every unit of GDP lost, the policy saves 10 lives per hundred thousand people. The same length blanket lockdown in the advanced economy reduces GDP by 16 percent and saves around 320 lives per hundred thousand people, amounting to 20 lives saved per hundred thousand for every lost unit of GDP. By this metric, developing countries save about half as many lives per unit of economic output lost as advanced economies. Using a consumption equivalent welfare metric, the lockdown in the advanced economy raises welfare by around 3 percent, compared to just 0.6 percent in the developing economy. We find that lockdowns that are shorter or longer are less effective, though still better than having no lockdown at all.

Blanket lockdowns in our model have sharply differing impacts across young and old households, just as in the work of Glover et al. (2020), Bairoliya and Imrohoroglu (2020), Acemoglu, Chernozhukov, Werning, and Whinston (2020) and others. Older households gain a lot more from lockdowns, since they have the greatest reduction in fatality risk. We find, in fact, that these heterogeneous impacts are even starker in developing economies, pointing to a potential role for age-specific lockdowns there as well. We therefore simulate the role of age-specific lockdowns that require that just older individuals remain in lockdown, and with larger transfers to each old individual such that the total amount spent on transfers is the same as under the blanket lockdown policies studied above.

Our model predicts that age-specific policies are even more potent in developing countries than in advanced economies. A medium-length age-specific lockdown saves around 95 lives per hundred thousand for every lost unit of GDP, which is twice as much as in advanced economies, and ten times as much as under blanket lockdowns in developing economies. The reason is that age-specific policies allow governments to isolate only those with the highest fatality risk, and to provide them with larger transfers than under blanket lockdowns. This is particularly attractive in developing countries, since older individuals reflect such a small share of the total population there. Overall, the quantitative analysis in this paper points to age-specific lockdowns as the most promising form of lockdown for developing countries, though of course many logistical issues are still open.

There are many aspects of developing economies that we have not modeled in this paper, and many of these are surely relevant for the study of optimal responses to the COVID-19 pandemic. Differential testing and tracing policies (Berger, Herkenhoff, and Mongey, 2020) are absent here but surely worth studying. Our model also abstracts from differential impacts by gender (Alon, Doepke, Olmstead-Rumsey, and Tertilt, 2020), policy uncertainty (Baker, Bloom, Davis, and Terry, 2020), and stock-market impacts (Toda, 2020), as well as differences in sanitation, living conditions and co-morbidities that may affect fatality rates. Perhaps the most conspicuous absences are open-economy considerations, given that developing countries are already witnessing negative impacts from capital outflows, and the effects of the decline in natural resource prices, which further depress fiscal space. We plan to add both of these to our analysis in the future, and other papers are already doing the same, in particular Çakmakh et al. (2020), who study the effects of COVID-19 in Turkey.

Covid Economics 22, 26 May 2020: 1-46

2. Motivating Facts for Differing Policy Responses in Developing Countries

We begin by summarizing four important demographic and economic characteristics that differ across countries in ways that we view as essential for understanding how policy responses to COVID-19 should differ in developing economies. These are: (i) the much younger populations in developing countries, (ii) their lower fiscal capacity, (iii) their more widespread informality, and (iv) their lower healthcare capacity. To be sure, all of these patterns are already known in some form or another. The goal of this section is to present these patterns in a systematic way and briefly highlight their relevance for the effects of the pandemic, which will help motivate the model and quantitative analysis that follows.

2.1. Younger Populations

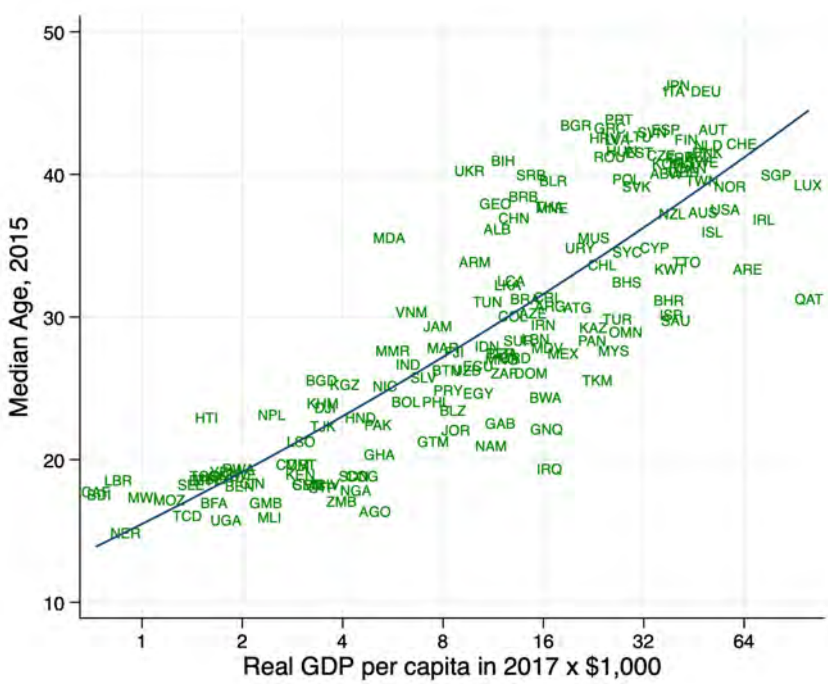
All available evidence so far suggests that COVID-19 poses dramatically different health risks to older individuals, in particular those over the age of 65. Early centers of infection in the west, such as Italy, experienced health impacts concentrated on those in this older age range, with particularly severe fatality rates for those in their 80s and 90s. At the same time, the number of deaths linked to COVID-19 for those under 20 has been negligible, though certainly not zero.

A basic demographic difference between advanced and developing economies is that populations are far younger in the developing world. Since fatality rates from COVID-19 are very low for young individuals but rise sharply with age, these demographic differences suggest much smaller populations of vulnerable individuals in the developing world. One can see these demographic differences starkly when looking at cross-country data on the median age. Figure 1 plots the median age against GDP per capita in a set of 158 countries using data from UN Population Division and Penn World Tables. Data from the UN Population Division show that countries in the bottom quartile of the world income distribution have a median age of 19.1 years. Nigeria, Africa's most populous country, has a median age of 17.9, while countries like Angola and the Democratic Republic of the Congo have median ages of just 16.4 and 16.8 years old. By contrast richer countries like Italy, the United Kingdom and France have median ages of 45.9, 40.2 and 41.2, respectively.

Covid Economics 22, 26 May 2020: 1-46

Covid Economics 22, 26 May 2020: 1-46

Figure 1: Median Age of the Population



Note: This figure plots the median age in 2015 across 158 countries. Median age is defined as the age that divides the population in two parts of equal size, that is, there are as many persons with ages above the median as there are with ages below the median. GDP per capita is expressed at PPP and taken from Penn World Table 9.1 (Feenstra et al., 2015). Median age data is from the UN Population Division.

Another statistic indicative of the much smaller vulnerable population in the developing world is the cross-country data on the population above 65. Figure A.1 plots the fraction of the population that is above 65 against GDP per capita in a set of 162 countries using data from the World Bank and the Penn World Tables. In the world's poorest countries the fraction of the population that is above age 65 is negligible, with an average of around 3 percent for countries in the bottom quartile of the world income distribution. The older population is much larger as a fraction of the total in richer economies, and reaches around one quarter of the population in Japan. Among countries in the topic quartile of the world, the average is about 15 percent of the population being above age 65.

It is hard to look at statistics like these and not see how sharply different the impacts of COVID-19 will be in less developed countries. Concretely, while almost everything about COVID-19 suggests a more severe impact in less-developed countries, the far younger demographic is clearly in their favor. In the model that we present in the following section, we reserve a central role these sharp demographic differences, and we explore how important age differences are for optimal policy responses to the pandemic.

2.2. Lower Fiscal Capacity

Developed nations take for granted the ability for their governments to raise tax revenues and use the proceeds to provide public goods and make transfers. This fiscal capacity is not shared by the public sectors in developing countries, as a long literature has emphasized (see Besley and Persson, 2013, for an overview). This literature has emphasized how developing nations generally lack the ability to monitor and enforce tax payments from its citizens, and have less efficient revenue authorities than do richer countries.

As a crude, but widely used, measure of fiscal capacity across countries, Figure 2 plots total tax revenues as a fraction of GDP taken from the ICTD Government Revenue Dataset against GDP per capita. The nearly linear positive relationship between taxation relative to GDP and income per capita highlights the much lower role that taxation plays in less developed economies. Similar patterns have been observed in the time series for countries as they develop and increase rates of taxation, particularly on labor income (Besley and Persson, 2013; Jensen, 2019). Although these patterns don't prove that developing economies have larger hurdles in raising tax revenue and spending public funds effectively – as opposed to just choosing to tax less – they are certainly consistent with the interpretation of lower fiscal capacity given by the literature, and taken in this paper.

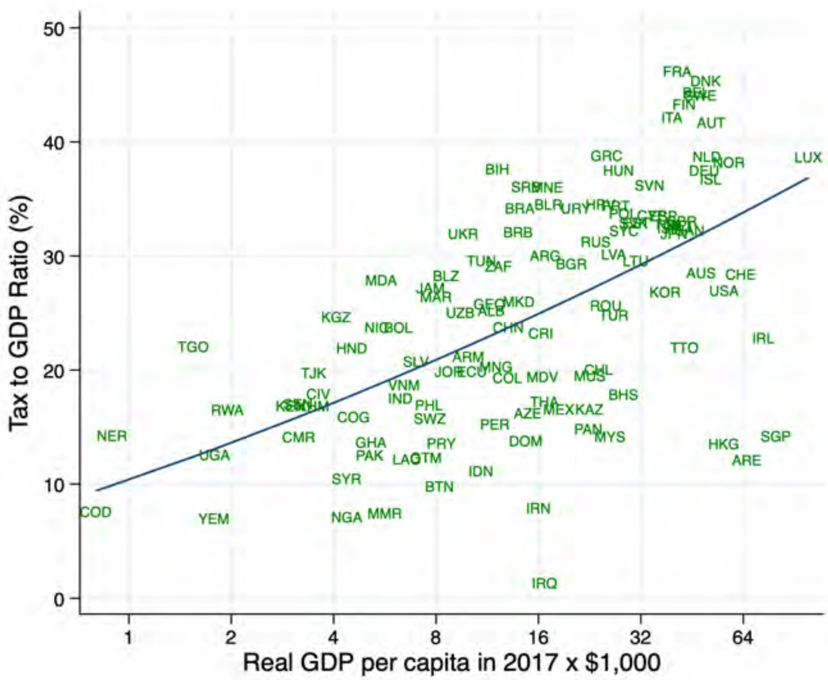
The lower fiscal capacity in poorer countries is relevant for studies of the pandemic for several reasons. Most importantly, it limits the ability of governments to institute large-scale income replacement programs for furloughed workers during lengthy lockdowns or in response to widespread business closures. Not receiving any payments is a clear disincentive for citizens to comply with a lockdown, especially for those that have little savings to fall back on. In addition, the inability to raise taxes effectively limits governments' ability to borrow, which further reduces their ability to make payments to furloughed workers. Other types of fiscal policy, such as Keynesian stimulus spending, are also limited by low fiscal capacity.

2.3. Larger Informal Sectors

A large share of employment in developing countries is concentrated in informal production activities. By definition, such markets are beyond the purview of the state to tax or regulate, and make law enforcement difficult. Lockdown policies, which call for citizens not to leave

Covid Economics 22, 26 May 2020: 1-46

Figure 2: Fiscal Capacity, Proxied by the Ratio of Taxes to GDP



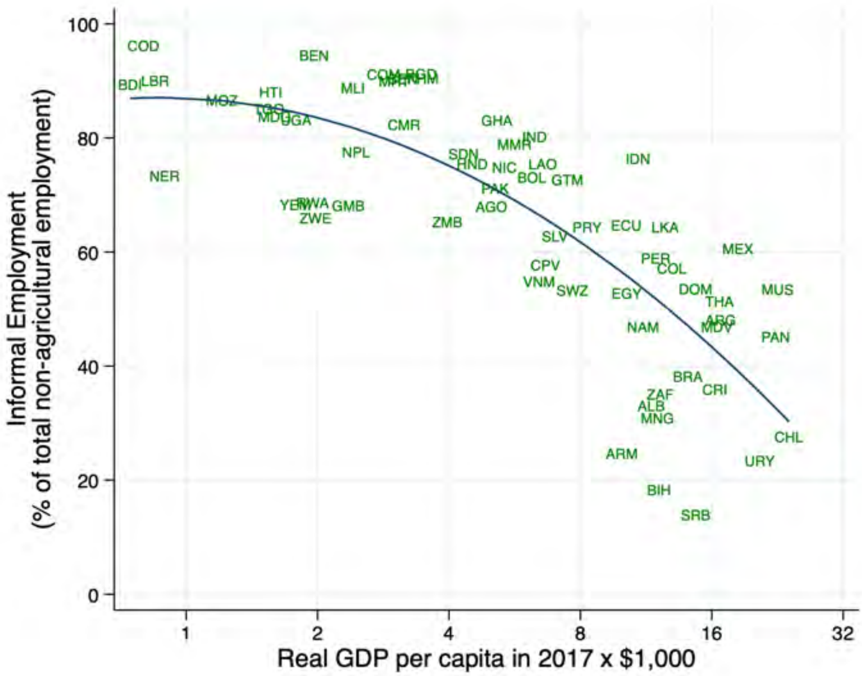
Note: This figure plots the ratio of taxation to GDP ratio across 116 countries. Tax revenues including social contributions. GDP per capita is expressed at PPP and taken from Penn World Table 9.1 (Feenstra et al., 2015). Tax revenue data is from the ICTD / UNU-WIDER Government Revenue Dataset 2019 (ICTD/UNU-WIDER, 2019).

home for work or for other public interactions, are difficult to enforce anywhere. Clearly, enforcing lockdowns is even harder in an environment with only a minority of the workforce employed at formal businesses.

While few would disagree that informality is more prevalent in less developed economies, measuring informality is not a straightforward enterprise. Figure 3 plots the size of the informal sector as a fraction of non-agricultural employment, as measured by the International Labor Organization (ILO), against income per capita. The ILO defines informal workers as those that produce goods or services meant for sale or barter. Self-employed street vendors, taxi drivers and home-based workers, regardless of size, are all considered informal workers. Excluded are agricultural and related activities, as are any households producing goods exclusively for their own use (e.g. subsistence farming, domestic housework, care work, and employment of paid

Covid Economics 22, 26 May 2020: 1-46

Figure 3: Size of the Informal Sector



Note: This figure plots the employment in the informal economy, measured by the ILO, as a percentage of total non-agricultural employment, in 63 countries. The informal economy is defined as in the text. GDP per capita is expressed at PPP and is taken from the Penn World Table 9.1 (Feenstra et al., 2015). Informality data is from the ILOSTAT database.

domestic workers), and volunteer services.

Figure 3 shows a sharp decline in informality rates in non-agricultural activities with GDP per capita. The countries with the lowest income have informality rates above 80 percent in most cases. The richest countries in this ILO database have informality rates below half in most cases, though this figure excludes most of the richest countries in the world, which undoubtedly have even lower rates of informality. A related statistic, for which data is readily available for almost every country in the world, is the fraction of the workforce that is self-employed. This fraction, which we plot in Appendix Figure A.2, runs from close to the entire workforce in the poorest countries to virtually none of it in the richest countries. This well-known pattern reinforces the fact that employment takes on a very different form in poorer countries, with own-account workers and family businesses being the dominant source of labor inputs.

Covid Economics 22, 26 May 2020: 1-46

An obvious way in which informality ties the hands of governments in low-income economies is that it reduces their ability to collect additional taxes and make transfers to those in lockdown. The widespread informality and limited fiscal capacity are of course very closely linked, with each reinforcing the other. During the pandemic, any attempts to keep households in lockdown may result in increases in the size of the informal sector, which may hurt attempts to control disease or raise new revenues.

A related feature of the informal sector relevant for policy responses to the pandemic is the concentration of low-skilled jobs there. To the extent that lockdown policy forces desperate workers that have run down their savings to enter the informal sector, these workers can be expected to perform marginal tasks that do not generate much income. For workers already in marginal tasks in the formal sector, this may not represent much of a change. But for those in more skilled jobs to begin with, having to work in low-skilled informal activities would represent a substantial decline in household income and therefore consumption. If enough workers become desperate and enter the informal sector, this could reduce aggregate productivity and further shrink the government's tax base.

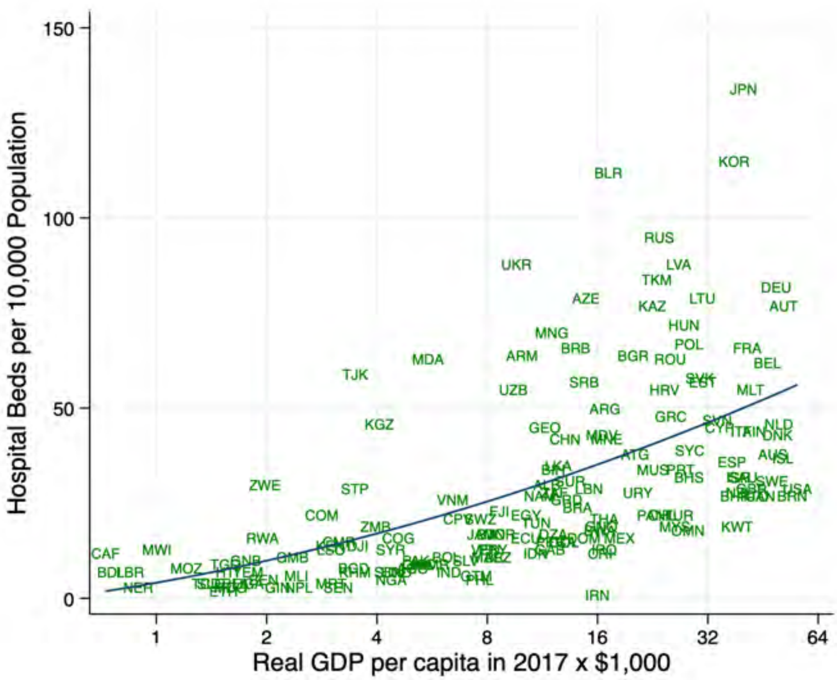
2.4. Lower Healthcare Capacity

Developing countries typically have substantially less ability to control disease than do richer countries. Sanitation and hygiene are more of an issue given the lack of widespread piped water and functioning sewage systems. Health infrastructure, especially hospital and health clinic capacity, is also less developed. For mild cases of COVID-19 infections, this may make little differences, as bed rest is likely to suffice in these mild cases. However, for critical cases, the lack of intensive-care capacity is a clear disadvantage for developing countries in their attempts to save lives during the pandemic.

Figure 4 plots the number of hospital beds per 10,000 people, as reported by the World Health Organization (WHO), against GDP per capita. The number of hospital beds is an imperfect measure of hospital capacity for many reasons, most importantly because it is not a bed per se that helps critical patients recover from COVID-19 but trained doctors, equipment like ventilators, and appropriate pharmaceuticals. Still, for lack of more comprehensive cross-country data, we take hospital beds as a proxy for medical care capacity.

By this metric there are stark differences in healthcare capacity across countries. Richer countries, which have quite some range amongst themselves, average around 49 hospital beds per 10,000 people. Countries like Japan and Korea have even more beds per capita, having 134 and 115 beds per 10,000 people, respectively. This is still far higher than the capacity in developing countries, which is a paltry 12 beds per 10,000 people on average in the bottom quartile of the

Figure 4: Healthcare Capacity, Proxied by Hospital Beds per 10,000 People



Note: This figure plots the number of hospital beds available per 10,000 inhabitants in 153 countries. GDP per capita is at PPP and taken from the Penn World Table 9.1 (Feenstra et al., 2015). The hospital bed data are from the World Health Organization's Global Health Observatory.

income distribution. In Appendix Table B.2, we report the availability of intensive care unit (ICU) beds and per capita healthcare costs across a limited set of countries. Consistent with the patterns observed from the number of hospital beds, it appears that low income countries possess significantly fewer ICU beds than high income countries. Systematic data on ventilators are harder to come by, but the available evidence so far points to even starker differences in ventilator supplies across countries. According to the New York Times, there are fewer than 2,000 working ventilators across 41 African countries, as of April 18, 2020. South Sudan has four ventilators for a population of 11 million, the Central African Republic has three for a population of five million, to name a few. Ten countries in Africa have none at all.[1].

[1]See Maclean, Ruth and Marks, Simon, "10 African Countries Have No Ventilators. That's Only Part of the Problem", April 18, 2020, The New York Times

Covid Economics 22, 26 May 2020: 1-46

Covid Economics 22, 26 May 2020: 1-46

3. The Model

Our analysis draws on a quantitative heterogenous-agent macroeconomic model with epidemiology as in the SICR model to analyze how policy responses to the COVID-19 pandemic should differ in developing countries. The model is equipped with several features that vary between advanced and developing economies that are relevant for the pandemic response, as motivated by the data presented in the previous section. These include uninsurable idiosyncratic health and income risks, age heterogeneity, fiscal capacity constraints, an informal sector, and healthcare capacity constraints. This section now presents these features in detail.

3.1. Households and Preferences

The economy is populated by a unit mass of heterogenous households who make consumption, savings, and sectoral employment decisions subject to idiosyncratic income and health risks. Individuals differ in their age $j \in \{\text{young}, \text{old}\}$, initial assets a, and permanent labor productivity $z \sim G$. Time is discrete and each period represents two weeks. Household preferences are given by:

$$U = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta_j^t \left\{ \log(c_t) + \bar{u} \right\}\right], \tag{1}$$

where $\beta_{\text{young}} < \beta_{\text{old}}$ captures age heterogeneity in the population and $\bar{u}$ represents the flow utility value of being alive. We follow the tractable formulation of Glover et al. (2020) which abstracts from explicitly modeling age, appealing to the logic that pandemics are sufficiently short-lived relative to entire lifetimes. It thus suffices to model only the expected number of years left to live, which is captured by the heterogeneity in discount factors. The term $\bar{u}$ follows the specification of Jones and Klenow (2016), and represents the reason that model households try to avoid fatality risk.

Households can choose to work in either the formal ($s = f$) or informal ($s = i$) labor markets where they can earn wage w_s per effective hour worked. At the beginning of life, workers draw their permanent sectoral productivity, $z \sim G$, and choose occupations as in a Roy (1951) model with one-sided selection. Since work in the informal sector is largely unskilled, we normalize z to unity for this sector so that there is no within sector variation in permanent productivity, as in the specification of Lagakos, Mobarak, and Waugh (2019).

Incomes in both sectors are subject to idiosyncratic productivity shocks as in the Aiyagari-Bewley-Huggett framework (Bewley, 1977; Huggett, 1993; Aiyagari, 1994). Specifically, we assume that individual labor productivity in each sector is composed of the sector-specific permanent component z and an idiosyncratic component v following the stochastic process,

$$\log v_{t+1} = \rho_v \log v_t + \epsilon_{t+1}, \qquad \epsilon_{t+1} \sim F(0, \sigma_v). \tag{2}$$

We include idiosyncratic income risk because developing countries are far from having full insurance, and so accounting for how people insure themselves in response to policies which may keep them away from work for prolonged periods of time is a first order consideration.

After choosing their occupation and observing their income realization, households make consumption and savings decisions given the interest rate, r, and subject to a no-borrowing condition, $a \geq 0$. Formally, the household budget constraint is given by,

$$c + a' \leq \mathbb{1}_{\{s=i\}} w_i v + (1-\tau) \times \lambda_{LD}^{w} \times \mathbb{1}_{\{s=f\}} w_f z v + (1+r)a + T \tag{3}$$

where τ is the income tax rate and T is government transfers. The term λ_{LD}^{w} parameterizes productivity lost during the imposition of a government lockdown and is equal to one in normal times and equal to $\lambda_{LD}^{w} = \lambda_w < 1$ during lockdowns. Importantly, limited state capacity implies that government taxes and commercial restrictions, such as the lockdown, can only be enforced in the formal employment sector. In reality, enforcement capabilities are probably more nuanced, but it is almost certainly much easier in formal places of business than in informal activities. The possibility of moving into the informal sector in response to a lockdown is similar to the movements out of market activities at the start of the pandemic emphasized in Krueger, Uhlig, and Xie (2020), and broadly consistent with the evidence of Zhao, Storesletten, and Zilibotti (2019) that workers respond to economic downturns by moving back into agriculture. There is substantial evidence since the onset of the pandemic in the developing world that many workers do indeed respond by moving into rural agriculture.

3.2. Aggregate Production Technology

The economy produces a single final good by combining domestic and foreign capital with labor services supplied by the formal and informal employment sectors. The aggregate production technology is given by,

$$Y = L^{\alpha} K^{1-\alpha},$$

where $0 < \alpha \leq 1$ is labor's share of value-added. The aggregate capital stock is composed of both domestic and foreign sources, $K = K^D + K^F$, which can be rented at an exogenously given international rental rate r^F (different from r, as we explain below) and which depreciates at rate δ.

Covid Economics 22, 26 May 2020: 1-46

Aggregate labor depends on the supply of both formal and informal labor services. Since skilled work is largely concentrated in the formal sector, and unskilled work in the informal sector, it is natural to model the two labor inputs as gross-substitutes in the aggregate (as in Ulyssea, 2018). Formally, aggregate labor supply is given by,

$$L = \left[A L_f^{\frac{\sigma-1}{\sigma}} + L_i^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where $0 < \sigma < \infty$ is the elasticity of substitution between formal and informal labor services and A indexes the relative productivity of formal sector employment. We allow technology A to augment skilled labor, and not unskilled labor, since a large literature finds that cross-country productivity differences are skill-biased, rather than skill neutral (Caselli and Coleman, 2006; Malmberg, 2018). This assumption is important for the sorting of workers by skill in the model, and the prediction that workers with higher skill (permanent productivity) levels sort into the formal sector, with less productive workers selecting into the informal sector.

3.3. Credit and Capital Markets

Credit market incompleteness prevents households from borrowing against future earnings. As a result, individuals must maintain assets $a \geq 0$ in formulating their consumption plans subject to (3), giving rise to hand-to-mouth consumers as well as a precautionary savings motive in response to idiosyncratic health and income risks. The precautionary motive is important for getting aggregate welfare measurements correct since it creates another feedback between the epidemiological and economic dynamics, as individuals withhold some consumption to increase precautionary savings in response to the pandemic's onset.

Furthermore, financial frictions in capital markets create a spread between the economy's borrowing and savings rates. Specifically, the interest rate paid on domestic savings is such that $r = r^F - \chi$ where $\chi > 0$ represents a financial wedge leading the returns on savings to be less than the rental rate of capital faced by governments and firms borrowing in international capital markets. These frictions increase the number of economically vulnerable hand-to-mouth consumers in developing countries relative to advanced ones, raise the cost of government borrowing to support welfare programs, and distort capital accumulation. This gives us a tractable way of controlling the level of hand-to-mouth consumers in the model, without having to model illiquid assets explicitly as in Kaplan et al. (2020).

Covid Economics 22, 26 May 2020: 1-46

3.4. Public Health and Hospital Capacity

Households face idiosyncratic health risk which can reduce their labor productivity and increase the probability of dying. Susceptibility to infection is determined in part by economic decisions taken by households. Once infected, progression of the disease depends on an individual's age and the availability of public health infrastructure offering treatments.

Health risks are modeled using an SICR epidemiological model with five health states: susceptible ($\mathbb{S}$), infected ($\mathbb{I}$), critial ($\mathbb{C}$), recovered ($\mathbb{R}$), and deceased ($\mathbb{D}$). We denote by N_t^x the mass of individuals in each health state $x \in \{\mathbb{S}, \mathbb{I}, \mathbb{C}, \mathbb{R}, \mathbb{D}\}$ at time t and use $N_t = N_t^{\mathbb{S}} + N_t^{\mathbb{I}} + N_t^{\mathbb{C}} + N_t^{\mathbb{R}}$ to measure the non-deceased population.

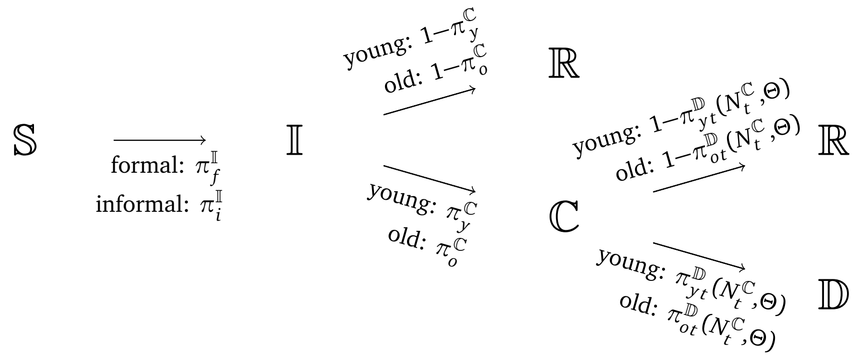


Figure 5: Dynamics of Health States and Transition Probabilities

Individuals who contract the virus experience a proportional drop in productivity of $1-\eta$ for one model period (two weeks), at which point they either recover or enter a critical health state. The probability of becoming critically ill depends on an individual's age and is given by π_j^C. Those in critical health are unable to work and require hospitalization. The likelihood of recovery in the hospital depends again on their age in addition to the availability of public health infrastructure, such as ICU beds and ventilators. In particular, the fatality rate of a critically ill patient of age j is given by:

$$\pi_{jt}^{\mathbb{D}}(N_t^{\mathbb{C}}, \Theta) = \begin{cases} \pi_j^{\mathbb{D}} & \text{if assigned ICU bed} \\ \kappa \times \pi_j^{\mathbb{D}} & \text{if not assigned} \end{cases}$$

where π_j^D is a baseline fatality rate for age j individuals in critical health and κ governs the impact on fatality rates of strained hospital resources. Whether or not a critically ill patient receives an ICU bed depends on overall hospital capacity and the number of other patients.

Covid Economics 22, 26 May 2020: 1-46

Specifically, letting Θ denote hospital ICU capacity, the probability a new patient receives an ICU bed is given by $\min\{\Theta/N_t^C, 1\}$. In other words, all critically-ill patients receive an ICU bed if hospital capacity constraints are not binding, and beds are rationed amongst the critically-ill with probability Θ/N_t^C when constraints bind (Kaplan, Moll, and Violante, 2020).

While the disease's progression is exogenous, the probability a susceptible person becomes infected depends on endogenous economic decisions and the prevalence of infections in the population. Specifically, the baseline probability a susceptible person becomes infected is:

$$\pi^{\mathbb{I}} = \beta^{\mathbb{I}} \times \frac{N^{\mathbb{I}}}{N}$$

where $N^{\mathbb{I}}/N$ is the share of infected people in the population and $\beta^{\mathbb{I}}$ is the "behaviorally adjusted infection rate," which accounts for both the disease's biological transmission rate as well as population wide behavioral responses to avoid being infected (i.e. improved hygiene, social distancing). Using behaviorally adjusted rates is quantitatively important since existing research has shown that these public behavioral responses can substantially reduce transmission rates in practice (Greenwood et al., 2019). Infection rates can be further mitigated by economic lockdowns which shutdown commercial activity. Importantly, such shutdowns only affect the formal sector so that population susceptibility to infection depends in part on individual occupational choice. As a result, individuals working in the informal sector always face the baseline infection rate, while those in the formal sector become infected with probability:

$$\pi^{\mathbb{I}}_{jt}(\text{lockdown}) = \begin{cases} \pi^{\mathbb{I}} & \text{without lockdown} \\ \lambda_h \times \pi^{\mathbb{I}} & \text{with lockdown} \end{cases}$$

where the parameter $\lambda_h \leq 1$ captures the effectiveness of lockdown policies at mitigating the spread of disease.

Our epidemiological model identifies several aggregate health externalities which contribute to the spread of disease. For example, infection probabilities depend in part on the aggregate population of infected individuals. Furthermore, hospitals face congestion inefficiencies which cause the fatality rate to increase as the number of critically ill patients being treated expands. These externalities, and their interaction with economic decisions, creates a margin upon which public health policy, such as lockdowns, could act to improve welfare.

Covid Economics 22, 26 May 2020: 1-46

Covid Economics 22, 26 May 2020: 1-46

3.5. Government and Taxation

The government has power to tax, transfer, and impose economic lockdowns subject to the constraints imposed by limited fiscal capacity and labor market informality. We further require that the government run a balanced flow budget which satisfies,

$$B_t + \Pi + \tau \int \int \mathbb{1}_{\{s=f\}} y(a,x,v) dQ dG = \Delta \times T$$

where Π represents natural resource revenue or foreign aid, $y(a,x,v)$ is pretax income for individual $(a,x,v) \sim Q$, τ is the prevailing tax rate, and T is aggregate transfers to households. Limited fiscal capacity is captured by the iceberg cost $\Delta > 1$, which require the government raise $1/\Delta$ dollars in revenue for every dollar of transfers to households. Modeling limited capacity through the iceberg costs Δ is a parsimonious way to represent the resources developing countries lose simply trying to collect taxes and the funds that are diverted to self interested parties before being spent on public programs, as emphasized by the literature on fiscal capacity. In the developing world, government resources lost to these inefficiencies is thought to be large, and, in the case of Ghana, have been shown to reach nearly 50 percent of property tax revenue collected (Dzansi et al., 2018).

In addition to tax revenue, we allow developing countries access to emergency bonds, B_t, which can be used to finance additional welfare transfers during government imposed lockdowns. The source of these funds is international donors and multinational institutions such as the IMF, World Bank, and World Health Organization. Funds borrowed for emergency transfers accrue interest at rate $1 + r^F$ until the pandemic ends, at which they are repaid through annual annuities. Formally, emergency transfers are given by:

$$B_t = \begin{cases} \bar{B} & \text{during the lockdown} \\ \frac{r^F}{1+r^F} \times \sum_{t_l - t_s}^{t_l - t_e} \left(1 + r^F\right)^t \bar{B} & \text{after pandemic ends} \\ 0 & \text{otherwise} \end{cases}$$

where $\bar{B}$ is the size of per-period emergency transfers during lockdown, which we take parametrically, and t_s, t_e, and t_l index the lockdown's start, the lockdown's end, and the pandemic's end, respectively.

Alongside its fiscal powers, the government can impose an economic lockdown on the formal sector. While in place, lockdowns reduce disease transmission rates by $1 - \lambda_h$ and reduces pro-

CEPR PRESS

ductivity in the formal sector by $1-\lambda_w$. The pair $0 < \lambda_w, \lambda_h < 1$ can therefore index government lockdown policies, with lower values indicating stricter lockdown measures.

4. Quantitative Analysis

In this section, we discuss the calibration strategy, validate the model's fit, and present the counterfactual results for the benchmark lockdown scenarios and age-dependent policies. After validating the calibration, we simulate the aggregate effect of the COVID-19 pandemic in developing and developed countries with and without aggregate policy responses. Specifically, we study the transition dynamics which emerge when an economy in steady state that is not expecting a pandemic is suddenly hit by the onset of COVID-19 and correctly anticipates its epidemiological dynamics. For each scenario, we report the cumulative changes in welfare, GDP, and aggregate fatalities over the pandemic's duration relative to the pre-pandemic steady state. We also report results on heterogeneity with respect to age and income. The final section reports alternative counter-factual outcomes if existing lockdown measures were made age-dependent, and targeted specifically at helping the elderly population.

4.1. Data Sources and Calibration

For expositional clarity, we divide the calibrated targets into three broad categories corresponding to those governing economic mechanisms, those controlling epidemiological dynamics, and those delineating differences between advanced and developing countries.

Table 1 reports parameters which govern the core economic dynamics of the model. Population demographics are modeled using age dependent discount factors accounting for differences in the remaining years of life for young and old workers. The age specific discount factors are taken from Glover et al. (2020), and the stochastic income processes are taken from Floden and Lindé (2001), who estimate similar income processes in the United States and Sweden. The distribution of permanent productivity $z \sim G$ in the formal sector is modeled by a Fréchet distribution with shape parameter ϕ, taken from Lagakos and Waugh (2013). While our formulation allows for imperfect substitutability between employment sectors, we take these to be perfect substitutes in our initial exercises. Finally, labor's share of income comes from Gollin (2002), and the rental rate of capital is set to the two-week return on pre-COVID Treasury Bills.

Table 2 reports parameters controlling the epidemiological transmission of disease and their interactions with public health infrastructure and lockdown policies. We take parameters governing the age-dependent disease progression probabilities from the epidemiological simulation studies of Ferguson et al. (2020). The effect of hospital congestion on disease fatality

Covid Economics 22, 26 May 2020: 1-46

Var	Description	Value	Source / Target
r^F	Exogenous interest rate	0.0006	Pre-COVID T-Bills rate 1.5%
ϕ	Shape-parameter of Frechet distribution G	2.7	Lagakos and Waugh (2013)
ρ_v	Persistence of idiosyncratic income shock	0.91	Floden and Linde (2001)
σ_v	St.Dev of idiosyncratic income shock	0.04	Floden and Linde (2001)
α	Labor share	0.6	Gollin (2002)
β_y	Discount factor for the young	0.9984	Glover et al. (2020)
β_o	Discount factor for the old	0.9960	Glover et al. (2020)

Table 1: Calibration of Economic Parameters

rates, κ, is taken from Glover et al. (2020). The productivity penalty of becoming infected, η, is set to match an 80 percent share of asymptomatic infection cases; such a choice is motivated by the observation that those known to be infected cannot work, and so have productivity of zero, while those who are infected but asymptomatic may continue to work unhindered.

The behavior-adjusted infection generating rate is chosen to match peak rates in an unchecked pandemic. Specifically, in the SIR class of models without policy interventions, there is generally a direct link between the infection generating rate and the peak infected population. We use this relationship to infer transmission rates, taking the expected infection peak from the cross-country estimates of Toda (2020).[2] The advantage of this approach is that while infection generating rates vary with the time-scale of a model, peak infection rates are invariant, and so inferring infection generating rates in this way maintains consistency with cited sources.

The final two parameters, λ_h and λ_w , summarize the effect of lockdown policies on disease transmission and labor productivity, respectively. We choose λ_h to match the trajectory of cumulative cases in the U.S. under lockdown measures. As many recent studies have documented that case counts in randomized public testing for antibodies generally exceed reported cases by substantial multiples, we convert data on confirmed cases to actual cases by rescaling the reported data by a factor of 20. There is no consensus yet as to this value, but our choice of 20 non-reported cases for every reported infection is well within the range estimated by (Hortaçsu, Liu, and Schwieg, 2020). The productivity loss from lockdown policies, λ_w is calibrated to match the 32 percent decline in hours worked during the U.S. lockdown, as documented in the weekly labor market surveys of Bick and Blandin (2020).

We choose not to differentially calibrate the severity of lockdown policies across developing

[2]In particular, we take the highest cross-country peak infection rates as our target. The logic is that these countries likely have the least effective aggregate mitigation policies beyond precautions taken at the individual levels, and hence peak infection rates best reflect the behaviorally adjusted transmission rate in our model.

Covid Economics 22, 26 May 2020: 1-46

Var	Description	Value	Source or Target
η	Effect of infection on productivity	0.8	Asymptomatic cases
κ	Impact of hospital overuse on fatality	2	Glover et al. (2020)
λ_w	Effect of lockdown on productivity	0.68	Blandin and Bick (2020)
λ_h	Effect of lockdown on infection rate	0.75	U.S. cumulative infections
$\pi_y^{\mathbb{C}}$	Rate of young entering $\mathbb{C}$ from $\mathbb{I}$	3.43%	Ferguson et al. (2020)
$\pi_o^{\mathbb{C}}$	Rate of old entering $\mathbb{C}$ from $\mathbb{I}$	19.88%	Ferguson et al. (2020)
$\pi_y^{\mathbb{D}}$	Rate of young entering $\mathbb{D}$ from $\mathbb{C}$	2.76%	Ferguson et al. (2020)
$\pi_o^{\mathbb{D}}$	Rate of old entering $\mathbb{D}$ from $\mathbb{C}$	10.86%	Ferguson et al. (2020)
$\beta^{\mathbb{I}}$	Behavior-adjusted infection generating rate	2.0	Peak Infection Rates

Table 2: Calibration of Epidemiological Parameters

Covid Economics 22, 26 May 2020: 1-46

and developed countries, instead allowing cross-country differences to emerge endogenously from agents' optimizing behavior. Furthermore, while conclusive evidence is not yet available, existing cross-country data suggests that instituted lockdown policies were broadly similar at the aggregate. For instance, Figure A.3 uses cross-country data from Google's *Community Mobility Report* to document the average change in residential and workplace mobility during government lockdowns by country's level of economic development. In all cases, lockdown policies lead to a substantial increase in time spent at home and decrease in time spent at work, and the magnitude of these changes far outweighs any changes across a country's level of development. Studies of specific developing countries yield similar results. For instance, Figure A.6 shows that a drop in cross-district mobility in Ghana – a proxy for traveling to work – fell by roughly 25 percent at the onset of lockdown policies. Similarly, Figures A.4 and A.5 use high frequency labor market surveys in Ghana during the same period to show declines in total hours worked of 20 to 25 percent during lockdowns, broadly similar to numbers documented in the United States. Taken altogether, these data suggest lockdown technologies that are largely similar across countries and motivate our parsimonious parameterization.

Finally, Table 3 summarizes parameters which vary across advanced and developing countries. Further evidence of such variation is provided in Section 2. Sectoral total factor productivities are chosen to match the extent of labor market informality across levels of development. The utility value of living, $\bar{u}$, is set to match the statistical value of a life, and comes from Glover et al. (2020), renormalized to the average consumption level in each country type. The financial wedge in capital markets for developing countries is taken from Donovan (2018), whose model matches the low savings rates among poor African households. We take the iceberg costs resulting from low fiscal capacity from the study of tax collection efficiency in Ghana by

Var	Description	Advanced Economies	Developing Economies	Source or Target
A	Formal sectors TFP	3.0	0.15	1% labor informality in US
$\bar{u}$	Flow value of being alive	$11.4\bar{c}^{US}$	$11.4\bar{c}^{DEV}$	Glover et al. (2020)
χ	Spread b/w borrowing and lending	0	0.66%	Donovan (2019)
τ	Marginal tax rate	0.25	0.15	Besley and Persson (2013)
Δ	Iceberg cost in tax collection	1	2.22	Dzansi et al. (2013)
$\bar{B}$	Lockdown emergency transfers	1%	0.1%	Lockdown transfer programs
ω	Share of young in population	73%	92%	2018 ACS / World Bank
Π	Int' aid / natural resources revenue	0	10% of GDP	World Bank
Θ	Hospital capacity per capita	0.00042	0.00011	Glover et al. (2020) / WHO

Table 3: Calibration of Parameters Varying between Advanced and Developing Economies

Dzansi et al. (2018). The tax rates for the advanced and developing countries are taken from Besley and Persson (2013). We normalize away the effect of financial wedges and fiscal iceberg costs in the calibration of advanced economies, setting them to zero and one, respectively. Comparative values of age demographics and exogenous government revenue in the form of aid and natural resources are taken from the World Bank. In particular, the fraction of young (those between 15 and 65) is 73 percent in advanced economies and 92 percent in developing ones. We exclude those below age 15 from the analysis.

For advanced economies, we calibrate the size of emergency transfers, $\bar{B}$, to reflect the benefits paid out during the lockdown in the United States. Renormalized, these programs totaled about 1 percent of annual U.S. GDP every two weeks. While there is more heterogeneity in the developing world, recent evidence suggests that stimulus programs in Africa are planned to be about one-tenth the size of U.S. programs, as a share of domestic GDP (Collier et al., 2020). Accordingly, we set the level of transfers to 0.1 percent of GDP in developing countries.

The final parameters to be set govern the ICU hospital capacity in developing and developed countries. One challenge is that while many countries report hospital bed capacity, few developing countries distinguish explicitly between general hospital capacity and ICU capacity in the data. To address this, we assume the ratio of hospital beds to ICU beds is constant across countries, and calibrate Θ by adjusting WHO data on the availability of hospital beds in the top and bottom quartiles of country income levels (as in Figure 4) by the ratio of hospital beds to ICU beds taken from Glover et al. (2020).

Covid Economics 22, 26 May 2020: 1-46

4.2. Model Validation

Before reporting results, we check to ensure that our calibration strategy provides a reasonable fit to relevant moments in the data. We focus specifically on four salient moments crucial to the credibility of subsequent quantitative exercises. These include (1) the relative income levels of advanced and developing countries, (2) the relative size of the informal sector, (3) the fraction of hand-to-mouth consumers, and (4) the epidemiological dynamics of the pandemic.

Overall, in spite of its simplicity, the model does reasonably well at matching key non-targeted moments in low-income countries. It predicts that the fraction of workers employed in the informal sector is 68 percent in the developing economy (rather than 1 percent in the advanced economy) which is consistent with the evidence from Figure 3. The model's predicted fraction of hand-to-mouth households is 21 percent in the advanced economy and 69 percent in the developing economy. Direct analogues from the data are not readily available for the developing economy, though the advanced economy value is in line with the estimates of Kaplan, Violante, and Weidner (2014). The level of GDP per capita in the developing economy is $1,100 per year, which is consistent with the average of the bottom quartile of countries.

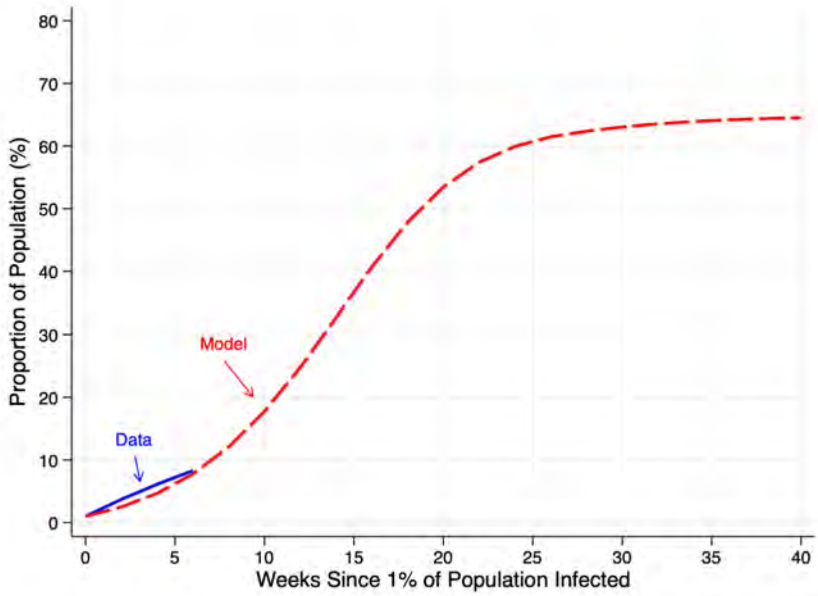
Figure 6 provides some validation for the epidemiological dynamics of the model by comparing the progression of infections in the model to data currently available in the United States. In particular we plot the model's predicted cumulative infection rate and the number of infections in the data, assuming that there are 20 non-reported infections for every reported infection. This multiple for non-reported infections is within the range estimated by Hortaçsu et al. (2020). While real world data on the entire progression of infection counts is limited by questions on the prevalence of asymptomatic cases and the fact that the pandemic is still in its early days, our model's predictions are broadly consistent with currently available data. In future work, we plan to update these parameters as better measurements become available with time.

4.3. Lockdowns in Advanced and Developing Countries

Table 4 summarizes results on welfare, GDP, and fatalities under various lockdown policies in advanced and developed countries. The welfare and GDP entries report the percent change in each outcome variable relative to the country's pre-pandemic steady state levels, and fatalities are reported per hundred thousand people. In our baseline results, we consider aggregate policies which range in length from "no lockdown" to a 70-week lockdown, which lasts through most of the epidemic in the model. We set the maximum duration of the pandemic to 500 days, which is what previous studies have assumed about the amount of time it would take to develop a commercial vaccine. This is, of course, little more than a guess.

Covid Economics 22, 26 May 2020: 1-46

Figure 6: Model Fit of Cumulative Infection Cases in the United States



Note: Data on reported infections in the United States come from the European Centre for Disease Prevention and Control. We assume that there are 20 non-reported infections for every reported infection, as explained in the text.

As a benchmark, it is useful to consider what unfolds in each country when no aggregate lockdown policy is put in place. In advanced economies, doing nothing in response to the pandemic results in 1,102 deaths per hundred thousand people, a 1.8 percent contraction in GDP, and an 8.3 percent decline in aggregate welfare. The consequences of doing nothing in the developing world are about half as severe as in advanced countries. With no lockdown in the developing world, the pandemic leads to 412 deaths per hundred thousand people, a 1.1 percent contraction in GDP, and a 4.1 percent reduction in aggregate welfare. The lower cost for developing countries stems largely from their younger population, which is less likely to lose productivity from being sick or to die. Of course, in reality GDP losses may be even greater than what our model predicts due to features we have omitted, such as disruptions in supply chains (Bonadio, Huo, Levchenko, and Pandalai-Nayar, 2020), Keynesian demand channels (Guerrieri et al., 2020), input-output linkages (Baqaee and Farhi, 2020), or other forces.

While developing countries fare better than advanced ones in the absence of an aggregate policy response, they appear less able to effectively mitigate these negative outcomes through

Table 4: Predicted Effects of the COVID-19 Pandemic

	Lifetime Welfare (%)	GDP (%)	Fatalities per 100,000 People
Panel A: Advanced Economies			
No Lockdown	−8.3	−1.8	1,102
Twelve-Week Lockdown	−7.8	−8.9	1,026
Twenty-Eight-Week Lockdown	−5.5	−18.2	778
Seventy-Week Lockdown	−5.8	−32.8	767
Panel B: Developing Economies			
No Lockdown	−4.1	−1.1	412
Twelve-Week Lockdown	−4.0	−4.0	383
Twenty-Eight-Week Lockdown	−3.6	−8.2	340
Seventy-Week Lockdown	−3.9	−12.7	340

Note: This table reports changes in lifetime consumption equivalent welfare, GDP and fatalities per 100,000 people over the course of the COVID-19 pandemic relative to the pre-pandemic period. In all three lockdown scenarios, the length of the lockdown refers to the number of weeks since one percent of the population is infected. Advanced economies refers to the model's predictions for an economy calibrated to match features of countries in the top quartile of the world income distribution. Developing Economies refers to the model's predictions for an economy calibrated to the bottom quartile of the world income distribution.

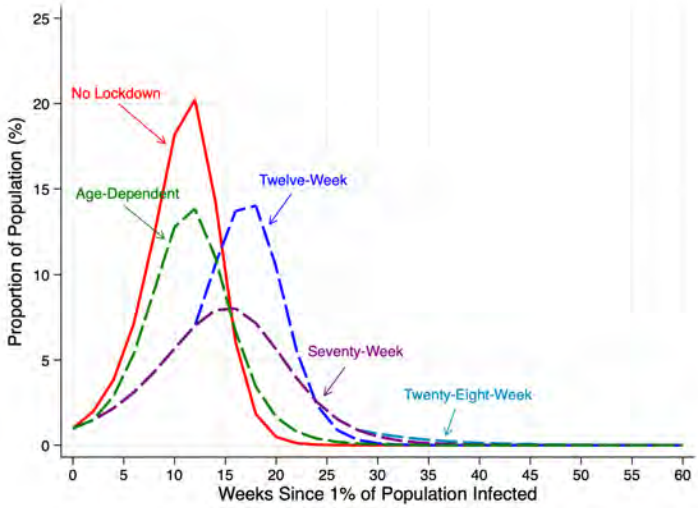
lockdown policies. Specifically, while lockdowns always save lives, the costs are higher, and benefits more modest, in developing countries. For example, under the twenty-eight week lockdown, fatalities decline by around 30 percent in advanced economies, from 1,102 to 778 deaths per hundred thousand people. In developing economies, fatalities fall by only 18 percent, from 412 to 340 per hundred thousand people. The GDP losses under lockdown policies are greater in advanced economies than in developing ones, but proportionally less than differences in fatalities. Consequently, lockdown policies are about half as effective in developing countries as in advanced ones, saving half as many lives per percentage point of GDP lost. These asymmetries are reflected in the differential welfare benefits of lockdowns in the two economies, with moderate lockdowns reducing welfare losses by 35.9 percent in advanced economies, but only 13.8 percent in developing ones.

The lower relative efficacy of lockdowns in developing countries is true across the various

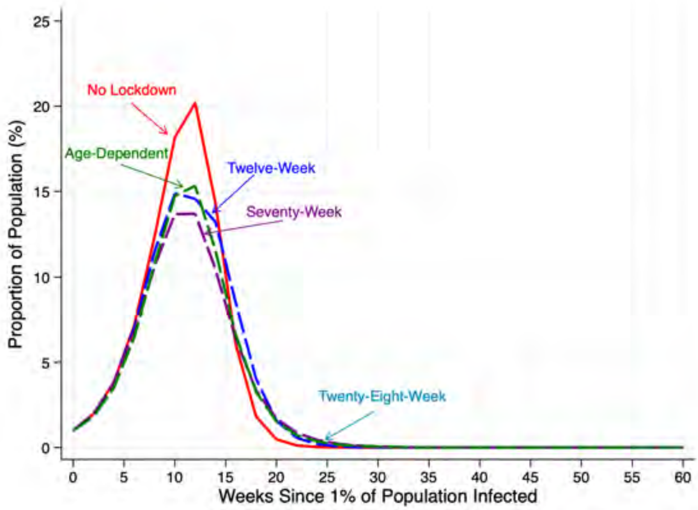
Covid Economics 22, 26 May 2020: 1-46

Figure 7: Simulated COVID-19 Infection Rates

(a) Advanced Economy



(b) Developing Economy



Covid Economics 22, 26 May 2020: 1-46

CEPR PRESS

policy durations we consider. The main reason is that in the absence of robust transfer programs and in the presence of widespread informality, lockdowns do little to stymy the spread of infections in developing countries. Figure 7 shows this explicitly by plotting the trajectory of infections (including non-reported infections) under each policy for advanced and developing countries. At every duration, lockdowns yield less public health benefits in developing countries since they are widely flouted by low income individuals who move to the informal sector to offset earnings losses. Due to public health externalities in the spread of disease, a large non-complying population will erode the public health benefits to the economy at large. In developing countries, where TFP differences between the formal and informal sectors are lower and where tax-and-transfer programs are small and inefficient, the incentives to disregard lockdowns and move to the informal sector are substantial.

An important implication of this is that developing countries may have to worry about extending lockdown policies for too long. In terms of welfare, our model predicts that a 28-week lockdown is greatly preferable to a 70-week lockdown. However, for the advanced economy, the 70-week lockdown achieves welfare gains very similar to the 28-week lockdown. In particular, the gains from locking down for 70 weeks are 88 percent of the gains of locking down for 28 weeks. In contrast, the developing country loses much of the benefits if it locks down for too long. The 70-week gains are only around one third of the 28-week gains. This result suggests that developing countries may have to be more conservative than advanced ones when considering the length of their lockdowns.

4.4. Counterfactual Accounting

To understand the economics driving differential outcomes in advanced and developing countries, Figure 8 reports welfare, GDP, and fatality outcomes under a 28-week lockdown in the advanced economy as we sequentially endow it with the salient characteristics of developing countries identified in Section 2. The top panel reports counterfactual results for each channel in isolation. Since the magnitude of these individual channels implies substantial equilibrium interactions, the bottom panel adds each mechanism sequentially and cumulates their economic impact. For completeness, Figure A.7 reports the effect of each channel in the absence of any lockdown.

Three main lessons can be drawn from the counterfactual results. First, differences in mortality rates are driven overwhelmingly by the age distributions of advanced and developing countries. Endowing advanced economies with the age distribution of developing ones cuts the number of deaths by 65 percent on its own, accounting for more than the total difference in mortality between the two countries in our benchmark results. Taken individually, changing

Covid Economics 22, 26 May 2020: 1-46

the age distribution alone can account for nearly all of the differences between advanced and developing countries in the "no lockdown" scenario where aggregate policy does not respond to the pandemic. Furthermore, while the limited ICU capacity of developing countries increases mortality, it does so only modestly, with widespread labor market informality contributing even more to differences in death rates. The reason is that the effect of hospital congestion on survival probabilities is modest relative to the negative public health externalities in infection rates generated by workers flouting lockdown by moving into the informal sector. Interestingly, even though on its own the informality channel leads to more deaths than limited ICU capacity, the latter generates larger welfare losses since the increase in deaths are not accompanied by lower losses to GDP, as they are in the case of informality.

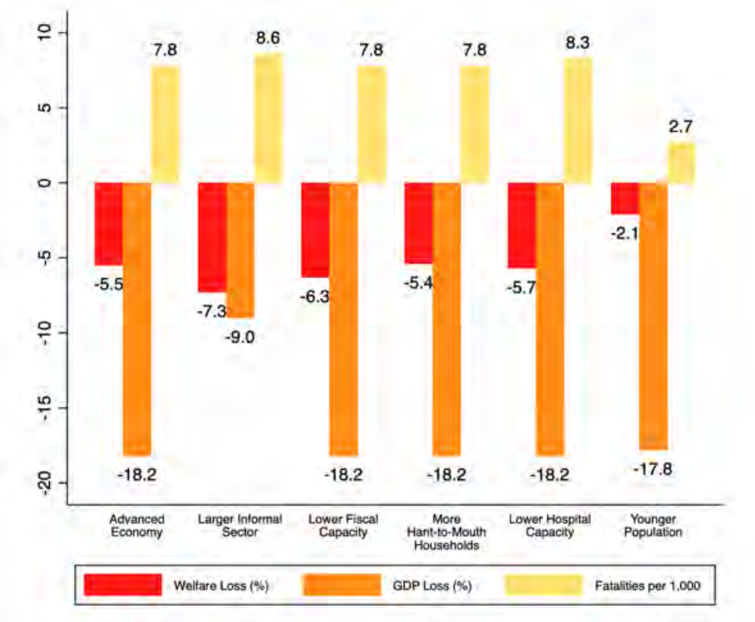
Turning to GDP outcomes, the most salient channel appears to be the extensiveness of labor market informality. On its own, endowing advanced economies with the labor market informality of developing ones serves to cut the output losses associated with lockdowns roughly in half. This is in part mechanical as the informal sector is not subject to lockdown measures, and so a larger informal sector means fewer workers being initially subject to the output losses associated with lockdowns. However, the informal channel also has important equilibrium interactions with the other mechanisms. Intuitively, the workers who find it optimal to circumvent lockdown orders by moving to the informal sector are those for whom the economic losses associated with lockdowns are greater than the health risks of the pandemic. Informality therefore allows these workers to self-select out of lockdown measures, incurring a smaller loss in income but greater health risk. Comparing the individual versus cumulative results, we see that this self-selection moderates the welfare and output losses associated with the other channels as well. This is especially true when one considers the interaction with ICU capacity and the share of hand-to-mouth; on their own, both lead to substantial welfare losses, but coupled with a reasonable option to move into informality, the losses are substantially lower. This result is far from obvious, as public health externalities in infection rates could have pushed outcomes in the opposite direction.

Given our heterogeneous agent setup, welfare outcomes under each scenario are driven not only by aggregate outcomes in GDP and fatalities, but also by how those changes are distributed in the population. For instance, on its own, lower fiscal capacity substantially increases the welfare costs of lockdowns even though it has negligible effects on output or fatalities. The reason of course is distributional, as low fiscal capacity limits the effectiveness of redistribution through tax-and-transfer and emergency relief programs. In this regard, the fiscal channel, labor market informality, and the age distribution play crucial roles in shaping welfare outcomes in the counterfactuals. The age distribution plays an important role in mitigating the effect of

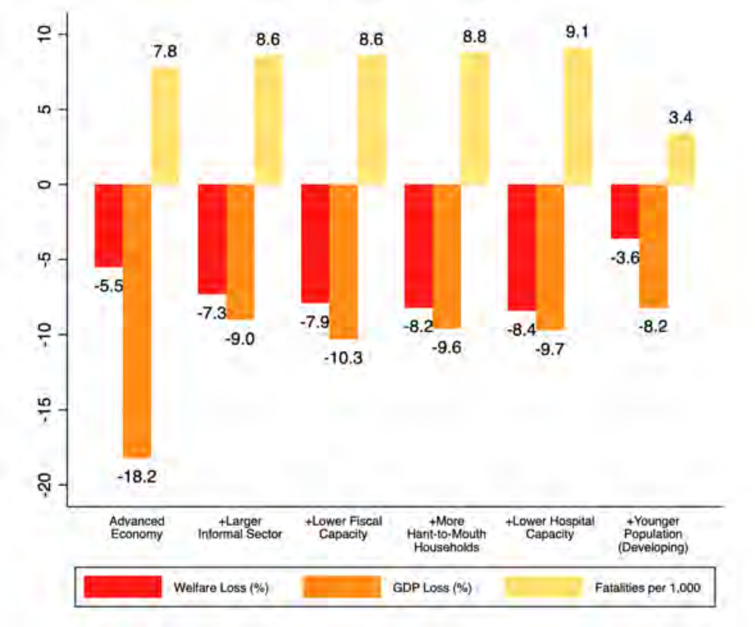
Covid Economics 22, 26 May 2020: 1-46

Figure 8: Counterfactual Economies under 28-Week Lockdown

(a) Individual Contributions



(b) Cumulative Contributions



weaker ICU capacity in developing countries by mechanically shrinking the share of the vulnerable population. The fiscal and informality channels are important for blunting the welfare losses associated with lower incomes and a higher shares of hand-to-mouth consumers in developing countries. The informal channel appears more pronounced in this regard partially because, for simplicity, we have ruled out more sophisticated reoptimization by governments in shaping their tax-and-transfer programs in response to the pandemic's evolution.

In summary, our counterfactual analysis finds meaningful roles for each of the channels in shaping at least one of the outcomes on welfare, GDP, or mortality. Comparing the top and bottom panels of Figure 8 indicates that there are substantial equilibrium interactions between the mechanisms we study. This observation motivates the necessity for modeling-based approaches to studying the consequences of various COVID-19 policies. Our current analysis suggests the most important of these interactions in a developing world context are those between lower fiscal capacities, extensive labor market informality, and age demographics.

4.5. Heterogenous Effects of Lockdown

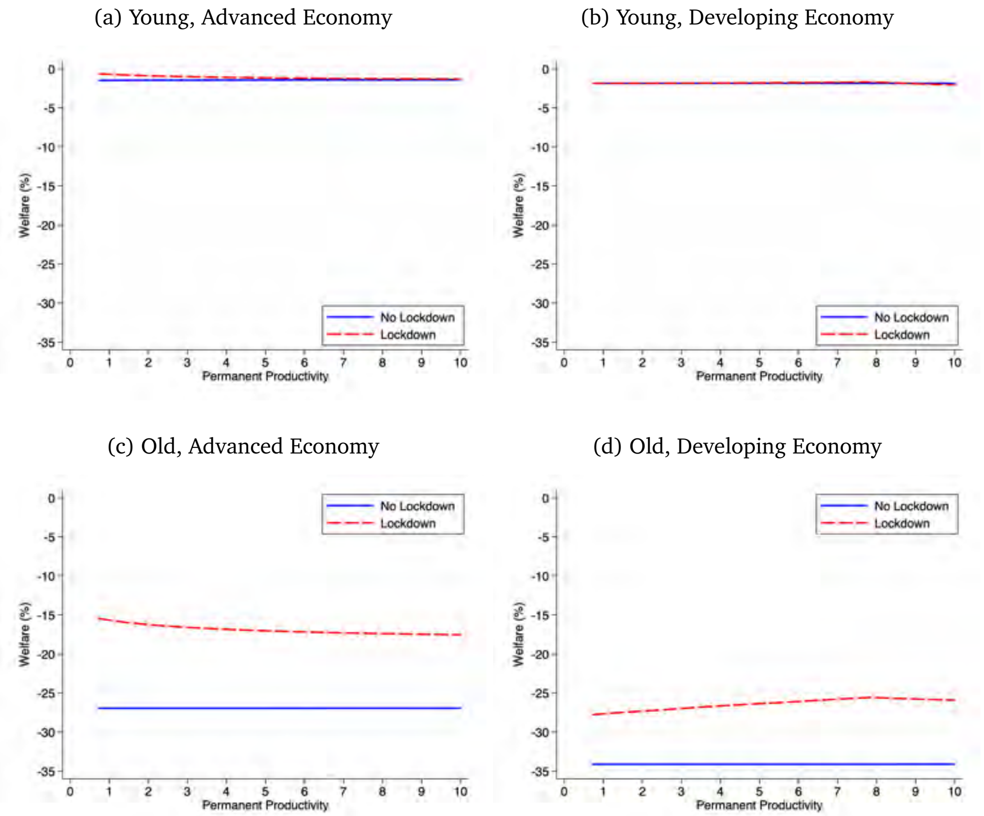
There is a growing body of research documenting substantial heterogeneity in who bears the costs and benefits associated with the pandemic's spread and the policy responses aimed at tackling it (e.g. Glover et al., 2020; Alon et al., 2020; Mongey et al., 2020). Accounting for such heterogeneity is important for understanding the economic incentives shaping behavioral responses to the pandemic and in evaluating the welfare consequences of different policy responses. The model accounts for these differences by including heterogeneity in age and incomes, both of which play an important role in propagating the economic consequences of the pandemic. Figure 9 summarizes the implications of this heterogeneity by plotting welfare changes by age and permanent productivity level (a proxy for permanent income in the model) under the lockdown and no-lockdown scenarios. The left column reports results for advanced economies, the right displays outcomes for developing ones.

Two trends are immediately clear from the Figure 9. First, in both countries, the welfare costs of the pandemic and welfare gains of lockdown policies accrue overwhelmingly to the old population. Second, heterogenous effects across the income distribution are relevant but less pronounced in both countries. Third, the welfare benefits of lockdowns broadly decrease with permanent productivity in advanced economies, but increase with income in developing ones. This final observation has an especially important implication for the aggregate effect of lockdowns in advanced and developing countries: in advanced countries, lockdown policies are generally progressive and benefit the poor more than the rich; in developing countries, lockdown policies appear to be regressive, and benefit the rich more than the poor.

Covid Economics 22, 26 May 2020: 1-46

Covid Economics 22, 26 May 2020: 1-46

Figure 9: Heterogeneous Effects of Lockdown (28-Weeks)



The fact that older individuals benefit disproportionately from lockdown measures is hardly surprising and is an immediate consequence of their substantially higher susceptibility to disease. On average, lockdown policies reduce welfare losses amongst the old in both countries by about ten percentage points. The young also gain from the public health benefits of lockdowns, though meaningfully less due to their lower inherent susceptibility, and these gains appear largely offset by the economic losses accompanying the lockdown.

A more nuanced result is that in advanced economies the welfare benefits of a lockdown falls with income levels, while in developing countries they broadly increase. This outcome is a consequence of the subtle interactions between fiscal capacity and informality with the differing income levels in the two countries. When the lockdown goes into effect, governments substantially increase transfers which implicitly transfer welfare from rich households to poor

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ones in both countries. As rich countries implement larger programs and have higher fiscal capacity, the overall impact of this redistribution is substantial, giving rise to the negative slope in welfare gains across the income distribution. In developing countries, these emergency transfer programs are smaller and waste substantial resources because of the lower fiscal capacity of governments in the developing world. Widespread labor market informality in developing countries compounds these effects, as many low income workers seek to offset their income losses by moving into the informal sector. While partly alleviating economic hardships, the move to informality increases the exposure of poor households to disease, offsetting the beneficial health effects of the lockdown relative to their richer compatriots who have sufficient assets to avoid informality. On balance, the informality channel supersedes the redistributive effects of transfers in developing countries, giving rise to the upward sloping curve in the figure.

4.6. Effectiveness of Age-Dependent Policies

The large and heterogenous effects of lockdowns suggest that targeted policies may be more effective than the benchmark lockdowns studied above. Specifically, while blanket lockdowns impose costs on the entire economy, the benefits accrue overwhelmingly to the old. Age-dependent lockdown policies which focus on shielding only the old could therefore deliver similar benefits as blanket lockdowns, but at a much lower cost. Several other recent research papers have similarly argued for the potential advantages of such age-targeted programs in advanced economies (Acemoglu et al., 2020; Bairoliya and Imrohoroglu, 2020). Our analysis suggests that these targeted policies may be even more potent in the developing world, which is more sensitive to the economic costs of lockdowns and where the old constitute a smaller and more vulnerable share of the population.

To evaluate the efficacy of more targeted programs in the developing world, we analyze how outcomes change when lockdown policies are targeted exclusively at the old. To facilitate comparability, we assume that the lockdown technology parameters are the same, but do not apply to the young population, and keep fixed the total amount of money spent on emergency transfers, B_t, simply redistributing the excess resources exclusively to the old population.

In both advanced and developing countries, age-dependent policies appear to greatly increase the efficacy of lockdown programs when assessed using lives saved per percentage of lost GDP. Broadly, the added potency of age-dependent policies appears greater in short lockdowns than in long ones, and far greater in developing countries than advanced ones. The added effectiveness of age-targeting for short lockdowns stems in part from the fact that short-lockdowns generally do little to stymy the spread of disease but still lead to large economic costs. As a result, introducing age targeting in these shorter programs proportionately increases the lives

Covid Economics 22, 26 May 2020: 1-46

Covid Economics 22, 26 May 2020: 1-46

Table 5: Lives Saved per 100,000 People per Unit of GDP Lost

	Advanced Economy		Developing Economy	
	Benchmark	Age-dependent	Benchmark	Age-dependent
Twelve-Week	10.6	54.0	9.8	148.3
Twenty-Eight-Week	19.8	54.0	10.2	95.2
Seventy-Week	10.8	29.8	6.2	44.5

Note: This table reports the number of lives saved per 100,000 people per unit of GDP lost to the lockdown. The Benchmark columns refers to the effects of a blanket lockdown, and the Age-Dependent columns refer to lockdowns which keep only the older population under lockdown.

saved by a greater amount than in longer lockdowns, which are already effective on this dimension.

More germane to our purposes is the fact that age-dependent policies appear to be far more potent in increasing the efficacy of lockdowns in the developing economies than in advanced ones. In advanced economies, a 28-week lockdown with age targeting saves 54 lives per hundred thousand people for every unit of lost GDP. In developing economies, the same ratio is 95.2. Consequently, age-targeting in advanced economies increases lives saved per percentage of GDP lost by a factor of 3 to 5 over non-targeted policies, while in developing countries, increases are on the order of 7 to 15. The result stems in part from the fact that developing countries have far smaller old populations than advanced ones, so targeted policies have the added benefit of partially offsetting the weaker fiscal capacity of developing countries by concentrating transfers on a smaller population. Furthermore, targeted policies are better at keeping workers in the formal sector in developing countries, muting output losses and boosting government revenue relative to blanket lockdowns. Taken together then, we conclude that targeted policies are more potent in the developing world because in equilibrium they serve to mitigate the negative drag from other channels that are otherwise reinforced in blanket lockdown policies.

5. Conclusion

This paper provides a preliminary quantitive analysis of how lockdown policy should differ between developing and developed economies. Developing economies have different charac-

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teristics that suggest differing lockdown policies from the west, including younger populations, larger informal sectors and lower healthcare and fiscal capacity. Our quantitative macroeconomic model predicts that blanket lockdowns are generally less effective in developing countries, and save fewer lives per unit of lost economic output. Nevertheless, in our simulations, blanket lockdowns still prove more effective in lowering the welfare costs of the pandemic than having no lockdown at all. The most effective type of lockdown for developing countries, according to our analysis, is one that locks down only the older population, sending transfers only to them. These age-dependent lockdowns have potent effects in our model, saving more lives per percent of GDP lost than the same policies in richer countries.

Our quantitative results for welfare, GDP losses, and fatality rates from the pandemic are best viewed as preliminary given that the pandemic is still, unfortunately, in its early stages, and reliable data are still scarce. Our conclusions about the differential effects of COVD-19 between advanced and developing economy may prove more enduring. There can be little doubt that developing economies have vastly younger populations, much larger informal economies and less fiscal capacity than advanced economies. These basic differences in demographic and economic structure point to optimal lockdown policies that are age-dependent, focusing on keeping just the older population under lockdown, and letting others resume normal economic activity, to the extent that it is possible.

Covid Economics 22, 26 May 2020: 1-46

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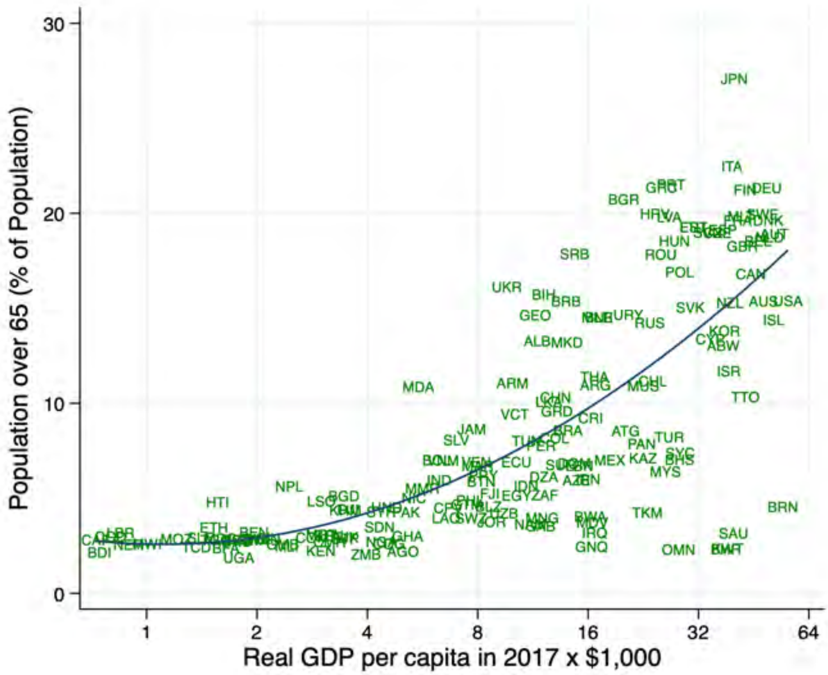
Covid Economics 22, 26 May 2020: 1-46

Covid Economics 22, 26 May 2020: 1-46

Appendix

A. Appendix Figures

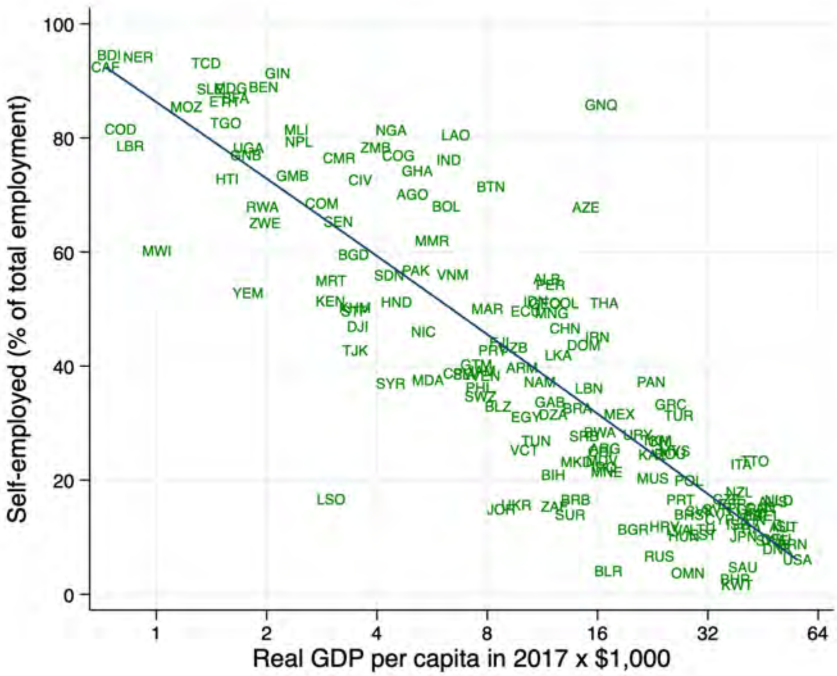
Figure A.1: Fraction of the Population Older than Age 65



Note: This figure plots the proportion of population ages over 65 and above as a percentage of total population across 162 countries. GDP per capita is from Penn World Table 9.1 (Feenstra et al., 2015). Population data is World Bank staff estimates using the World Bank's total population and age/sex distributions of the United Nations Population Division's World Population Prospects: 2019 Revision.

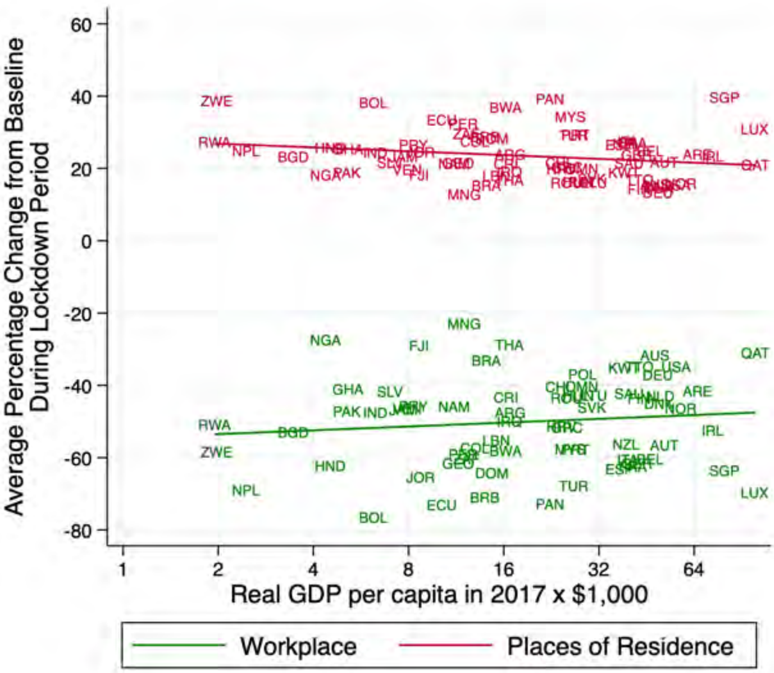
Covid Economics 22, 26 May 2020: 1-46

Figure A.2: Share of Self-Employed Workforce



Note: This figure plots the self-employed workers as a percentage of total employment across 153 countries. Self-employed workers are those workers who, working on their own account or with one or a few partners or in cooperative, hold the type of jobs defined as a "self-employment jobs." i.e. jobs where the remuneration is directly dependent upon the profits derived from the goods and services produced. Self-employed workers include four sub-categories of employers, own-account workers, members of producers' cooperatives, and contributing family workers. GDP per capita is from Penn World Table 9.1 (Feenstra et al., 2015). Self-employment data is from ILOSTAT database.

Figure A.3: Changes in Mobility Across Countries During Lockdown Periods



Note: This figure plots the average percentage changes of the mobility metric in the 'Places of Residence' and 'Workplace' categories in the Google Community Mobility Report (Aktay et al., 2020), during the lockdown periods for the 65 countries which had implemented or are implementing lockdown. GDP per capita is from Penn World Table 9.1 (Feenstra et al., 2015). The average across all 65 countries is 23.44 percent. The slope of the fitted line is 1.52, with p-value of 0.354 for the 'Workplace' category. For the 'Places of Residence' category, the slope of the fitted line is -1.52, with p-value of 0.083.

Covid Economics 22, 26 May 2020: 1-46

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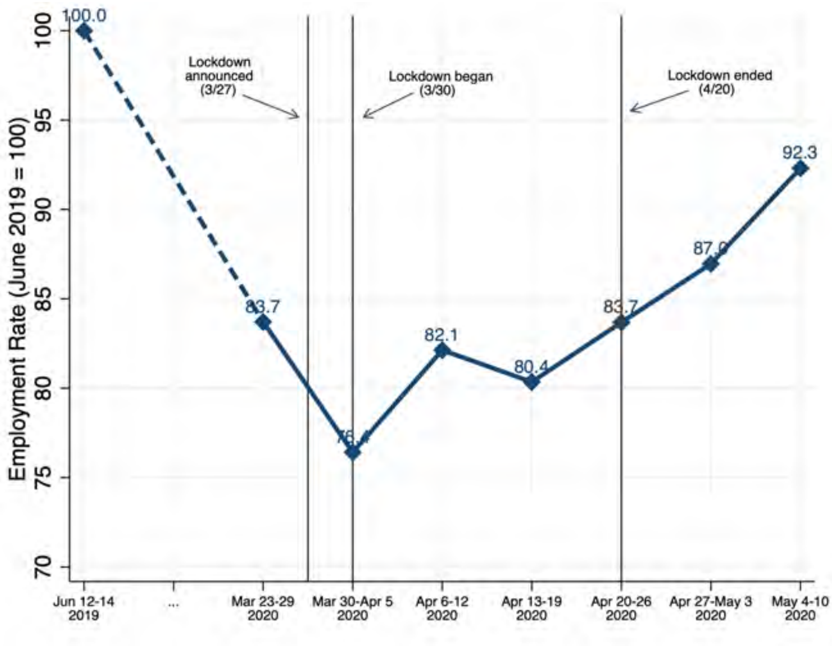
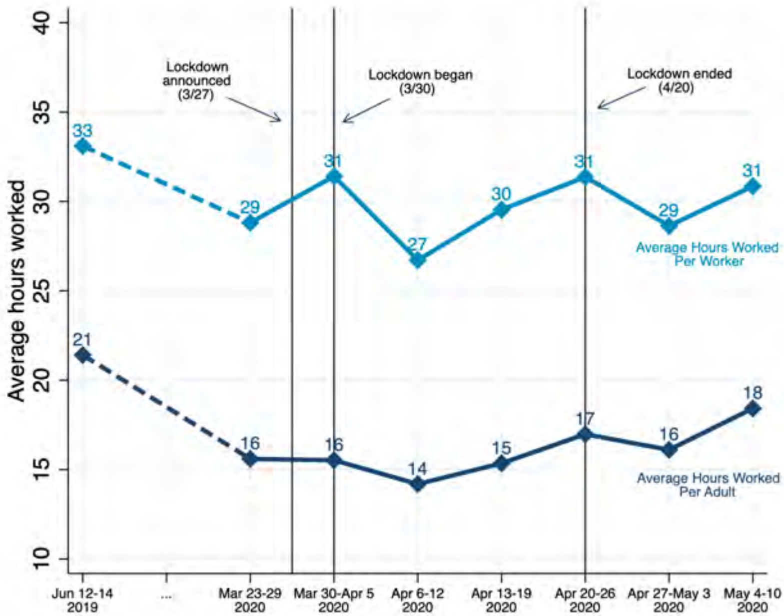
Figure A.4: Employment Rate in Ghana Around the Lockdown Period



Note: This figure plots the employment in Accra and Kumasi, the two biggest cities in Ghana, proxied by Google survey data. The survey question was "In the last WEEK, how many hours did you work for pay or profit?". Employment rate is the proportion of people who reported they had worked in last week. The employment rate from the same survey conducted in June 2019 was normalized to one. Sample size was 266 in March 23-29, 342 for April 1-5, 281 for April 6-12, 302 for April 13-19, and 500 for the rest.

Covid Economics 22, 26 May 2020: 1-46

Figure A.5: Hours Worked in Ghana Around the Lockdown Period



Note: This figure plots the employment in Accra and Kumasi, the two biggest cities in Ghana, proxied by Google survey data. The survey question was "In the last WEEK, how many hours did you work for pay or profit?". Average hours per worker is calculated by taking the average of hours among those who reported they had worked in the last week. Average hours per adult is calculated by taking the average of hours including those who reported they had not worked in the last week. Sample size was 266 in March 23-29, 342 for April 1-5, 281 for April 6-12, 302 for April 13-19, and 500 for the rest.

Covid Economics 22, 26 May 2020: 1-46

Figure A.6: Mobility in Ghana Around the Lockdown Period

Note: This figure plots the percentage change in the number of trips between any two districts in Greater Accra, Ghana in each day, relative to the baseline value. The baseline value is calculated as the median value of the metric during the four weeks prior to the introduction of the first restriction on March 16th. The trips mainly comprise short-distance, routine daily trips that correspond to activities such as commuting to work, shopping, and entertainment. Anonymized and aggregated mobile phone data from Vodafone Ghana, analysis by Flowminder. Source: Flowminder (2020)

Covid Economics 22, 26 May 2020: 1-46

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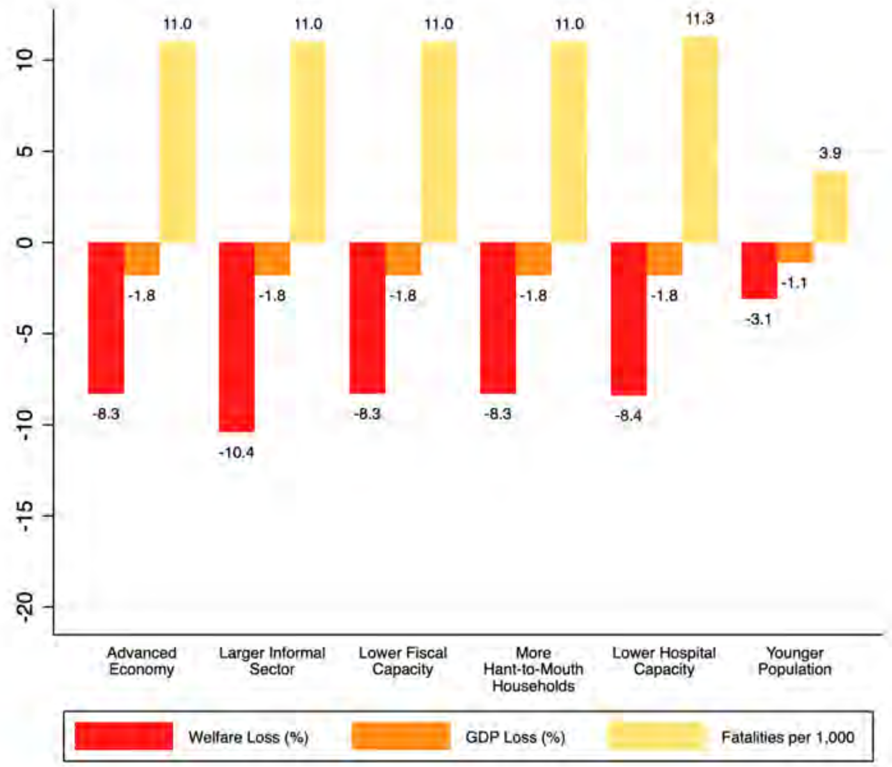
Figure A.7: Counterfactual Economies in No Lockdown Scenario



Covid Economics 22, 26 May 2020: 1-46

B. Appendix Tables

Table B.1: Counterfactual Exercise

	Lifetime Welfare (%)	GDP (%)	Fatalities per 100,000 People
Panel A: Advanced Economy at Baseline			
No Lockdown	−8.34	−1.76	1,102
Twenty-Eight-Week Lockdown	−5.45	−18.17	778
Panel B: Advanced economy with lower fiscal capacity			
No Lockdown	−8.30	−1.76	1,102
Twenty-Eight-Week Lockdown	−6.28	−18.17	778
Panel C: Advanced economy with large informal sector			
No Lockdown	−10.40	−1.76	1,102
Twenty-Eight-Week Lockdown	−7.32	−8.96	859
Panel D: Advanced economy with younger population			
No Lockdown	−3.11	−1.12	395
Twenty-Eight-Week Lockdown	−2.12	−17.81	271
Panel E: Advanced economy with lower hospital capacity			
No Lockdown	−8.44	−1.78	1,131
Twenty-Eight-Week Lockdown	−5.68	−18.19	825
Panel F: Advanced economy with more hand-to-mouth households			
No Lockdown	−8.28	−1.76	1,102
Twenty-Eight-Week Lockdown	−5.40	−18.17	778

Covid Economics 22, 26 May 2020: 1-46

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Table B.2: ICU Bed Availability Across Countries

Country	ICU beds per 100,000 population	Per capita healthcare cost
United States	20.0-31.7	$7,164
Canada	13.5	$3,867
Denmark	6.7-8.9	$3,814
Australia	8.0-8.9	$3,365
South Africa	8.9	$843
Sweden	5.8-8.7	$3,622
Spain	8.2-9.7	$2,941
Japan	7.9	$2,817
UK	3.5-7.4	$3,222
New Zealand	4.8-5.5	$2,655
China	2.8-4.6	$265
Trinidad and Tobago	2.1	$1,237
Sri Lanka	1.6	$187
Zambia	0	$80

Source: Table 1 in Prin and Wunsch (2012). Healthcare cost includes all public and private expenditures, not limited to critical care.

Covid Economics 22, 26 May 2020: 1-46

Socioeconomic determinants of Covid-19 infections and mortality: Evidence from England and Wales[1]

Filipa Sá[2]

Date submitted: 18 May 2020; **Date accepted:** 21 May 2020

I use simple correlations and regression analysis to study how the number of confirmed Covid-19 cases and the number of deaths with Covid-19 per 100,000 people is related with the socioeconomic characteristics of local areas in England and Wales. I find that local areas that have larger households, worse levels of self-reported health and a larger fraction of people using public transport have more Covid-19 infections per 100,000 people. For mortality, household size and use of public transport are less important, but there is a clear relation with age, ethnicity and self-reported health. Local areas with an older population, a larger share of black or Asian population and worse levels of self-reported health have more Covid-19 deaths per 100,000 people. The relation between self-reported health and infections and mortality suggests that encouraging a healthy lifestyle can help prevent the spread of infection and reduce mortality. Also, as many countries now begin to relax lockdown measures, policymakers should pay particular attention to reducing the risk of infection in public transport.

1 I would like to thank my colleagues Brian Bell and Mary O'Mahony and my husband Paul Bedford for reading my draft at short notice and providing useful comments.

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Covid Economics 22, 26 May 2020: 47-58

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1 Introduction

The Covid-19 pandemic raises many important research questions for economists. This paper combines data on the number of confirmed Covid-19 cases and the number of deaths with Covid-19 per 100,000 people for local areas in England and Wales with socioeconomic data from the 2011 Census to study the socioeconomic determinants of infections and deaths. I examine, in particular, the correlation with population density and household size, ethnicity, health, an index of multiple deprivation and use of public transport.

The first confirmed case of Covid-19 in England was registered in York on January 30th 2020. As of May 6th 2020, there have been 206,715 positive tests and 30,615 deaths (in all settings and not just in hospitals) in the UK. The number of deaths is the highest among European countries.

Behind these overall numbers, there is considerable regional variation. Figure 1 shows the number of confirmed cases per 100,000 people in different local authority districts and Table 1 lists the 10 local authorities with highest infection rates in England and Wales and in England only. These are cumulative cases as of May 5th 2020 in Wales and May 8th 2020 in England. Infection rates depend on two factors: the frequency of testing and the fraction of tests with a positive result.[1] England and Wales have different public health agencies and different policies on testing, which may explain the relatively high infection rates recorded in Wales. When looking at England only, the highest infections rates are in Barrow-in-Furness and nearby Lancaster and South Lakeland. The North East region around Gateshead, Sunderland and South Tyneside is another hot spot. The London borough with the highest infection rate is Brent, with 421 cases per 100,000 people.

Covid Economics 22, 26 May 2020: 47-58

[1] It would be interesting to study these two factors separately, as Borjas (2020) does for New York City neighbourhoods. However, data on the number of tests by local authority is not available for England.

Figure 1

Confirmed Covid-19 cases (per 100,000 people)

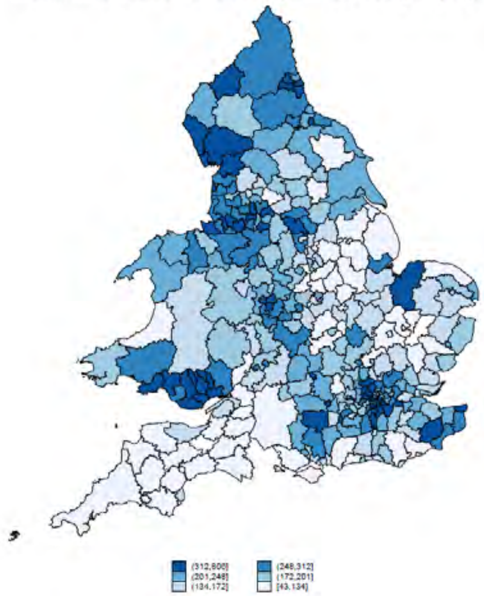


Table 1

Local authorities with the largest number of Covid-19 cases per 100,000 people

England and Wales	Covid-19 cases per 100,000 people	England only	Covid-19 cases per 100,000 people
Barrow-in-Furness	805.8	Barrow-in-Furness	805.8
Lancaster	515.1	Lancaster	515.1
Rhondda Cynon Taf	497.6	South Lakeland	483.1
Cardiff	491.1	Gateshead	466.2
South Lakeland	483.1	Sunderland	460
Newport	480.1	Ashford	450.2
Merthyr Tydfil	478.5	Middlesbrough	437.6
Gateshead	466.2	South Tyneside	427.9
Sunderland	460	Brent	421.4
Swansea	458.1	Knowsley	405.2

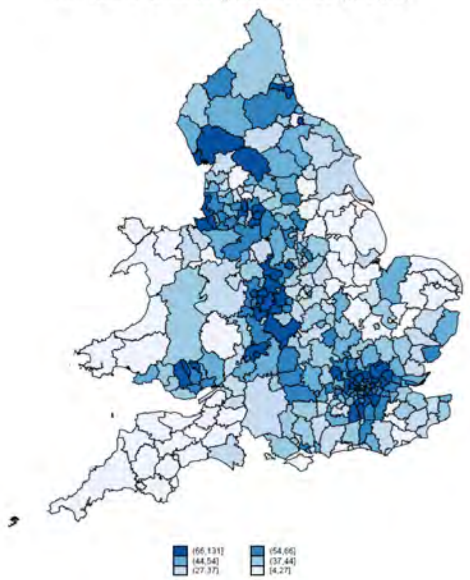
Figure 2 and Table 2 show the number of deaths per 100,000 people. The data record the cumulative number of deaths that mention Covid-19 on the death certificate as of April 24th 2020. Importantly, geographic disaggregation is by area of usual residence rather than place of death. Because the vast majority of deaths (70%) occur in hospital, it is important to look at area of

Covid Economics 22, 26 May 2020: 47-58

residence rather than place of death when analysing the socioeconomic determinants of mortality. The borough with the highest mortality rate, at 131 deaths per 100,000 people is Hertsmere in Hertfordshire, which borders with the North London boroughs of Harrow, Barnet and Enfield. These London boroughs as well as Brent, Ealing and Croydon also have high mortality rates. Outside London, mortality rates are highest in Epping Forest in Essex, South Lakeland in Cumbria and Middlesbrough in North Yorkshire. The South West counties of Cornwall and Devon and West Wales have low Covid-19 mortality rates.

Figure 2

Covid-19 deaths (per 100,000 people)



Covid Economics 22, 26 May 2020: 47-58

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Covid Economics 22, 26 May 2020: 47-58

Table 2

Local authorities with the largest number of Covid-19 deaths per 100,000 people

	Covid-19 deaths per 100,000 people
Hertsmere	131.5
Harrow	122.3
Brent	116.4
Epping Forest	107.5
South Lakeland	101.4
Enfield	94.9
Ealing	94.5
Barnet	93.8
Croydon	90.3
Middlesbrough	88.9

To examine which socioeconomic characteristics of local authorities are correlated with Covid-19 infections and mortality, I first look at simple correlations. I then estimate a regression model which examines all factors together. The evidence suggests that infection rates are higher in local areas with larger households, more extensive use of public transport and worse levels of self-reported health. Mortality is higher in local areas that are more densely populated, have an older population, worse levels of self-reported health and a larger share of black or Asian population.

2 Data

Data on the cumulative number of confirmed Covid-19 cases by local authority district are from Public Health England (as of May 8th 2020) and Public Health Wales (as of May 5th 2020). Data on the number of deaths related to Covid-19 are from the ONS and are based on any mention of Covid-19 in the death certificate. For the descriptive evidence, I use the cumulative number of deaths as of April 24th 2020 by local authority district of usual residence. For the regression analysis, I use more disaggregated data by Middle Layer Super Output Area (MSOA) on the number of deaths occurring between March 1st and April 17th 2020. This finer level of disaggregation makes it possible to include local authority fixed effects in the mortality regressions.

I merge these data on infections and mortality with data on socioeconomic characteristics of local authorities. Data on ethnicity, age, household size, health and use of public transport are from the 2011 Census. Data on population and density are from the ONS 2018 population estimates. Data

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Covid Economics 22, 26 May 2020: 47-58

on deprivation are from the 2019 English and Welsh Indices of Multiple Deprivation (IMD), which combine the following categories of deprivation: income, employment, education, crime, housing and living environment. This index is available by Lower Layer Super Output Area (LSOA). To aggregate the data to local authority or MSOA level, I use the proportion of LSOAs in a given local authority or MSOA that are in the most deprived 10% nationally. Table 3 presents descriptive statistics and lists the data sources. The final dataset contains 337 local authorities and 7,201 MSOAs in England and Wales.

Table 3

	Mean	Standard deviation	Source
Covid-19 cases per 100,000 people	222.749	98.653	Public Health England (updated May 8th 2020) and Public Health Wales (updated May 6th 2020); population from ONS 2018 population estimates
Covid-19 deaths per 100,000 people (by local authority district)	46.946	20.834	ONS weekly deaths dataset up to April 24th 2020
Covid-19 deaths per 100,000 people (by MSOA)	34.362	32.753	ONS weekly deaths dataset covering the period from March 1st to April 17th 2020
Log population density	1.929	1.407	ONS 2018 population estimates
Percent female	50.683	0.745	2011 Census
Percent age 60 and over	25.355	5.583	2011 Census
Percent black/African/Caribbean/black British	2.261	4.351	2011 Census
Percent Asian/Asian British	5.593	7.634	2011 Census
Average household size	2.349	0.120	2011 Census
IMD – proportion of LSOAs in most deprived 10% nationally	7.408	10.336	English Index of Multiple Deprivation and Welsh Index of Multiple deprivation
Percent reporting health as bad or very bad	5.437	1.520	2011 Census
Percent travelling to work by public transport	13.201	13.262	2011 Census (public transport includes underground, metro, light rail or tram; train; and bus, minibus or coach)

3 Descriptive evidence

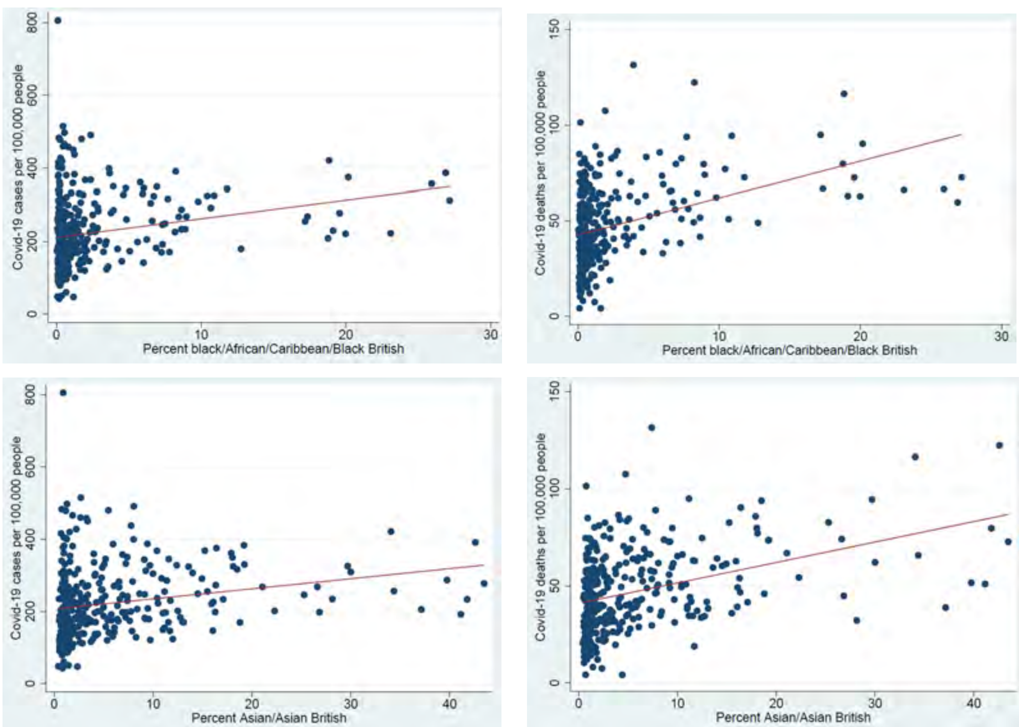
Before presenting the regression results, I examine simple correlations between Covid-19 infections and mortality and socioeconomic characteristics of local authorities.

Covid Economics 22, 26 May 2020: 47-58

3.1 Ethnicity

There is a positive correlation between both infections and mortality and the percentage of black or Asian population in the local authority. This correlation is larger for mortality than for infections. A similar pattern is found in New York City in Borjas (2020) and Almagro and Orane-Hutchinson (2020). For England and Wales, analysis by the ONS (ONS (2020)) shows that people of black ethnicity are 1.9 times more likely to die with Covid-19 than those of white ethnicity, after controlling for age, measures of self-reported health and disability and sociodemographic characteristics. Their analysis is based on individual level data, obtained by linking information on the death certificate with data from the 2011 Census.

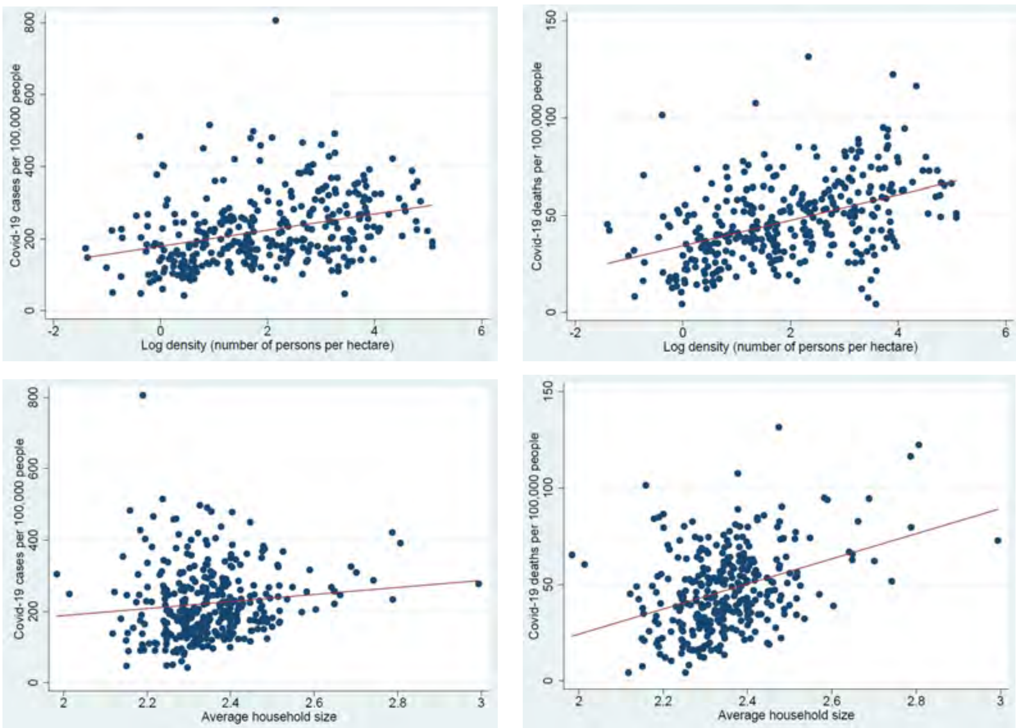
Figure 3



3.2 Population density and household size

Population density and average household size are also positively correlated with infections and mortality. This is again consistent with the findings for New York City reported in Borjas (2020) and Almagro and Orane-Hutchinson (2020).

Figure 4



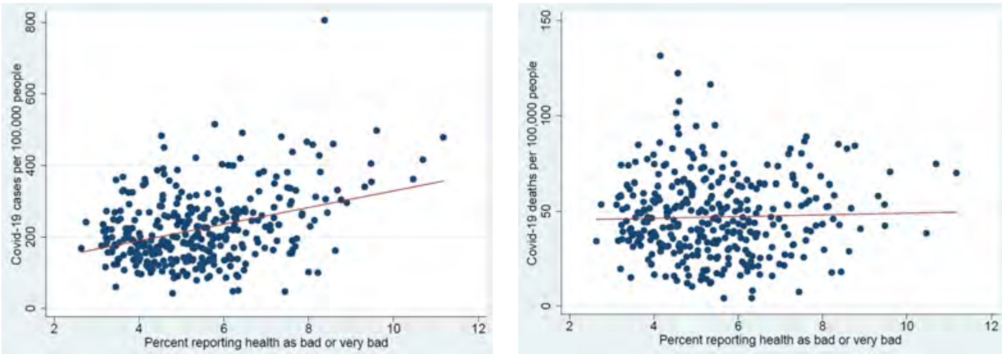
3.3 Health

To measure health conditions in different local authorities, I use data on self-reported health from the 2011 Census and calculate the percentage of the population reporting their health as bad or very bad. This measure is positively correlated with infections, but does not appear to be correlated with mortality. The lack of correlation with mortality seems puzzling. However, the regression analysis for mortality presented in the next section, which uses more disaggregated data and includes local authority fixed effects, does suggest that MSOAs with worse levels of self-reported health have significantly higher mortality rates.

Covid Economics 22, 26 May 2020: 47-58

Covid Economics 22, 26 May 2020: 47-58

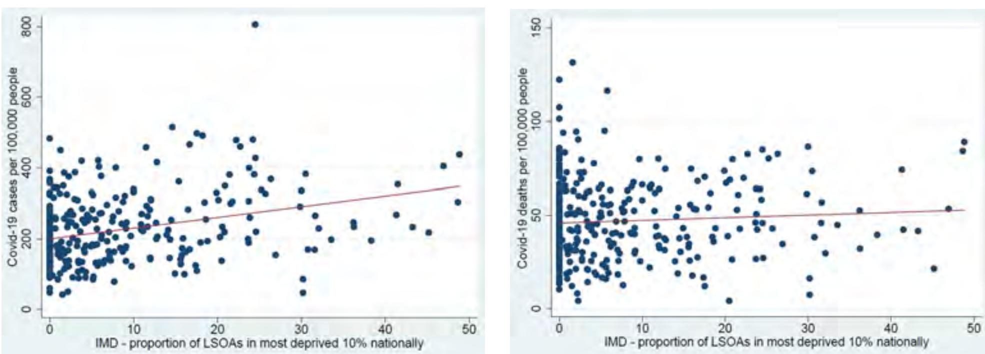
Figure 5



3.4 Deprivation

More deprived local authorities have more confirmed cases of Covid-19, but there is no correlation between deprivation and mortality.

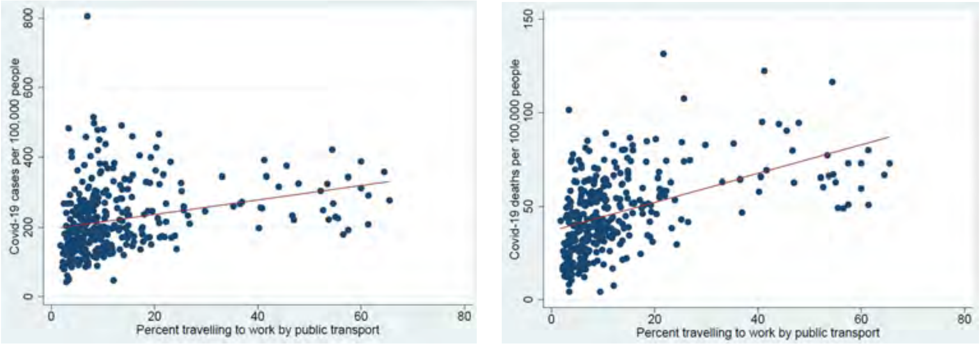
Figure 6



3.5 Use of public transport

I measure the intensity of use of public transport by calculating the percentage of people in each local authority who travel to work by underground, metro, light rail, tram, train, bus, minibus or coach. Data on method of travel to work are from the 2011 Census. There is a positive correlation between use of public transport and infections and mortality.

Figure 7



4 Regression results

I estimate a simple linear regression of infections and mortality on socioeconomic characteristics. I first include only basic demographic characteristics and then add deprivation, use of public transport and self-reported health. Data on the number of confirmed Covid-19 cases is only available by local authority district, but data on mortality is available at a finer level of geographic disaggregation (MSOA). By using more disaggregated data I am able to include local authority fixed effects in the mortality regressions. This is important because fixed effects capture local authority characteristics that have not been included in the model.

Looking at infections, local authorities with larger households have a higher number of Covid-19 cases per 100,000 people. The coefficient on the England dummy variable is very large and negative, confirming that the incidence of testing is higher in Wales. Local authorities where a larger share of the population commute by public transport and those with worse levels of self-reported health have significantly more Covid-19 cases per 100,000 people.

Mortality is higher in more densely populated MSOAs, but household size is less important than for infections and is not significant. After controlling for local authority fixed effects, the relation with age is much clearer and MSOAs with an older population have a higher number of Covid-19 deaths per 100,000 people. The relation with public transport, which is positive and significant for infections, is not present for mortality, but the relation with self-reported health is still strongly significant. Infections and mortality appear to be higher in more deprived areas, but in both cases the relation disappears after controlling for self-reported health. The relation with

Covid Economics 22, 26 May 2020: 47-58

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ethnicity is much clearer for mortality than for infections, with local areas with a larger share of black or Asian population recording higher Covid-19 mortality rates. This relation with ethnicity remains after controlling for other factors, such as household size, age, deprivation and health.

Table 4

	Covid-19 cases per 100,000 people			Covid-19 deaths per 100,000 people		
Log population density	24.498***	13.616*	6.353	1.822***	1.892***	1.251***
	(8.017)	(7.963)	(7.932)	(0.343)	(0.342)	(0.345)
Percent female	22.371***	13.853*	20.109**	1.153***	1.001***	0.431*
	(7.600)	(8.068)	(8.177)	(0.236)	(0.238)	(0.239)
Percent age 60 and over	-0.819	1.371	-2.007	1.131***	1.196***	1.080***
	(2.133)	(2.057)	(2.274)	(0.073)	(0.075)	(0.075)
Percent black/African/Caribbean/black British	0.944	-1.379	-2.166	0.428***	0.393***	0.232*
	(1.347)	(1.912)	(2.038)	(0.128)	(0.131)	(0.132)
Percent Asian/Asian British	0.631	-1.331	-1.163	0.335***	0.320***	0.246***
	(1.001)	(1.118)	(1.113)	(0.055)	(0.056)	(0.055)
Average household size	24.963	145.043**	158.407**	-2.605	-2.578	2.675
	(56.794)	(59.034)	(62.154)	(2.326)	(2.355)	(2.323)
England	-145.239***	-140.032***	-96.279***			
	(25.343)	(25.785)	(33.368)			
IMD – proportion of LSOAs in most deprived 10% nationally		2.477***	0.692		10.113***	-5.396**
		(0.556)	(0.788)		(1.928)	(2.480)
Percent travelling to work by public transport		2.454***	2.268***		-0.168	-0.143
		(0.691)	(0.676)		(0.106)	(0.104)
Percent reporting health as bad or very bad			19.935***			3.253***
			(6.642)			(0.313)
Observations	337	337	337	7,201	7,201	7,201
R-squared	0.249	0.313	0.341	0.309	0.312	0.323

Weighted OLS by population size. Robust standard errors in parentheses.

Mortality regressions use data disaggregated by MSOA and include local authority fixed effects.

*** Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level.

5 Conclusions

The results of the simple correlations and the regression analysis presented in this paper show that local areas that have larger households, worse levels of self-reported health and a larger fraction of people using public transport have more Covid-19 infections per 100,000 people. For mortality, household size and use of public transport are less important, but there is a clear relation with age, ethnicity and self-reported health. Local areas with an older population, a larger share of black or

Covid Economics 22, 26 May 2020: 47-58

Asian population and worse levels of self-reported health have more Covid-19 deaths per 100,000 people.

These results are useful to inform our understanding of the socioeconomic factors that affect infections and mortality. The relation between self-reported health and infections and mortality suggests that encouraging a healthy lifestyle can help prevent the spread of infection and reduce mortality. Also, as many countries now begin to relax lockdown measures, policymakers should pay particular attention to reducing the risk of infection in public transport. This can be done by encouraging people to use other forms of transport, as is being done in the UK, but also by increasing the frequency of services to avoid overcrowding. Businesses should also take the risk of infection in public transport into account when deciding how to get their employees back to the office. Working from home should continue to be encouraged when possible, especially for those who have to travel to work by public transport.

Covid Economics 22, 26 May 2020: 47-58

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Covid Economics **Issue 22, 26 May 2020**

Covid-19 and people's health-wealth preferences: information effects and policy implications[1]

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Policy makers responding to COVID-19 need to know people's relative valuation of health over wealth. Loosening and tightening lockdowns moves a society along a (perceived) health-wealth trade-off and the associated changes have to accord with the public's relative valuation of health and wealth for maximum compliance. In our survey experiment (N=4,618), we randomize information provision on economic and health costs to assess public preferences over this trade-off in the UK and the US. People strongly prioritize health over wealth, but the treatment effects suggest these priorities will change as experience of COVID-19 deaths and income losses evolves. Information also has heterogeneous/polarizing effects. These results encourage policy caution. Individual differences in health-wealth valuation highlight this study's importance because they map onto compliance with current lockdown measures.

Covid Economics 22, 26 May 2020: 59-116

1 The data collection benefitted from a grant from the King's Together Seed Fund. All authors contributed equally to the study.
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At the onset of the COVID-19 pandemic and in the absence of medicine-based responses, policy makers had to rely on behavioral interventions to slow the spread of the virus [1]. They restricted individual freedom in many countries to prevent deaths through the transmission of Covid-19. The reduction in deaths came, however, with an economic cost: the lockdown restricted economic activity and led to falling output and income [2]. In effect, policy makers opted for health over wealth in what was a health-wealth trade-off at the beginning of the pandemic. They now face a similar trade-off over how quickly and comprehensively to loosen the lockdown. The quicker and more complete, the stronger the initial economic recovery but also the greater the risk that COVID-19 deaths will increase again. Indeed, such trade-offs are likely to be a recurring feature of the foreseeable future until medicine-based responses are developed. When deciding where to position on such (perceived) trade-offs, policy makers need to take account of the extent to which people think health matters more than wealth. This is not just for the politics of these decisions but also for their efficacy: people tend to comply with policies they agree with [3]. Policy makers also need to know how such valuations might change as events unfold. For these reasons, it is important to understand the public's current valuation of health versus wealth and how this might change with new information. This paper reports on a survey experiment designed to address these questions in a representative sample of the UK and the US.

The survey consists of a sequence of binary choices between pairs of health and wealth outcomes. Figure 1 shows the actual sequence of eight decisions between these pairs given to UK and US respondents. If a person values both life and income and has a preference ordering [4] over their various combinations, they should choose option A in Decision 1 and option B in Decision 8. This is because, in Decision 1, A dominates B in both the health and wealth outcomes, whereas in Decision 8, B weakly dominates A as both have the same death outcome, but B is better on income loss. In the intermediate Decisions 2-7, option A has the better health outcome and option B has the better wealth outcome. As subjects move through Decisions 2-7, the health advantage of A over option B becomes progressively

Covid Economics 22, 26 May 2020: 59-116

smaller in terms of death avoided per unit of income lost. In this way, a person with a preference ordering will switch from option A to B as they progress through Decisions 1-8. Where they switch indicates how strongly they prioritize health over wealth: the later the switch, the stronger the preference for health over wealth [5], [6].

Figure 1: Decisions for preference elicitation

	United Kingdom		United States	
	Option A	Option B	Option A	Option B
Decision 1	445 lives lost per million, £2,700 average disposable income loss	460 lives lost per million, £2,750 average disposable income loss	320 lives lost per million, $4,000 average disposable income loss	335 lives lost per million, $4,150 average disposable income loss
Decision 2	412 lives lost per million, £2,500 average disposable income loss	431 lives lost per million, £2,420 average disposable income loss	310 lives lost per million, $3,850 average disposable income loss	325 lives lost per million, $3,740 average disposable income loss
Decision 3	383 lives lost per million, £2,300 average disposable income loss	393 lives lost per million, £2,200 average disposable income loss	247 lives lost per million, $3,670 average disposable income loss	256 lives lost per million, $3,500 average disposable income loss
Decision 4	360 lives lost per million, £2,150 average disposable income loss	367 lives lost per million, £2,020 average disposable income loss	213 lives lost per million, $3,500 average disposable income loss	219 lives lost per million, $3,300 average disposable income loss
Decision 5	300 lives lost per million, £2,000 average disposable income loss	305 lives lost per million, £1,850 average disposable income loss	200 lives lost per million, $3,300 average disposable income loss	204 lives lost per million, $3,100 average disposable income loss
Decision 6	240 lives lost per million, £1,900 average disposable income loss	243 lives lost per million, £1,750 average disposable income loss	188 lives lost per million, $3,120 average disposable income loss	192 lives lost per million, $2,820 average disposable income loss
Decision 7	230 lives lost per million, £1,800 average disposable income loss	232 lives lost per million, £1,640 average disposable income loss	177 lives lost per million, $2,350 average disposable income loss	180 lives lost per million, $2,000 average disposable income loss
Decision 8	210 lives lost per million, £1,550 average disposable income loss	210 lives lost per million, £1,450 average disposable income loss	165 lives lost per million, $1,950 average disposable income loss	165 lives lost per million, $1,800 average disposable income loss

The experimental element of the survey comes from our test of the stability of these revealed preferences for health versus wealth. We asked respondents to make these decisions a second time. After the first round of these decisions, they engaged in an unrelated task and answered questions regarding their likely estimates of COVID-19 deaths and income loss given the current lockdown. They were then divided randomly into 3 sub-groups and, before the second round of decisions, one sub-group received information about predicted COVID-19 deaths and another received information on predicted income losses due to COVID-19 mitigation measures. The final sub-group was our control and they heard a short piece of instrumental music instead of information. If individuals change how they prioritize health over wealth in one or both information treatments, this suggests priorities will change in certain predictable ways as the experience of death and economic loss unfolds in the coming

Covid Economics 22, 26 May 2020: 59-116

weeks and months. In so far as there are no treatment effects and individuals do not change their revealed priorities significantly between the first and second round, the results point to stability in priorities in the face of changing information.

Finally, we asked a series of demographic and attitudinal questions. This enabled us to assess whether individual compliance with current lockdown measures is indeed predicted by individual differences in the valuation of health over wealth. We also tested for what individual objective characteristics (e.g., age and income) and subjective ones (e.g., risk tolerance and their perception of the threat of COVID-19) help predict these individual differences in the valuation of health versus wealth.

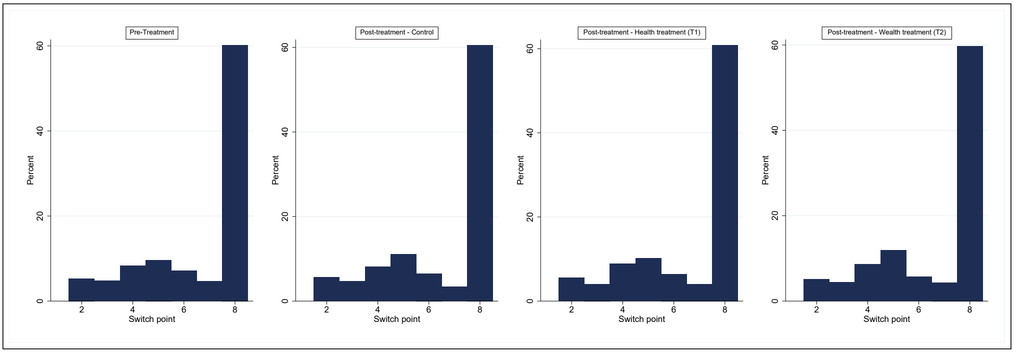
The survey was conducted between Friday 17 and Tuesday 21 April 2020: at the end of the week when both the UK and the US were predicted to hit peak deaths [7], [8]. 2385 and 2233 respondents participated in the UK and the US respectively. The survey was conducted using Prolific Academic and was pre-registered with EGAP [9]. We present full details on sampling, the survey instrument and our estimation strategy in SM (section S1 and S4).

Figure 2 reports on the distribution of switch points in the UK and the US for those switching only once in both the first and the second round, disaggregated by treatment and control. The majority in both countries switch at Decision 8 in both rounds, indicating a very high valuation of health over wealth for the majority. Based on such high valuations, the original lockdown measures, that may have saved several hundred thousand lives in both countries at the loss of perhaps as much as 10% of GDP, were consistent with the public's preferences for health over wealth. This, in turn, fits with the high trust and approval ratings that governments enjoyed when the lockdown measures were introduced [10]. However, if these high valuations remain [11], policy makers have a daunting task in calibrating the relaxation of the lockdown. If the relaxation is accompanied by relatively modest increases in deaths, then it will not be popular with the majority of the population in both countries, even if it restores income losses. Therefore, it is important to assess this interpretation of the survey results and the likely stability of this apparent high valuation of health over wealth.

Covid Economics 22, 26 May 2020: 59-116

This is what we do next.

Figure 2: Percentage of those who switch once, by decision switch point



On the interpretation of the evidence, a high valuation of health over wealth comes from the analysis of those who had a single switch point and so behaved in a manner consistent with having a preference ordering. This was the case for most observations: 75% fall into this category. 15% showed multiple switch points; hence, though revealing a preference in their individual decisions, these decisions do not cohere to form a preference ordering over health and wealth. Such a proportion is typical [4]. The remaining subjects have no switch points: respondents either always chose A, favoring health independently of the wealth consequences (9%), or always B (1%). The preponderance in this group of non-switchers of those who have a strict preference for health, whatever the wealth cost, reinforces the conclusion that health is highly valued over wealth.

On the stability of this high valuation, we first analyzed the constancy of individual behavior in the control group across the two rounds decisions are made (SM, section S3a). Although some respondents change their switch point, most people in the control group plausibly exhibit a stable preference ordering across the two rounds. With this result for the control group, we now turn to the possible treatment effects. We examined whether the changes in respondents' switch point between the two rounds are significantly different in either of the treatments as compared to the changes observed in the control group. The

Covid Economics 22, 26 May 2020: 59-116

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Covid Economics 22, 26 May 2020: 59-116

changes in switch point are, importantly, within-subject and we therefore make comparisons between-subjects in a treatment and the control group with treatment dummies in the regressions in Figures 3-4 (also see SM section S2b-c).

We have three treatment effects to report. First, an unconditional COVID-19 death information treatment effect in the UK: there is a significant increase in the number of subjects who switch from having a single switch point on the first occasion to always choosing option A (see Panel A in Figure 3). That is, they shift from having a preference ordering over health and wealth to a strict preference for health, whatever its wealth cost.

Second, Panel B in Figure 3 shows a significant conditional treatment effect in both the US and the UK. Those in the income loss information treatment group who learned that they underestimated the income loss are significantly more likely to move down from the Decision 8 switch point. 60% of the population switch at Decision 8 and 28% underestimated the income loss. These effects are very robust: they are supported by the between subject analysis when comparing across the two treatment groups and the control (we report ATEs in SM, section S3f). The last two plots in Panel B suggest that this treatment effect, however, does not occur throughout the range of possible switch points (i.e., for the other 40% of this group).

These two treatment effects suggest that people's relative valuation of health over wealth will change in predictable ways as the experience of death and income loss unfolds. In particular, the longer the lockdown in both countries, the bigger the income losses and the less likely are these losses to have been anticipated, leading to a reduction of the high relative valuation of health over wealth. This has important policy implications. The public will likely become more willing to countenance increases in deaths as the lockdown is relaxed, the later and the slower is the loosening. This message is reinforced in the UK where this valuation is likely to tilt in the opposite direction if COVID-19 deaths are salient, which is more likely under an earlier relaxation of the lockdown.

The third treatment effect can be seen in the second plot of Panel B. It is conditional

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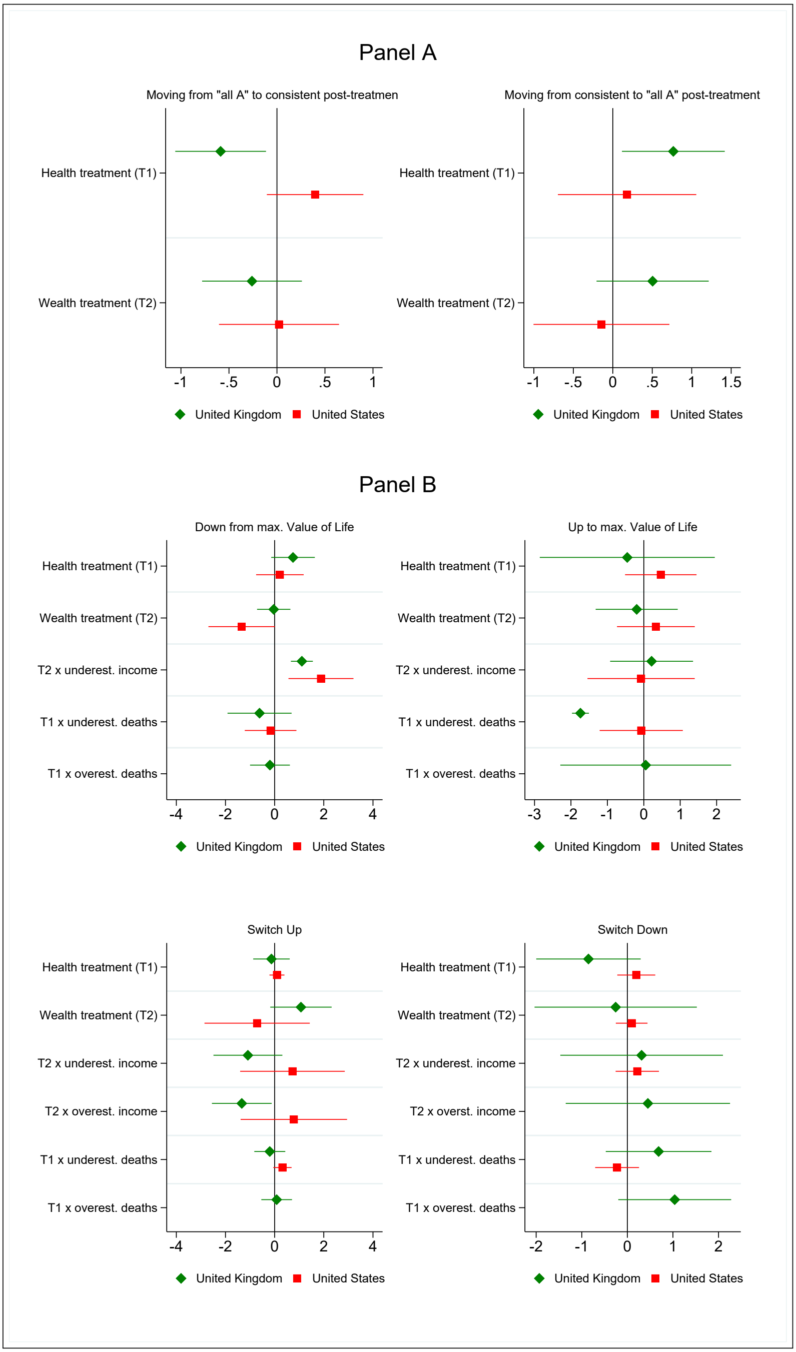
Covid Economics 22, 26 May 2020: 59-116

Figure 3: Treatment effects



and qualifies the first effect for those who underestimate COVID-19 deaths in the death information treatment of the UK. Those who underestimate go in the opposite direction to the general treatment effect: they are less likely to move up to the maximum relative valuation of health over wealth than in the control group. Examining the possible reasons for this, we find that it is associated with individual respect for authority (SM, section S2e). Those who have less respect for authority are, it seems, more likely to react perversely to the death information by becoming less likely to value health relative to wealth so highly. It is 'as if' they respond to information about the death toll being worse than anticipated by 'refusing' to update and decide instead that lives matter less: an informational backlash. This treatment effect—together with the first one—has the important implication that unexpected deaths will polarize the UK public: death information generally increases the valuation of health, but the reverse is true for those who underestimate the deaths.

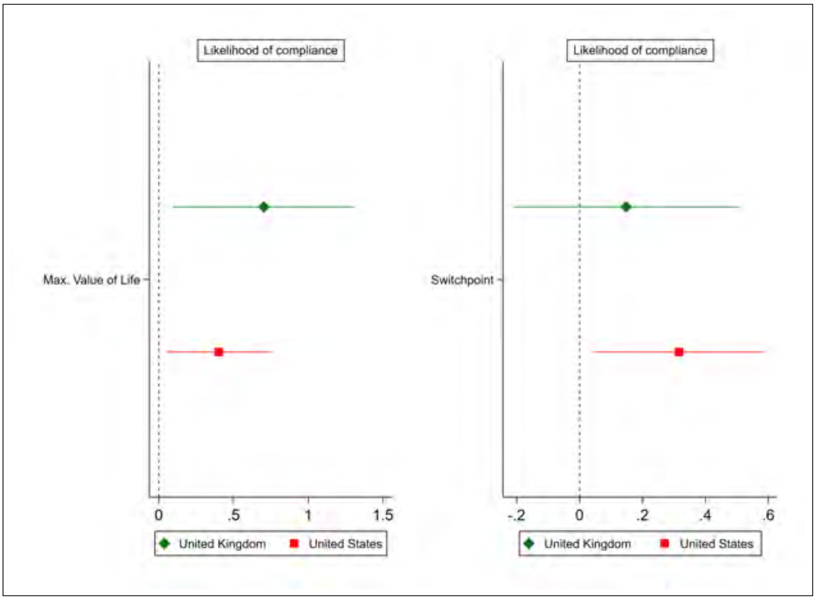
Finally, in Figure 4, we present the regression results testing whether individual differences in the valuation of health versus wealth are likely to influence policy efficacy because they help predict differences in individual compliance with the current lockdown in both countries. They do indeed. Those who choose the maximum valuation of health over wealth are twice as likely to strictly comply with lockdown guidelines in the UK and 1.5 times as likely in the US compared to everyone else (see SM, section 2d). Thus, policy makers must pay attention to the public's valuation of health over wealth not only for electoral reasons but also for reasons of policy efficacy.

We also considered whether any objective or subjective characteristics of an individual help predict their relative valuation of health over wealth (SM, section S2g). In the US, the key objective characteristic is voting for Trump, which is associated with an earlier switch point and a lower relative valuation of health over wealth. By contrast, in the UK, voting for Brexit does not help predict individual valuations, but age and education do. They are associated, respectively, with higher and lower valuation of health over wealth.

We conclude that caution in relaxing the lockdown will allow the public's currently high

Covid Economics 22, 26 May 2020: 59-116

Figure 4: Health over wealth preference and lockdown compliance



prioritization of health over wealth to evolve in ways that make compliance with a relaxation more likely. Furthermore, as there are individual differences that are also sensitive to information (see also SM, section 2h), policy makers need to be aware that the communication of policy changes could polarize these differences.

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Covid Economics 22, 26 May 2020: 59-116

Supplementary Material for

COVID-19 and people's health-wealth preferences: information effects and policy implications

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Covid Economics 22, 26 May 2020: 59-116

Contents

Covid Economics 22, 26 May 2020: 59-116

1. Materials and methods

a. Data and sampling

To conduct the online experiment, we teamed up with Prolific Academic, a web-based panel with about 35,500 participants in the United States (US) and 44,600 participants in the United Kingdom (UK) as of May 2020. Our quota-based sample was recruited between the 17th and 21st of April 2020. To generate samples for the US and the UK, we used the US Current Population Survey (*1*), the 2011 UK Census (*2*), and the Scotland's Census 2011 (*3*). We excluded Northern Ireland from the survey. We created a total of 170 subgroups weighted based on age, gender, region and work status. Table 1 and 2 are the stratification tables for the United Kingdom and United States, respectively, assuming a total (targeted) sample size of 2,500 respondents in each country. Table 3 reports the subgroups that we could not fill our quotas completely on Prolific and thus weighted accordingly in our analysis to ensure representativeness.

The average completion time was 33.58 minutes and respondents earned on average £3.08 for their participation. The full survey instrument that we used is available in Section 4 of this SM appendix. The data and code used for the analysis will be made available online at Harvard's Dataverse for replication purposes upon acceptance for publication.

Table 1: Stratification – United Kingdom

	Work Status								
	Employed (For 65+ and Scotland both Employed and Unemployed)					Unemployed			
	Regions					**Regions**			
Age	North	Midlands	South	Wales	Scotland	North	Midlands	South	Wales
16-24	22.96	23.82	32.71	4.53	15.82	22.85	22.05	31.15	4.64
25-34	34.18	36.26	62.10	6.59	16.98	13.02	13.47	20.65	2.39
35-49	61.11	66.48	91.56	12.09	29.46	18.07	19.28	29.52	3.63
50-64	40.92	45.57	61.00	8.54	26.67	29.80	29.31	36.14	6.58
65+	69.89	75.83	95.66	15.60	25.39				
16-24	23.11	24.62	32.91	4.70	15.88	23.63	22.95	32.27	4.87
25-34	38.23	41.61	70.96	7.35	16.47	8.82	7.89	11.71	1.74
35-49	64.79	73.30	103.95	12.66	27.97	12.74	11.08	15.29	2.55
50-64	47.57	54.28	70.33	9.80	25.62	22.05	19.19	23.50	4.82
65+	55.18	61.67	75.87	12.60	19.23				

Table 2: Stratification – United States

		Work Status							
		Employed (also includes unemployed 65+)				Unemployed			
		Regions				Regions			
	Age	Northeast	Midwest	South	West	Northeast	Midwest	South	West
Female	18-24	14.11	20.39	31.58	20.17	10.98	10.49	23.89	14.10
	25-34	28.92	34.16	61.33	38.53	10.40	9.66	25.07	16.27
	35-44	25.44	32.29	55.80	36.64	9.14	9.48	22.33	15.41
	45-54	28.51	33.40	57.51	34.90	9.26	10.88	24.31	13.91
	55-64	24.98	28.73	45.27	27.63	15.91	16.95	37.60	21.58
	65+	52.43	60.08	106.15	62.46				
Male	16-24	13.10	19.64	33.75	21.07	12.00	11.59	23.25	14.48
	25-34	33.26	38.67	67.53	48.23	6.55	6.87	14.51	10.02
	35-44	28.69	35.94	64.57	45.16	4.56	5.09	10.29	7.07
	45-54	29.68	35.36	65.08	39.56	6.59	6.96	13.42	7.38
	55-64	24.84	30.99	49.21	31.59	11.89	12.37	23.93	14.87
	65+	42.59	49.76	86.33	52.67				

Table 3: Subgroups not filled completely

United Kingdom			United States		
Subgroup	**Sample no.**	**Reached no.**	**Subgroup**	**Sample no.**	**Reached no.**
Female/North/65+	70	64	Female/Northeast/65+	52	33
Male/North/65+	55	38	Male/Northeast/55-64/e	25	12
Male/Midlands/65+	62	34	Male/Northeast/65+	43	32
Female/South/65+	96	92	Male/Northeast/55-64/u	12	8
Male/South/65+	76	43	Female/Midwest/65+	60	28
Female/Wales/65+	16	8	Male/ Midwest/65+	50	27
Male/Wales/65+	13	8	Female/South/65+	106	57
Female/Scotland/65+	25	21	Male/South/55-64/e	49	40
Male/Scotland/65+	19	10	Male/ South/65+	86	37
-	-	-	Male/South/55-64/u	24	22
-	-	-	Female/West/65+	62	34
-	-	-	Male/West/55-64/e	32	20
-	-	-	Male/ West/65+	53	34
-	-	-	Male/West/55-64/u	15	12

Notes: Subgroups for respondents above the age of 65 do not include a work status variable. For those below the age of 65, e indicates "employed" and u indicates "unemployed".

b. Experimental design

Our survey experiment consisted of a sequence of eight binary choices between pairs of health and wealth outcomes. Respondents read a short text on how restrictions on personal movements help contain the spread of coronavirus and save lives but with a cost of disrupting and lowering economic activity. They were then presented with eight decisions with each option giving a combination of 'lives lost per 1 million of the population through Covid-19 over the next 3 months' and 'the average loss of household income due to measures to prevent transmission of Covid-19 over the next 3 months. In each of the eight decisions, they clicked on the option that they think has the best combination.

We asked respondents to make these decisions a second time after engaging in an unrelated task. Prior to repeating the task, respondents were divided into three groups. One treatment had information about COVID-19 deaths; the other had information on income losses due to COVID-19 lockdown. A control group heard a short piece of music instead of information. Prior to treatment, they were further asked to provide their estimates of the (expected) number of lives and amount of income lost due to COVID-19 and the associated lockdown.

Treatment information: Our treatment consists of two types of information prompts that are shown to the survey respondents. The first prompt provides information about estimated lives that will be lost (in the US and the UK) by August 2020 according to the IMHE (*4*). The second prompt provides respondents with information on expected income (GDP) loses based on estimates presented by the IMF (*2*). We present the exact wording of the two information treatments in Section 4 of this SM appendix.

c. Empirical strategy

To estimate our main treatment effects, we analysed the data using two statistical forms – an ordinary least squares (OLS) regression and a logistic regression – in order to identify the causal effects of our treatment and how they interacted with respondent *i*'s estimate of deaths and income lost. Treatment assignment to one of the two groups (plus the control group) was fully randomized. Such analysis allows us to understand which of the variables has a significant impact on health-wealth prioritization.

We estimated the following two basic empirical models, whereby HL_i is the *change* (between the two rounds) in respondent i's preference over health and wealth, δ_1 is the treatment effect, δ_2 the effect of respondent i's estimate of deaths interacted with the health treatment (T1), δ_3 the effect of respondent i's estimate of the income loss interacted with the wealth treatment (T2) and ε_i the error term. In all our main specifications we used population weights (as specified in Section 1a above) in order to able to make inference for the general US and UK populations. We also clustered our standard errors at the regional level (US States and UK NUTS-2 areas). Formally, we estimate the following equations:

(1) $$HL_i = \beta_0 + \delta_1 treatment + \varepsilon_i$$

(2) $$HL_i = \beta_0 + \delta_1 treatment + \delta_2 t1\ x\ deathest_i + \delta_3 t2\ x\ incomeest_i + \varepsilon_i$$

Given that we are interested in within subject changes between pre- and post-treatment preferences we do not control for demographics in our main estimation. Section 3b includes the main treatment effects with demographic controls. Parameters δ_1, δ_2, and δ_3 capture the causal estimates of our treatment effects. Random assigned to treatment ensures the causal interpretation of OLS estimates. The results of our main analysis are reported in tables 4-7 below.

Covid Economics 22, 26 May 2020: 59-116

Outcomes: Our outcome variable *HL* is measured in five different ways. We have two categories of outcomes: a) binary ones (Switching Up; Switching Down; Down from maximum value of life (VoL); Up to maximum VoL) and b) a continuous one (VoL). We detail each one of them (and how we computed them) in S2a. In order to collect the outcome information, we simply analyzed the responses that subjects gave in the two parts of the survey that contained the eight binary decisions. The exact phrasing of those binary decisions and the questions used to collect the outcome data can be found in Section 4 of this SM appendix where we have included the full survey instrument.

2. Main empirical analysis

a. Coding of main variables of interest

Switch point

Categorical variable between 1 and 8 depending on the decision at which respondent *i* switched from option A to B.

Switching Up

Binary variable equal to 1 if respondent *i*'s switch point is earlier post-treatment than pre-treatment.

Switching Down

Binary variable equal to 1 if respondent *i*'s switch point is later post-treatment than pre-treatment.

Top Value of Life (or maximum Value of Life)

Binary variable equal to 1 if respondent *i* switched from A to B at decision 8.

Down from max. VoL

Binary variable equal to 1 if respondent *i* switched from A to B at decision 8 pre-treatment but switched at an earlier decision post-treatment.

Up to max. VoL

Binary variable equal to 1 if respondent *i* switched from A to B at decision 8 post-treatment but switches at an earlier decision pre-treatment.

Value of Life (VoL)

Continuous variable capturing respondent *i*'s minimum value of life elicited by the implied value of life of respondent *i*'s switch point. Section 2f lists the implied value of life for each switch point in the UK and US, respectively.

Death estimates

Categorical variable equal to 0 if respondent *i*'s estimate of deaths due to covid-19 is within a range of +/- 5,000 relative to the IMHE estimate at the time of surveying, equal to 1 if above and equal to -1 if below the range.

Covid Economics 22, 26 May 2020: 59-116

Covid Economics 22, 26 May 2020: 59-116

Income estimates

Categorical variable equal to 0 if respondent *i*'s estimate of the income loss due to covid-19 is within a range of +/- 1% relative to the IMF estimate at the time of surveying, equal to 1 if above and equal to -1 if below the range.

b. Main treatment effects

Table 4: Main treatment effects without interactions (Top Value of Life)

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.383 (0.367)	-0.987 (0.600)	0.141 (0.431)	0.434 (0.466)
Wealth treatment (T2)	0.514* (0.306)	-0.121 (0.477)	-0.506 (0.556)	0.309 (0.533)
Constant	-3.711*** (0.221)	-3.608*** (0.310)	-3.516*** (0.343)	-4.001*** (0.345)
Regional clustering	✓	✓	✓	✓
Observations	1,661	1,661	1,382	1,382
Pseudo R-squared	0.005	0.015	0.007	0.003

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Main treatment effects without interactions (Switch point)

	Main treatment effects			
	Switch up (UK)	Switch down (UK)	Switch up (US)	Switch down (US)
Treatment				
Health treatment (T1)	-0.209 (0.192)	-0.061 (0.129)	0.235* (0.137)	0.099 (0.163)
Wealth treatment (T2)	-0.131 (0.112)	0.136 (0.177)	0.045 (0.142)	0.135 (0.154)
Constant	-1.169*** (0.107)	-1.478*** (0.112)	-2.039*** (0.087)	-2.068*** (0.093)
Regional clustering	✓	✓	✓	✓
Observations	2,399	2,399	2,245	2,245
Pseudo R-squared	0.001	0.001	0.002	0.001

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Main treatment effects with interactions (Top Value of Life)

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.748* (0.453)	-0.453 (1.226)	0.215 (0.493)	0.467 (0.501)
Wealth treatment (T2)	-0.036 (0.346)	-0.195 (0.575)	-1.341* (0.690)	0.332 (0.545)
Income Estimate				
T2 x Underestimate	1.108*** (0.228)	0.214 (0.581)	1.886*** (0.675)	-0.074 (0.751)
T2 x Overestimate	omitted	omitted	omitted	omitted
Death Estimate				
T1 x Underestimate	-0.613 (0.665)	-1.739*** (0.119)	-0.165 (0.536)	-0.070 (0.583)
T1 x Overestimate	-0.190 (0.413)	0.054 (1.197)	omitted	omitted
Constant	-3.711*** (0.221)	-3.608*** (0.310)	-3.516*** (0.343)	-4.001*** (0.345)
Regional clustering	✓	✓	✓	✓
Observations	1,654	1,654	1,379	1,379
Pseudo R-squared	0.020	0.027	0.027	0.003

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

Table 7: Main treatment effects with interactions (Switch point)

	Main treatment effects			
	Switch up (UK)	Switch down (UK)	Switch up (US)	Switch down (US)
Treatment				
Health treatment	-0.129 (0.379)	-0.853 (0.584)	0.095 (0.155)	0.196 (0.213)
Wealth treatment	1.071* (0.637)	-0.256 (0.908)	-0.712 (1.092)	0.095 (0.177)
Income Estimate				
T2 x Underestimate	-1.087 (0.715)	0.313 (0.910)	0.726 (1.086)	0.218 (0.243)
T2 x Overestimate	-1.336** (0.620)	0.451 (0.920)	0.782 (1.105)	omitted
Death Estimate				
T1 x Underestimate	-0.198 (0.321)	0.686 (0.591)	0.318* (0.190)	-0.225 (0.246)
T1 x Overestimate	0.083 (0.318)	1.039 (0.632)	omitted	omitted
Constant	-1.175*** (0.105)	-2.033*** (0.088)	-1.494*** (0.112)	-2.060*** (0.094)
Regional clustering	✓	✓	✓	✓
Observations	2,380	2,380	2,229	2,220
Pseudo R-squared	0.004	0.005	0.004	0.002

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

c. "All A" – group

A significant proportion of respondents (12% pre-treatment and 9% post-treatment) chose option A for all eight decisions. Given that these respondents chose a weakly dominated option (the same number of deaths for a higher income loss), we do not include these subjects into our main treatment effects analysis. Instead, we analyzed separately how our treatments affected respondents' move to and from choosing option A for all decisions. Table 8 reports the treatment effects on this particular group of respondents.

Table 8: "All A" main treatment effects

	Main treatment effects			
	Down from "all A" (UK)	Up to "all A" (UK)	Down from "all A" (US)	Up to "all A" (US)
Treatment				
Health treatment (T1)	-0.587** (0.241)	0.767** (0.332)	0.397 (0.256)	0.181 (0.47)
Wealth treatment (T2)	-0.260 (0.265)	0.505 (0.363)	0.022 (0.319)	-0.144 (0.439)
Constant	-2.760*** (0.130)	-4.506*** (0.329)	-2.768*** (0.201)	-3.695*** (0.264)
Regional clustering	✓	✓	✓	✓
Observations	1,884	1,884	1,665	1,665
Pseudo R-squared	0.007	0.009	0.005	0.002

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

d. Health-wealth preferences and compliance with guidelines

To assess the likelihood of compliance with government guidelines, we use pre-treatment question 3 ("How likely are you to follow the government's guidance for reducing the spread of Covid-19?") and regress our outcome variables on the answer respondents gave to this question. Specifically, we formally estimate the below model, whereby $Compl_i$ is measured as 1) a categorical variable, ranging from 1 to 5, equal to the value respondents selected on pre-treatment question 3 with a higher value indicating a higher likelihood of compliance and 2) as a binary variable equal to 1 if respondents selected the answer "Very likely" and equal to 0 otherwise. As we are estimating the pre-treatment relationship, we include a vector of controls γ_i.

(3) $$Compl_i = \beta_0 + \delta_1 HL_i + \gamma_i + \varepsilon_i$$

Table 9 reports the results using the categorical outcome variable and table 10 reports the results of the binary outcome variable. Both, choosing the maximum value of life and the switch point, excluding the maximum value of life, affect compliance with government guidelines in the US; yet, only the maximum value of life affects compliance in the UK. This finding further emphasizes the importance of our main treatment effects, as these are all related to the maximum value of life and not to the switch point people have more broadly.

Covid Economics 22, 26 May 2020: 59-116

Covid Economics 22, 26 May 2020: 59-116

Table 9: Compliance with guidelines

	Pre-treatment compliance (categorical)			
	Max. Value of Life (UK)	Switch point (UK)	Max. Value of Life (US)	Switch point (US)
Max Value of Life	0.702** (0.310)	-	0.402** (0.178)	-
Switch point	-	0.148 (0.184)	-	0.316** (0.138)
Demographic controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	1,131	506	1,142	409
Pseudo R-squared	0.178	0.253	0.118	0.188

Notes: Estimates come from an ordered logistic regression. The Switch point regressions exclude those respondents with a switch point equal to 8 to capture the difference across switch points as opposed to the effect of choosing the maximum value of life. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Compliance with guidelines

	Pre-treatment compliance (binary)			
	Max. Value of Life (UK)	Switch point (UK)	Max. Value of Life (US)	Switch point (US)
Max Value of Life	0.761*** (0.280)	-	0.378** (0.181)	-
Switch point	-	0.163 (0.179)	-	0.289** (0.115)
Demographic controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	1,026	426	1,120	400
Pseudo R-squared	0.197	0.266	0.139	0.226

Notes: Estimates come from a logistic regression. The Switch point regressions exclude those respondents with a switch point equal to 8 to capture the difference across switch points as opposed to the effect of choosing the maximum value of life. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

e. Respecting authority in the UK

As can be seen in table 6, UK respondents who underestimated the number of deaths and were assigned the Covid-19 deaths treatment were less likely to move to the top value of life post-treatment. This surprising result can be explained by people's respect for authority as table 11 reports below. The higher people scored on demographic question D9 (a higher score indicating a preference to question authority), the more likely people who underestimated deaths and were assigned the deaths information treatment were to reduce their likelihood of choosing the maximum value of life. We interpret this result as an information backlash. People who question authority are sceptical of the information we provide them with and subsequently do not update their preferences on the health-wealth trade-off in response to our information. Table 11 also indicates that including this interaction switches the signs of the interaction between death treatment and underestimate of deaths without authority into the 'correct' direction, further supporting the explanatory power of including respect for authority into the analysis.

Table 11: Authority interaction in the UK

	Interactions with respect for Authority			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Switch up (UK)	Switch down (UK)
Treatment				
Health treatment	0.588 (1.646)	-4.694*** (1.473)	0.073 (0.721)	-2.245*** (0.452)
Wealth treatment	-0.022 (0.349)	-0.177 (0.577)	1.047 (0.636)	-0.262 (0.910)
Income Estimate				
T2 x Underestimate	1.074*** (0.232)	0.202 (0.585)	-1.132 (0.711)	0.328 (0.923)
T2 x Overestimate	omitted	omitted	-1.302** (0.614)	0.468 (0.928)
Death Estimate				
T1 x Underestimate	-0.179 (1.687)	6.351*** (0.896)	-0.535 (0.959)	2.092*** (0.721)
T1 x Overestimate	-0.883 (2.238)	5.569*** (1.578)	0.472 (0.863)	2.541*** (0.707)
Questioning Authority	-0.039 (0.042)	0.044 (0.055)	-0.039** (0.019)	-0.029 (0.032)
T1 x Underest. x Authority	-0.062 (0.081)	-1.639*** (0.304)	0.019 (0.065)	0.000 (0.066)
T1 x Overest. x Authority	0.162 (0.170)	-0.280 (0.243)	-0.124** (0.056)	-0.028 (0.064)
T1 x Correct est. x Authority	0.031 (0.326)	0.630*** (0.165)	-0.041 (0.158)	0.254*** (0.084)
Constant	-3.515*** (0.320)	-3.813*** (0.425)	-0.970*** (0.127)	-1.896*** (0.173)
Regional clustering	✓	✓	✓	✓
Observations	1,628	1,628	2,321	2,321
Pseudo R-squared	0.023	0.049	0.010	0.006

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

f. Estimation of implied value of life

Further to our main analysis of individuals' switch points we estimated their implied minimum value of life. Table 12 lists the implied value of life for the UK and the US given the decision at which subject i switched from A to B.

Table 12: Implied value of life

	Minimum Value of Life given switch from A to B	
	United Kingdom	United States
Decision 1	-	-
Decision 2	£1.73m	$2.9m
Decision 3	£4.1m	$7.4m
Decision 4	£7.8m	$13m
Decision 5	£12.3m	$19.5m
Decision 6	£20.5m	$29.2m
Decision 7	£32.8m	$45.5m
Decision 8	-	-

g. Individual characteristics on health-wealth trade-off

To assess the impact of demographic variables on individuals' perceptions of the health-wealth trade-off, we regressed our set of demographic variables on the estimated minimum value of life implied by people's choices in the preference elicitation task. Table 13 reports the results for the United Kingdom and table 14 the results for the United States.

Table 13: Value of life pre-treatment demographics UK in £100,000

	Without death estimates	Including death estimates
Estimates of Covid-19 deaths	-	-0.00 (0.00)
Female	-5.64 (7.42)	-10.40 (7.67)
Age (categories)	11.62*** (3.40)	15.64*** (4.36)
Regions		

Covid Economics 22, 26 May 2020: 59-116

Covid Economics 22, 26 May 2020: 59-116

Wales	-12.85 (10.56)	-16.64 (10.47)
Scotland	-3.05 (8.25)	0.09 (7.48)
Ethnicity		
Any other white background	17.91* (8.47)	22.21** (8.07)
White and Black Caribbean	-211.80*** (30.55)	-231.67*** (30.67)
White and Black African	22.85 (37.81)	-10.69 (94.75)
White and Asian	35.23 (45.63)	49.39 (42.25)
Any other mixed background	-34.24 (43.68)	-19.24 (54.07)
Indian	27.28 (58.21)	-10.08 (61.71)
Pakistani	-62.98 (97.61)	-62.09 (124.86)
Bangladeshi	40.48 (59.14)	38.54 (103.82)
Chinese	-11.32 (85.45)	-4.49 (86.50)
Any other Asian background	-47.08 (37.97)	032.54 (86.19)
Black Caribbean	40.80 (54.22)	14.22 (53.17)
Black African	89.53** (39.78)	95.30* (43.95)
Other ethnic group	-78.49 (78.63)	-169.44*** (29.53)
Prefer not to answer	98.26** (31.16)	106.93** (45.48)
Income	-0.93 (1.35)	-2.25 (2.31)
Political Party		
Labour	9.27 (16.28)	2.26 (14.80)
Liberal Democrat	5.10 (15.76)	-5.50 (15.36)
Scottish National Party (SNP)	29.61* (15.81)	35.30** (13.57)
Plaid Cymru	-39.36 (44.03)	-28.05 (38.30)
The Brexit Party	-6.60 (26.09)	-20.27 (32.44)
Green Party	1.41 (13.49)	0.53 (15.52)
UKIP	-4.09 (29.62)	-11.89 (39.87)
Sinn Fein	88.56** (37.68)	-
SDLP	-29.63 (33.26)	-87.75 (75.85)
Brexit Vote		
Leave	22.79 (16.88)	23.67 (20.89)
Remain	10.66 (14.88)	12.82 (14.84)

Prefer not to say	38.52 (32.87)	36.50 (28.09)
Pol. Left-right self-placement	-4.91 (2.91)	-6.67* (3.04)
Less redistribution	-4.08* (1.90)	-3.61 (2.49)
Respect for authority	-1.56 (0.94)	-2.59 (1.76)
News consumption	3.06 (4.36)	3.35 (4.88)
Most people can be trusted	13.10* (7.06)	17.68** (7.45)
Trust in government		
Some of the time	-6.47 (9.39)	6.31 (10.08)
Most of the time	2.41 (10.44)	12.18 (15.46)
Just about always	13.68 (31.20)	37.51 (28.20)
Employment Status		
Working part-time (8-29hrs)	-8.94 (14.48)	-15.55 (17.91)
Working part-time (less than 8hrs)	20.60 (16.63)	40.26 (31.43)
On furlough	-4.93 (17.40)	1.04 (18.18)
Unemployed	1.61 (26.84)	-3.15 (23.40)
Full time university student	-3.64 (17.60)	-14.14 (18.53)
Other full time student	13.38 (30.58)	32.22 (45.78)
Retired	-21.86* (10.98)	-29.36* (15.52)
Not in paid work	-5.01 (13.90)	-1.15 (17.19)
Other	-26.72 (24.79)	0.69 (30.49)
Education	-17.78** (7.56)	-23.30** (7.73)
Religion		
Church of England	8.93 (12.93)	6.70 (14.03)
Roman Catholic	8.79 (24.67)	19.44 (26.05)
Presbyterian	-15.23 (23.09)	-42.45 (26.47)
Methodist	41.35 (39.54)	33.06 (46.29)
Baptist	11.65 (54.96)	13.33 (54.05)
United Reformed Church	84.90** (27.15)	96.67** (34.31)
Free Presbyterian	-62.98 (46.71)	1.74 (53.12)
Judaism	75.45 (44.52)	102.96*** (20.86)
Hinduism	153.41*** (40.12)	184.51** (64.74)

Islam	21.94 (67.89)	37.58 (110.83)
Sikhism	-58.19 (55.41)	-4.29 (59.520
Buddhism	-87.68* (45.42)	-60.24 (59.24)
Other	-52.27 (30.95)	-54.50 (34.85)
Orthodox Christian	-2.39 (38.02)	13.12 (42.75)
Pentecostal	17.00 (27.85)	19.01 (32.21)
Evangelical	50.06* (26.73)	54.63* (28.41)
Prefer not to say	-37.10 (29.31)	-76.26* (36.96)
How often going to church		
Less often than once a year	-3.66 (15.71)	-6.08 (14.77)
less often but at least once a year	-27.88 (21.49)	-20.94 (23.03)
less often but at least twice a year	-32.04 (24.37)	-27.72 (25.76)
less often but at least once a month	-8.72 (29.93)	-35.55 (35.97)
less often but at least once every two weeks	-54.51 (43.58)	-75.30 (49.76)
Once a week or more	18.86 (30.48)	9.41 (35.78)
Varies too much to say	-65.65** (29.32)	-47.07 (27.72)
Ability to cover living costs	2.20 (3.46)	4.74 (3.82)
Earning due to pandemic	6.26 (7.69)	3.70 (8.96)
How healthy felt recently	-1.66 (1.07)	-3.27* (1.47)
Risk-group dummy	1.18 (11.58)	-2.61 (15.21)
Likelihood of contracted covid-19	0.77 (3.38)	-0.08 (4.67)
Risk seeking	-4.62** (1.58)	-2.55 (1.90)
Patience	1.36 (1.89)	0.38 (1.77)
Altruism	-0.01 (0.02)	-0.01 (0.03)
Constant	282.99*** (35.73)	297.69*** (48.98)
Observations	1,041	815
R-squared	0.1117	0.1309

Notes: Estimates come from a linear regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Value of life pre-treatment demographics US in $100,000

	Without death estimates	Including death estimates
Estimates of Covid-19 deaths	-	-0.00*** (0.00)
Female	2.25 (9.33)	8.60 (11.95)
Age (categories)	-5.00 (5.72)	-8.46 (6.52)
Spanish, Hispanic or Latino dummy	7.92 (20.46)	15.86 (19.54)
Race (multiple possible)		
White	-31.96 (22.51)	-6.10 (31.68)
Black or African-American	-95.73*** (22.50)	-20.37 (26.66)
American Indian or Alaska Native	5.99 (26.74)	6.86 (39.25)
Asian	-28.94 (23.20)	-4.42 (27.25)
Native Hawaiian or other Pacific Islander	-	-
Income	-2.28 (2.00)	-1.83 (2.40)
Political Party		
Republican Party	25.08 (28.83)	4.84 (35.72)
Other	30.06* (15.10)	27.50 (21.72)
2016 Vote		
Didn't vote	-17.90 (15.21)	-21.10 (21.21)
Donald Trump	-48.67** (23.63)	-36.25 (29.35)
Prefer not to say	-8.15 (20.52)	-13.54 (22.92)
Pol. Left-right self-placement	-5.21 (4.35)	-1.98 (4.88)
Less redistribution	-8.03*** (2.23)	-9.86*** (2.91)
Respect for authority	0.98 (2.48)	0.84 (3.31)
News consumption	12.10*** (4.04)	11.37** (5.43)
Most people can be trusted	26.75** (10.18)	29.01** (12.47)
Trust in government		
Some of the time	-7.08 (14.51)	-5.11 (18.21)
Most of the time	-10.80 (21.93)	-7.34 (26.41)
Just about always	115.33*** (31.60)	139.94*** (39.94)
Employment Status		
Working part-time (8-29hrs)	5.03	6.50

Covid Economics 22, 26 May 2020: 59-116

	(17.58)	(22.66)
Working part-time (less than 8hrs)	8.11 (22.29)	8.44 (34.85)
On furlough	-9.25 (16.37)	4.20 (23.46)
Unemployed	25.29 (16.89)	10.60 (21.56)
Full time university student	-46.97 (30.68)	-21.94 (35.49)
Other full time student	9.36 (47.58)	45.66 (70.64)
Retired	-6.86 (21.54)	-4.29 (25.24)
Not in paid work	16.13 (35.04)	26.12 (21.56)
Other	-19.90 (35.04)	-31.21 (52.00)
Education	0.69 (10.55)	12.34 (13.20)
Religion		
Protestant	36.66* (18.56)	40.13* (22.15)
Roman Catholic	2.83 (20.63)	-6.94 (26.14)
Mormon	-21.25 (54.39)	-116.65** (51.53)
Other Christian	21.86 (19.34)	11.59 (31.43)
Jewish	-15.28 (38.08)	-15.04 (41.58)
Muslim	75.63*** (25.89)	91.22** (39.26)
Other non-Christian	-23.19 (26.16)	-4.21 (33.58)
Prefer not to say	-88.50 (60.51)	-129.40** (50.27)
How often going to church		
Less often than once a year	13.57 (13.37)	12.20 (18.17)
less often but at least once a year	-20.98 (26.86)	4.78 (38.74)
less often but at least twice a year	-9.06 (30.55)	-21.98 (41.92)
less often but at least once a month	11.80 (28.39)	0.22 (33.08)
less often but at least once every two weeks	48.31 (33.07)	50.05 (32.05)
Once a week or more	27.12 (20.40)	9.84 (26.73)
Ability to cover living costs	5.05* (2.82)	5.14 (3.71)
Earning due to pandemic	11.71 (10.58)	10.64 (14.55)
How healthy felt recently	0.89 (2.48)	-1.79 (3.44)
Risk-group dummy	21.28 (13.44)	17.53 (17.17)

Covid Economics 22, 26 May 2020: 59-116

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Likelihood of contracted covid-19	-2.62 (4.71)	-6.56 (6.50)
Risk seeking	0.17 (1.64)	2.11 (2.20)
Patience	-2.78 (2.28)	-2.17 (2.81)
Altruism	0.01 (0.02)	0.02 (0.03)
Constant	397.82*** (44.58)	333.15*** (79.77)
Observations	996	723
R-squared	0.1285	0.1299

Notes: Estimates come from a linear regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

h. Additional subgroup analysis of main treatment effects

In addition to the analysis of our main treatment effects, we tested for interactions of treatment effects with demographic variables. Table 15 and table 16 report two significant interactions. Table 15 reports treatment effects in the UK interacted with age and table 16 reports treatment effects in the US interacted with redistributive preferences. In the UK we find that respondents over the age of 50 who were assigned to the wealth treatment were more likely to move away from the maximum value of life post-treatment. In the US we find that people who support more redistribution significantly reduce their implied value of life when assigned to the health treatment. This effect is driven by those who underestimate deaths.

Table 15: Likelihood of moving away from maximum value of life post treatment – age interactions

	UK
Treatment	
Health treatment (T1)	-0.41 (0.69)
Wealth treatment (T2)	-1.43 (1.22)
Age	
25-34	-0.89 (0.88)
35-49	0.10 (0.79)
50-64	0.10 (0.36)
65+	-0.17 (0.39)
Treatments x Age	
T1 x 25-34	1.20 (1.08)
T1 x 35-49	0.42 (0.78)
T1 x 50-64	0.87 (0.84)
T1 x 65+	0.49 (0.49)
T2 x 25-34	2.13 (1.39)
T2 x 35-49	1.55 (1.56)
T2 x 50-64	1.87* (1.03)
T2 x 65+	1.87* (0.97)
Constant	-3.26*** (0.51)
Observations	2,399
Pseudo R-squared	0.0159

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Change in Value of life in £100,000/$100,000 – redistribution interactions

	US	US (only those that underestimated deaths)
Treatment		
Health treatment (T1)	26.15** (12.59)	28.17* (14.01)
Wealth treatment (T2)	15.74* (9.02)	19.58 (18.59)
Redistributive Preferences		
More redistribution	2.94 (3.75)	-1.46 (5.16)
Less redistribution	3.82 (8.21)	4.91 (5.43)
Treatments x Redistributive Preferences		
T1 x more redistribution	-28.17** (12.13)	-30.66** (13.29)
T1 x less redistribution	-31.88* (17.11)	-22.16 (22.33)
T2 x more redistribution	-13.49 (9.77)	-15.44 (20.28)
T2 x less redistribution	-14.50 (14.26)	-24.57 (20.70)
Constant	-4.75 (3.32)	-2.97 (2.45)
Observations	1,263	698
R-squared	0.0060	0.0135

Notes: Estimates come from a linear regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The categorical redistribution variable is based on demographic question D9 and coded as "more redistribution" if respondent *i* indicated a value of below 5, as "less redistribution" if respondent *i* indicated a value of above 5 and as "indifferent" for a value of 0.

3. Robustness

a. Preference stability in control group

To have a preference ordering, there must be only one switch point each time a person faces the eight binary decisions. There are some people who exhibit more than one switch point, either the first or the second time they confront the binary options. We typically ignore a person's choices when this happens. Those respondents – as well as those who did not choose a switch point in either the first or second round of the experiment – are coded as missing in our main variables.

To interpret our treatment effects as effects on preferences, it matters whether we can reasonably assume that people who have a single switch point on each set also have a

Covid Economics 22, 26 May 2020: 59-116

preference ordering. This is not necessarily the case because anyone who chose a switch point randomly would satisfy the condition of only switching once. And if random selection explained their switch point then the treatment effect would be better interpreted as some interaction with the randomization process. To test for this possibility, we analyze the stability of preferences in the control group where no treatment effect could occur. We have evidence of such consistency of choice between the first and second time these decisions are made, and this would be unusual if people chose the switch point randomly (805 of 1,006 control group-respondents who chose a switch point both pre- and post-treatment expressed stable preferences). In fact, the probability of choosing the same switch point twice if the choice of switch point on each occasion was random would be 1/8 (i.e. 8x 1/64), while we have 80% consistent choices.

The number of preference-based choosers might be plausibly calculated in the following way by allowing for strict preference followers, 'fuzzy' ones (defined below) and random choosers.

'Fuzzy' preference followers are people that know the region they like but not the precise point: they cannot distinguish between adjacent switching points and so toss a coin. For example, if someone thinks they should switch at decision 6 or decision 7, they toss a coin and might choose 7. When asked again they toss the coin again and there is a 50% chance they choose 7 again and a 50% chance they now choose 6. Thus, there is a 50% chance that we observe one downward movement. Alternatively, they could have chosen 6 in first place; then they have an equal chance of staying at 6 or moving up to 7 in the second decision. For this person there is a 50% chance they pick the same, a 25% chance that they move up and a 25% chance that they move down. We have 136 respondent who change by one decision point, which would arise if there were 272 people who had fuzzy preferences as defined above.

However, some people who just choose randomly would also change their switch point by one position = 7/32. Since 1/8 of these random choosers would select the same point, it follows that 21/32 of the random choosers would move their decision by more than one point. We have 65 choices that move by more than one switch point. This would imply 99 random choosers in our sample. This being the case, the random choosers would also account for 22 of the observations of one switch point changes. We had 136 observations with one switch and so that leaves 114 of these choices to be accounted for by respondents with fuzzy preferences.

These overall 228 respondents with fuzzy preferences would produce 114 of the consistent choices we observe (and we would expect 12 of these observations to come from the random choosers). Thus, our residual number of genuine preference-based choosers is 679, with 228 fuzzy preference choosers and 99 random choosers. Overall, our sample therefore consists of 90% either consistent or fuzzy preference-choosers.

b. Main treatment effects with demographic controls

To further test the robustness of our results we estimated all our main treatment effects with the within subject analysis and additionally included our demographic covariates. The results of this analysis are reported in tables 17-20. All our main treatment results hold.

Covid Economics 22, 26 May 2020: 59-116

Table 17: Main treatment effects without interactions (Top Value of Life)

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.797 (0.640)	-0.995* (0.585)	0.581 (0.662)	0.333 (0.557)
Wealth treatment (T2)	0.741** (0.310)	-0.469 (0.887)	0.241 (0.604)	-0.011 (0.544)
Constant	-4.094** (1.602)	13.881*** (3.657)	-0.907 (2.800)	-8.221** (3.323)
Demographic controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	617	732	835	764
Pseudo R-squared	0.142	0.380	0.169	0.159

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 18: Main treatment effects without interactions (Switch point)

	Main treatment effects			
	Switch up (UK)	Switch down (UK)	Switch up (US)	Switch down (US)
Treatment				
Health treatment (T1)	-0.143 (0.209)	0.047 (0.197)	0.282* (0.152)	0.145 (0.199)
Wealth treatment (T2)	0.001 (0.123)	0.084 (0.292)	0.070 (0.169)	0.215 (0.203)
Constant	-0.790 (0.682)	-3.605*** (0.934)	-1.180* (0.676)	-2.265*** (0.783)
Demographic controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	1,419	1,383	1,619	1,600
Pseudo R-squared	0.050	0.072	0.042	0.057

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

Table 19: Main treatment effects with interactions (Top Value of Life)

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	1.142 (0.970)	-1.535* (0.901)	0.913 (0.675)	0.224 (0.663)
Wealth treatment (T2)	-0.492 (0.439)	-0.240 (1.060)	-0.502 (0.746)	-0.084 (0.582)
Income Estimate				
T2 x Underestimate	1.982*** (0.481)	-0.537 (0.812)	1.828** (0.759)	0.285 (0.818)
T2 x Overestimate	omitted	omitted	omitted	omitted
Death Estimate				
T1 x Underestimate	-0.423 (1.153)	1.793* (0.998)	-0.861 (0.636)	0.230 (0.669)
T1 x Overestimate	-0.392 (1.054)	omitted	omitted	omitted
Constant	-4.264** (1.801)	14.281*** (3.477)	-1.048 (2.845)	-8.240** (3.344)
Demographic controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	615	600	833	762
Pseudo R-squared	0.174	0.389	0.194	0.160

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

Covid Economics 22, 26 May 2020: 59-116

Table 20: Main treatment effects with interactions (Switch point)

	Main treatment effects			
	Switch up (UK)	Switch down (UK)	Switch up (US)	Switch down (US)
Treatment				
Health treatment	-0.385 (0.401)	-0.739 (0.606)	0.098 (0.171)	0.284 (0.236)
Wealth treatment	0.779 (0.977)	0.154 (1.151)	0.348 (1.007)	0.240 (0.229)
Income Estimate				
T2 x Underestimate	-0.724 (1.068)	-0.254 (1.079)	-0.315 (1.019)	-0.050 (0.373)
T2 x Overestimate	-0.901 (0.992)	0.051 (1.067)	-0.282 (1.034)	omitted
Death Estimate				
T1 x Underestimate	0.165 (0.432)	0.693 (0.652)	0.373* (0.202)	-0.292 (0.287)
T1 x Overestimate	0.384 (0.404)	1.070 (0.654)	omitted	omitted
Constant	-0.865 (0.622)	-3.664*** (0.892)	-1.175* (0.678)	-2.160*** (0.812)
Demographic controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	1,412	1,377	1,609	1,585
Pseudo R-squared	0.054	0.077	0.045	0.058

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

c. Main treatment effects with alternative coding of outcome variables

Our main analysis coded each of the main outcome variables as 0 if either, subjects did not move from their original switch point post-treatment or, if they moved in the opposite direction to the captured direction of the outcome variable. To check the robustness of our estimates we estimated our models included outcome variables only then equal to 0, when subjects did not move from their original switch point post-treatment. Tables 21-24 report the main treatment effects with this alternative coding of the outcome variables. The main results of our analysis hold.

Table 21: Main treatment effects without interactions (Top Value of Life) – alt. variable

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.366 (0.361)	-0.976 (0.594)	0.151 (0.427)	0.438 (0.461)
Wealth treatment (T2)	0.511* (0.305)	-0.105 (0.477)	-0.500 (0.552)	0.297 (0.526)
Constant	-3.684*** (0.220)	-3.497*** (0.340)	-3.583*** (0.309)	-3.971*** (0.341)
Regional clustering	✓	✓	✓	✓
Observations	1,628	1,607	1,351	1,344
Pseudo R-squared	0.005	0.015	0.007	0.003

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 22: Main treatment effects without interactions (Switch point) – alt. variable

	Main treatment effects			
	Switch Up (UK)	Switch Down (UK)	Switch Up (US)	Switch Down (US)
Treatment				
Health treatment (T1)	-0.225 (0.193)	-0.117 (0.122)	0.259** (0.129)	0.159 (0.152)
Wealth treatment (T2)	-0.114 (0.116)	0.106 (0.182)	0.067 (0.140)	0.149 (0.151)
Constant	-1.006*** (0.110)	-1.728*** (0.090)	-1.330*** (0.110)	-1.833*** (0.087)
Regional clustering	✓	✓	✓	✓
Observations	2,114	1,880	1,973	1,801
Pseudo R-squared	0.001	0.001	0.002	0.001

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

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Table 23: Main treatment effects with interactions (Top Value of Life) – alt. variable

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.739* (0.442)	-0.427 (1.219)	0.226 (0.488)	0.474 (0.494)
Wealth treatment (T2)	-0.041 (0.345)	-0.196 (0.575)	-1.334* (0.685)	0.310 (0.539)
Income Estimate				
T2 x Underestimate	1.115*** (0.221)	0.261 (0.573)	1.885*** (0.671)	-0.031 (0.747)
T2 x Overestimate	omitted	omitted	omitted	omitted
Death Estimate				
T1 x Underestimate	-0.628 (0.667)	-1.763*** (0.130)	-0.167 (0.540)	-0.076 (0.586)
T1 x Overestimate	-0.189 (0.412)	0.045 (1.195)	omitted	Omitted
Constant	-3.684*** (0.220)	-3.583*** (0.309)	-3.497*** (0.340)	-3.971*** (0.341)
Regional clustering	✓	✓	✓	✓
Observations	1,621	1,600	1,348	1,341
Pseudo R-squared	0.020	0.027	0.027	0.003

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

Table 24: Main treatment effects with interactions (Switch point) – alt. variable

	Main treatment effects			
	Switch Up (UK)	Switch Down (UK)	Switch Up (US)	Switch Down (US)
Treatment				
Health treatment (T1)	-0.224 (0.377)	-0.908 (0.579)	0.129 (0.148)	0.224 (0.207)
Wealth treatment (T2)	1.099 (0.681)	0.172 (0.965)	-0.862 (1.091)	0.113 (0.173)
Income Estimate				
T2 x Underestimate	-1.107 (0.761)	-0.117 (0.983)	0.927 (1.086)	0.213 (0.244)
T2 x Overestimate	-1.342** (0.652)	-0.036 (0.977)	0.947 (1.104)	omitted
Death Estimate				
T1 x Underestimate	-0.137 (0.319)	0.657 (0.586)	0.295 (0.187)	-0.149 (0.243)
T1 x Overestimate	0.208 (0.308)	1.090* (0.628)	omitted	omitted
Constant	-1.011*** (0.108)	-1.722*** (0.090)	-1.345*** (0.110)	-1.828*** (0.088)
Regional clustering	✓	✓	✓	✓
Observations	2,095	1,868	1,957	1,784
Pseudo R-squared	0.005	0.005	0.004	0.002

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

d. Main treatment effects with continuous death and loss estimates

As we are primarily interested in how people respond to either underestimating or overestimating the death and income loss of the pandemic, we used a categorical variable that classified people as either underestimating, overestimating or having a correct estimate for both variables. For robustness, we also ran our main analysis with a continuous variable for people's estimates. The results of this test are reported in table 25. Unsurprisingly, the results of this analysis differ from those of our main analysis and there are no significant interactions between the treatments and continuous estimates of death and income loss. This result indicates that the magnitude of respondents' estimates does not affect their change in preferences over health and wealth but rather whether these estimates over- or underestimate the impact of the pandemic.

Covid Economics 22, 26 May 2020: 59-116

Table 25: Main treatment effects with interaction of death and income estimates – continuous

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.186 (0.440)	-1.307* (0.700)	-0.134 (0.561)	0.321 (0.569)
Wealth treatment (T2)	1.014*** (0.342)	-0.282 (0.532)	-0.882 (0.696)	0.528 (0.566)
Income Estimate	-0.002** (0.001)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
T2 x Income Estimate	-0.032* (0.018)	0.010 (0.011)	0.000 (0.000)	-0.000 (0.000)
Death Estimate	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
T1 x Death Estimate	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-3.605*** (0.287)	-3.394*** (0.302)	-3.410*** (0.420)	-3.866*** (0.400)
Regional clustering	✓	✓	✓	✓
Observations	1,274	1,274	971	971
Pseudo R-squared	0.030	0.029	0.014	0.016

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

e. Main treatment effects with alternative coding of death and loss estimates

As outlined in section 1c of this SM appendix, we generated the categorical over- and underestimate of death and income loss variables by using the IHME and IMF estimates at the time of surveying. A respondent's estimate is thereby categorized as correct if it falls within a range of +/- 5,000 deaths or +/- 1% income loss, respectively, relative to the IHME and IMF estimates. An estimate below the specified range is categorized as an underestimate, an estimate above the specified range is categorized as an overestimate. In this subsection we ran our main analysis with an alternative range to test for robustness. Table 26 reports the results of the main treatment effects with interactions for a range of +/- 2,500 deaths and +/- 0.5% average income loss. The main treatment effects hold. Additionally, the health treatment now increases the likelihood of subjects in the UK to move away from the maximum value of life post-treatment. Given that this effect does not hold in our models with the original range of death estimates, we did not include this effect in our main analysis.

Table 26: Main treatment effects with interactions – alternative range

	Main treatment effects			
	Down from max. VoL (UK)	Up to max. VoL (UK)	Down from max. VoL (US)	Up to max. VoL (US)
Treatment				
Health treatment (T1)	0.926** (0.417)	-0.282 (1.235)	0.215 (0.493)	0.467 (0.501)
Wealth treatment (T2)	-0.036 (0.346)	-0.195 (0.575)	-1.341* (0.690)	0.332 (0.545)
Income Estimate				
T2 x Underestimate	1.076*** (0.236)	0.183 (0.578)	1.886*** (0.675)	-0.074 (0.751)
T2 x Overestimate	omitted	omitted	omitted	omitted
Death Estimate				
T1 x Underestimate	-0.822 (0.653)	-1.940*** (0.153)	-0.165 (0.536)	-0.070 (0.583)
T1 x Overestimate	-0.368 (0.407)	-0.118 (1.188)	omitted	omitted
Constant	-3.711*** (0.221)	-3.608*** (0.310)	-3.516*** (0.343)	-4.001*** (0.345)
Regional clustering	✓	✓	✓	✓
Observations	1,660	1,660	1,379	1,379
Pseudo R-squared	0.020	0.027	0.027	0.003

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

f. Average treatment effect using post-treatment data

Due to our survey design, we were able to conduct a within-subject analysis of respondents' change from pre- to post-treatment. As a robustness check, we additionally ran our main analysis on the post-treatment data to estimate the average treatment effect (ATE) between treatment and control groups. Table 27 reports the ATE for both the US and the UK, without death and income estimates; table 28 reports the ATE including interactions with those estimates. Our treatment effects do not survive this alternative estimation, suggesting that our demographics do not capture all differences between the control and two treatment groups. Given that our within-subject analysis indirectly accounts for such differences, the results from these models (tables 4-7) are less biased than those reported in table 27 and 28.

Covid Economics 22, 26 May 2020: 59-116

Table 27: ATE without interactions

	Main treatment effects			
	Max. VoL (UK)	Switch point (UK)	Max. VoL (US)	Switch point (US)
Treatment				
Health treatment (T1)	0.122 (0.180)	0.207 (0.162)	0.133 (0.143)	0.164 (0.132)
Wealth treatment (T2)	-0.116 (0.129)	-0.001 (0.100)	-0.025 (0.148)	0.036 (0.157)
Constant	1.183** (0.517)	-	-0.112 (0.660)	-
Demographic Controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	1,222	1,230	1,282	1,282
Pseudo R-squared	0.075	0.041	0.100	0.055

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 22, 26 May 2020: 59-116

Table 28: ATE with interactions of death and income estimates

	Main treatment effects			
	Max. VoL (UK)	Switch point (UK)	Max. VoL (US)	Switch point (US)
Treatment				
Health treatment (T1)	0.427* (0.255)	0.626*** (0.216)	0.342* (0.185)	13.318*** (0.960)
Wealth treatment (T2)	-0.284 (0.924)	-0.030 (0.927)	0.017 (0.163)	14.087*** (0.685)
Income Estimate				
T2 x Underestimate	0.119 (0.899)	0.053 (0.952)	-0.231 (0.279)	-14.178*** (0.705)
T2 x Overestimate	0.203 (0.916)	0.032 (0.912)	omitted	-14.019*** (0.704)
Death Estimate				
T1 x Underestimate	-0.313 (0.416)	-0.499 (0.340)	-0.445** (0.207)	-13.426*** (0.982)
T1 x Overestimate	-0.369 (0.359)	-0.407 (0.292)	omitted	-12.902*** (1.010)
Constant	1.219** (0.513)	-	-0.151 (0.656)	-
Demographic Controls	✓	✓	✓	✓
Regional clustering	✓	✓	✓	✓
Observations	1,219	1,227	1,272	1,276
Pseudo R-squared	0.075	0.041	0.104	0.058

Notes: Estimates come from a logistic regression. Regional clustering is done based on either the 12 regions of the UK, as defined by the ONS or the 50 states of the United States, as defined by the Census Bureau. Clustered standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4. Survey instrument

a. United Kingdom

PART I – Preference elicitation

When the restrictions on personal movement are increased, coronavirus spreads more slowly and so causes less loss of life because there is less peak pressure on the healthcare system. However, increasing the restrictions on personal movement also tends to disrupt and lower economic activity and this is associated with loss of income and jobs and some psychological and health costs.

It is difficult to put numbers on these. Nevertheless, we present 8 decisions below and ask you in each case to choose between two options. Each option has a combination of 'lives lost per 1 million of the population through Covid-19 over the next 3 months' and 'the average loss of household income due to measures to prevent transmission of Covid-19 over the next 3 months'. In each of the 8 decisions, click on the option that you think has the best combination.

	Lives lost per 1 million of population	Average loss of disposable household income	Lives lost per 1 million of population	Average loss of disposable household income
Decision 1	445	£2700	460	£2750
Decision 2	412	£2500	431	£2420
Decision 3	383	£2300	393	£2200
Decision 4	360	£2150	367	£2020
Decision 5	300	£2000	305	£1850
Decision 6	240	£1900	243	£1750
Decision 7	230	£1800	232	£1640
Decision 8	210	£1550	210	£1450

PART II – Pre-treatment questions

Perception

Please answer the following questions about the spread of the coronavirus Covid-19.

1. How serious do you think Covid-19 is compared to the seasonal flu?

- Not at all serious
- Not very serious
- Fairly serious
- Very serious
- Don't know

2. How concerned are you for you and your family about Covid-19?

- Not at all concerned
- Not very concerned
- Fairly concerned
- Very concerned
- Don't know

3. How likely are you to follow the government's guidance for reducing the spread of Covid-19?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don't know

Covid Economics 22, 26 May 2020: 59-116

Knowledge

1. How many people in the UK would you estimate will die in total due to coronavirus?
2. By what percentage would you estimate average income in the UK will be lower in 2020 as compared to 2019?

PART III: Treatment

Subjects now divide into 3 groups

Control group: *listens to music*

Treatment 1: *Covid-19 information*

The Washington-based Institute for Health Metrics and Evaluation (IHME) predicts that – with the current government guidance in place – about 23,791 people in the UK will have died due to the coronavirus by August 4. This means that the number of Covid-19 deaths per one million people would be 357.

Please answer the following questions about the spread of the coronavirus Covid-19.

1. How serious do you think Covid-19 is compared to the seasonal flu?

- Not at all serious
- Not very serious
- Fairly serious
- Very serious
- Don't know

2. How concerned are you for you and your family about Covid-19?

- Not at all concerned
- Not very concerned
- Fairly concerned
- Very concerned
- Don't know

3. How likely are you to follow the government's guidance for reducing the spread of Covid-19?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don't know

Treatment 2: *Income loss information*

The International Monetary Fund (IMF) expects the UK economy to shrink by 6.5% in 2020 compared with 2019. This estimated loss of 6.5% equates to a loss of around £2154 per person in 2020 compared with 2019.

Covid Economics 22, 26 May 2020: 59-116

Covid Economics 22, 26 May 2020: 59-116

Please answer the following questions about the spread of the coronavirus Covid-19.

1. How serious do you think Covid-19 is compared to the seasonal flu?

- Not at all serious
- Not very serious
- Fairly serious
- Very serious
- Don't know

2. How concerned are you for you and your family about Covid-19?

- Not at all concerned
- Not very concerned
- Fairly concerned
- Very concerned
- Don't know

3. How likely are you to follow the government's guidance for reducing the spread of Covid-19?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don't know

PART IV: Repeat of preference elicitation

PART V: Demographic and attitudinal questions

D1. Which area of the United Kingdom do you live in?

- England
- Scotland
- Wales
- Northern Ireland

D2. What is your postcode sector?

This is the first part of your postcode (the postcode area) and the first digit of the second part of the postcode (the inward code)

[Open]

D3. To which of these groups do you consider you belong?

- White British
- Any other white background
- White and Black Caribbean

- White and Black African
- White and Asian
- Any other mixed background
- Indian
- Pakistani
- Bangladeshi
- Chinese
- Any other Asian background
- Black Caribbean
- Black African
- Any other black background
- Other ethnic group
- Prefer not to answer

D4. What is your household income before tax?

- Under £10,000
- £10,000 – £20,000
- £20,001 – £30,000
- £30,001 – £40,000
- £40,001 – £50,000
- £50,001 – £60,000
- £60,001 – £80,000
- £80,001 – £100,000
- £100,001 – £150,000
- Above £150,000
- Don't know
- Prefer not to answer

D5. Which party do you feel closest to?

- Conservative
- Labour
- Liberal Democrat
- Scottish National Party (SNP)
- Plaid Cymru
- The Brexit Party
- Green Party
- United Kingdom Independence Party (UKIP)
- Democratic Unionist Party
- Sinn Féin
- Social Democratic and Labour Party (SDLP)
- Alliance Party
- Ulster Unionist Party
- Other
- Don't know

Covid Economics 22, 26 May 2020: 59-116

D6. Thinking about the 2016 Brexit referendum, to your best recollection, which side did you vote for, 'Leave' or 'Remain'?

- Leave
- Remain
- Didn't vote
- Don't know
- Prefer not to say

D7. In politics people sometimes talk of left and right. Where would you place yourself on the following scale?

Left										Right		Don't know
0	1	2	3	4	5	6	7	8	9	10	

D8. Some people feel that government should make much greater efforts to make people's incomes more equal. Other people feel that government should be much less concerned about how equal people's incomes are. Where would you place yourself on this scale?

Try to make incomes equal						Be less concerned about equal incomes						Don't know
0	1	2	3	4	5	6	7	8	9	10		

D9. Some people think that society would be a better place if people had more respect for authority. Other people think society would be a better place if people questioned authority more often. Where would you place yourself on this scale?

Respect authority										Question authority		Don't know
0	1	2	3	4	5	6	7	8	9	10		

D10. During the last seven days, on average how much time (if any) have you spent *per day* following the news?

- None, no time at all
- Less than ½hour
- ½hour to 1 hour
- 1 to 2 hours
- More than 2 hours
- Don't know

D11. Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?

- Most people can be trusted
- Can't be too careful
- Don't know

Covid Economics 22, 26 May 2020: 59-116

D12. How much of the time do you think you can trust the Westminster government to do what is right?

- Hardly ever
- Some of the time
- Most of the time
- Just about always
- Don't know

D13. Which of these best describes what you were doing last week?

- Working full time (30 or more hours per week)
- Working part time (8-29 hours a week)
- Working part time (less than 8 hours a week)
- On furlough (temporary leave)
- Unemployed and looking for work
- Full time university student
- Other full time student
- Retired
- Not in paid work for any other reason
- Other

For those who choose options 1-4 (including furlough) on previous question:

D1301. Are you an employee or self-employed/an independent contractor?

- An employee on a permanent contract
- An employee on a temporary contract
- Self-employed/an independent contractor
- Don’t know

D14. What is your highest level of educational attainment?

- Higher Education and above
- Secondary education
- Primary education
- No formal education

D15. Do you have a religious affiliation?

- No, I do not regard myself as belonging to a religion
- Yes –Church of England/Anglican/Episcopalian
- Yes –Roman Catholic
- Yes –Presbyterian/Church of Scotland
- Yes –Methodist
- Yes –Baptist
- Yes –United Reformed Church
- Yes –Free Presbyterian
- Yes –Brethren
- Yes –Judaism

- Yes -Hinduism
- Yes –Islam
- Yes –Sikhism
- Yes –Buddhism
- Yes –Other
- Yes –Orthodox Christian
- Yes –Pentecostal
- Yes –Evangelical –independent/non-denominational
- Prefer not to say

D16. Apart from such special occasions such as weddings, funerals and baptisms, how often do you attend services or meetings connected with your religion?

- Less often than once a year
- Less often but at least once a year
- Less often but at least twice a year
- Less often but at least once a month
- Less often but at least once in two weeks
- Once a week or more
- Varies too much to say
- I am not religious
- Don’t know

D17. During the next months, how likely or unlikely is it that you will not have enough money to cover your day to day living costs?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don’t know

D18. Thinking about the past month, did you, as a result of the Covid-19 pandemic, earn less, about the same or more money than usual?

- Less than usual
- About the same
- More than usual
- Don't know

D19. How healthy have you felt in the last weeks?

Not healthy at all — Very healthy — Don’t know

0	1	2	3	4	5	6	7	8	9	10		

Covid Economics 22, 26 May 2020: 59-116

D20. According to UK government guidelines, those above the age of 70 and/or those with underlying health conditions are at an increased risk from Covid-19. Do you consider yourself to be in this group?

- Yes
- No
- Don't know
- Prefer not to say

D21. How likely or unlikely do you think it is that you have contracted the coronavirus?

- Very unlikely
- Fairly unlikely
- Fairly likely
- Very likely
- Don't know

D22. Please tell us, in general, how willing or unwilling you are to take risks. Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and a 10 means you are "very willing to take risks". You can also use any number between 0 and 10 to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

D23. Are you generally an impatient person, or someone who always shows great patience? Please use a scale from 0 to 10 where 0 means "very impatient" and a 10 means you are "very patient". You can also use any number between 0 and 10 to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

D24. Imagine you won 1,000 pounds in a lottery. Considering your current situation, how much would you donate to charity?

[Open]

b. United States

PART I – Preference elicitation

When the restrictions on personal movement are increased, coronavirus spreads more slowly and so causes less loss of life because there is less peak pressure on the healthcare system. However, increasing the restrictions on personal movement also tends to disrupt and lower economic activity and this is associated with loss of income and jobs and some psychological and health costs.

It is difficult to put numbers on these effects. Nevertheless, we present 8 decisions below and ask you in each case to choose between two options. Each option has a combination of 'lives

Covid Economics 22, 26 May 2020: 59-116

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lost per 1 million of the population through Covid-19 over the next 3 months' and 'the average loss of household income due to measures to prevent transmission of Covid-19 over the next 3 months'. In each of the 8 decisions, click on the option that you think has the best combination.

	Lives lost per 1 million of population	Average loss of disposable household income	Lives lost per 1 million of population	Average loss of disposable household income
Decision 1	320	$4000	335	$4150
Decision 2	310	$3850	325	$3740
Decision 3	247	$3670	256	$3500
Decision 4	213	$3500	219	$3300
Decision 5	200	$3300	204	$3100
Decision 6	188	£3120	192	$2820
Decision 7	177	$2350	180	$2000
Decision 8	165	$1950	165	$1800

PART II – Pre-treatment questions

Perception

Please answer the following questions about the spread of the coronavirus Covid-19.

1. How serious do you think Covid-19 is compared to the seasonal flu?

- Not at all serious
- Not very serious
- Fairly serious
- Very serious
- Don't know

2. How concerned are you for you and your family about Covid-19?

- Not at all concerned
- Not very concerned
- Fairly concerned
- Very concerned
- Don't know

3. How likely are you to follow the government's guidance for reducing the spread of Covid-19?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don't know

Covid Economics 22, 26 May 2020: 59-116

Knowledge

1. How many people in the US would you estimate will die in total due to coronavirus?
2. By what percentage would you estimate average income in the US will be lower in 2020 as compared to 2019?

PART III: Treatment

Subjects now divide into 3 groups

Control: *they listen to music*

Treatment 1: *Covid-19 information*

The Washington-based Institute for Health Metrics and Evaluation (IHME) predicts that – with the current government guidance in place – about 68,841 people in the US will have died due to the coronavirus by August 4. This means that the number of Covid-19 deaths per one million people would be 210.

Please answer the following questions about the spread of the coronavirus Covid-19.

1. How serious do you think Covid-19 is compared to the seasonal flu?

- Not at all serious
- Not very serious
- Fairly serious
- Very serious
- Don't know

2. How concerned are you for you and your family about Covid-19?

- Not at all concerned
- Not very concerned
- Fairly concerned
- Very concerned
- Don't know

3. How likely are you to follow the government's guidance for reducing the spread of Covid-19?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don't know

Treatment 2: *Income loss information*

The International Monetary Fund (IMF) expects the US economy to shrink by 5.9% in 2020 compared with 2019. This estimated loss of 5.9% equates to a loss of around $3848 per person in 2020 compared with 2019.

Covid Economics 22, 26 May 2020: 59-116

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Please answer the following questions about the spread of the coronavirus Covid-19.

1. How serious do you think Covid-19 is compared to the seasonal flu?

- Not at all serious
- Not very serious
- Fairly serious
- Very serious
- Don't know

2. How concerned are you for you and your family about Covid-19?

- Not at all concerned
- Not very concerned
- Fairly concerned
- Very concerned
- Don't know

3. How likely are you to follow the government's guidance for reducing the spread of Covid-19?

- Very unlikely
- Fairly unlikely
- Neither likely nor unlikely
- Fairly likely
- Very likely
- Don't know

PART IV: Repeat of preference elicitation

PART V: Demographic and attitudinal questions

D1. Which US state do you live in?

1. Alabama
2. Alaska
3. Arizona
4. Arkansas
5. California
6. Colorado
7. Connecticut
8. Delaware
9. Florida
10. Georgia
11. Hawaii
12. Idaho
13. Illinois
14. Indiana
15. Iowa
16. Kansas
17. Kentucky

Covid Economics 22, 26 May 2020: 59-116

18. Louisiana
19. Maine
20. Maryland
21. Massachusetts
22. Michigan
23. Minnesota
24. Mississippi
25. Missouri
26. Montana
27. Nebraska
28. Nevada
29. New Hampshire
30. New Jersey
31. New Mexico
32. New York
33. North Carolina
34. North Dakota
35. Ohio
36. Oklahoma
37. Oregon
38. Pennsylvania
39. Rhode Island
40. South Carolina
41. South Dakota
42. Tennessee
43. Texas
44. Utah
45. Vermont
46. Virginia
47. Washington
48. West Virginia
49. Wisconsin
50. Wyoming
51. District of Columbia

D2. In which county do you live?

[Open]

D3. Are you Spanish, Hispanic, or Latino?

- Yes
- No

D4. Below you will find a list of five race categories. Please choose one or more races that you consider yourself to be:

D401. White [yes/no]
D402. Black or African-American [yes/no]
D403. American Indian or Alaska Native [yes/no]
D404. Asian [yes/no]

Covid Economics 22, 26 May 2020: 59-116

D405. Native Hawaiian or other Pacific Islander [yes/no]
Other group
Prefer not to answer

D5. What is your household income before tax?

- Under $10,000
- $10,000 – $20,000
- $20,001 – $30,000
- $30,001 – $40,000
- $40,001 – $50,000
- $50,001 – $60,000
- $60,001 – $80,000
- $80,001 – $100,000
- $100,001 – $150,000
- $150,001 – $200,000
- Above $200,000
- Don't know
- Prefer not to answer

D6. Which party do you feel closest to?

- Democratic Party
- Republican Party
- Other
- Don't know

D7. Thinking about the 2016 Presidential Election, to your best recollection, whom did you vote for?

- Hillary Clinton
- Donald Trump
- Didn't vote
- Don't know
- Prefer not to say

D8. In politics people sometimes talk of left and right. Where would you place yourself on the following scale?

Left Right Don't know

0	1	2	3	4	5	6	7	8	9	10	

D9. Some people feel that government should make much greater efforts to make people's incomes more equal. Other people feel that government should be much less concerned about how equal people's incomes are. Where would you place yourself on this scale?

Try to make incomes equal Be less concerned about equal incomes Don't know

0	1	2	3	4	5	6	7	8	9	10	

D10. Some people think that society would be a better place if people had more respect for authority. Other people think society would be a better place if people questioned authority more often. Where would you place yourself on this scale?

Respect authority | Question authority | Don't know

0	1	2	3	4	5	6	7	8	9	10		

D11. During the last seven days, on average how much time (if any) have you spent *per day* following the news?

- None, no time at all
- Less than ½hour
- ½hour to 1 hour
- 1 to 2 hours
- More than 2 hours
- Don't know

D12. Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?

- Most people can be trusted
- Can't be too careful
- Don't know

D13. How much of the time do you think you can trust the federal government in Washington to do what is right?

- Hardly ever
- Some of the time
- Most of the time
- Just about always
- Don't know

D14. Which of these best describes what you were doing last week?

- Working full time (30 or more hours per week)
- Working part time (8-29 hours a week)
- Working part time (less than 8 hours a week)
- On furlough (temporary leave)
- Unemployed and looking for work
- Full time university student
- Other full time student
- Retired
- Not in paid work for any other reason
- Other

Covid Economics 22, 26 May 2020: 59-116

For those who choose options 1-4 (including furlough) on previous question:

D1401. Are you an employee or self-employed/an independent contractor?

– An employee on a permanent contract
– An employee on a temporary contract
– Self-employed/an independent contractor
– Don't know

D15. What is your highest level of educational attainment?

– College and above
– High school
– Elementary school
– No formal education

D16. Do you have a religious affiliation?

– No, I do not regard myself as belonging to a religion
– Yes – Protestant
– Yes – Roman Catholic
– Yes – Mormon
– Yes – Other Christian
– Yes – Jewish
– Yes – Muslim
– Yes – Other non-Christian religion
– Prefer not to say

D17. Apart from such special occasions such as weddings, funerals and baptisms, how often do you attend services or meetings connected with your religion?

– Less often than once a year
– Less often but at least once a year
– Less often but at least twice a year
– Less often but at least once a month
– Less often but at least once in two weeks
– Once a week or more
– Varies too much to say
– I am not religious
– Don't know

D18. During the next months, how likely or unlikely is it that you will not have enough money to cover your day to day living costs?

– Very unlikely
– Fairly unlikely
– Neither likely nor unlikely
– Fairly likely
– Very likely
– Don't know

Covid Economics 22, 26 May 2020: 59-116

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D19. Thinking about the past month, did you, as a result of the Covid-19 pandemic, earn less, about the same or more money than usual?

- Less than usual
- About the same
- More than usual
- Don't know

D20. How healthy have you felt in the last weeks?

Not healthy at all — Very healthy — Don’t know

0	1	2	3	4	5	6	7	8	9	10		

D21. According to UK government guidelines, those above the age of 70 and/or those with underlying health conditions are at an increased risk from Covid-19. Do you consider yourself to be in this group?

- Yes
- No
- Don’t know
- Prefer not to say

D22. How likely or unlikely do you think it is that you have contracted the coronavirus?

- Very unlikely
- Fairly unlikely
- Fairly likely
- Very likely
- Don’t know

D23. Please tell us, in general, how willing or unwilling you are to take risks. Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and a 10 means you are "very willing to take risks". You can also use any numbers between 0 and 10 to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

D24. Are you generally an impatient person, or someone who always shows great patience? Please use a scale from 0 to 10 where 0 means “very impatient” and a 10 means you are “very patient”. You can also use any numbers between 0 and 10 to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

D25. Imagine you won 1,000 dollar in a lottery. Considering your current situation, how much would you donate to charity?

[Open]

Covid Economics 22, 26 May 2020: 59-116

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Covid Economics Issue 22, 26 May 2020

Lost in lockdown? Covid-19, social distancing, and mental health in Germany

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Covid Economics 22, 26 May 2020: 117-153

The COVID-19 pandemic and social-distancing as well as stay-at-home orders can directly affect mental health and quality of life. In this ongoing project, we analyze rich data from Telefonseelsorge, the largest German emergency helpline service, to better understand the effect of the pandemic and of local lockdown measures on mental health–related helpline contacts. First, looking at Germany–wide changes, we find that overall helpline contacts increase by around 25% in the first week of the lockdown and slowly decrease again after the third lockdown week. Our results suggest that the increase is not driven by financial worries or fear of the virus itself, but reflects heightened loneliness, anxiety, and suicidal ideation. Second, we exploit spatial variation in policies among German federal states to assess whether the effect depends on the stringency of local measures. Preliminary evidence suggests that the average effect is more pronounced in states that implemented stricter measures.

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1 Introduction

There is widespread concern that the current COVID-19 outbreak is associated with increased psychological distress, mental illness, and suicide (Rajkumar 2020). Evidence from global economic crises suggests that periods of high unemployment rates are followed by significant increases in suicide (Parmar et al. 2016), and an exceptionally large number of suicide deaths occurred at the time of the SARS epidemic in 2003 (Yip et al. 2010).[1] Social distancing measures such as stay–at–home orders are effective in containing the spread of COVID-19 (Fang et al. 2020), but, in addition to the outbreak of a pandemic itself, potentially cause severe mental illness (Brooks et al. 2020). A better understanding of mental health trends during the COVID-19 outbreak, and particularly the implications of social-distancing policies, is essential to inform policy in the current situation, where the net benefit of releasing lockdown measures is unclear (Layard et al. 2020).

In this study, we focus on Germany, where various social-distancing policies were enacted on the national level as well as by the 16 federal states. The majority of shops were closed on March 17th, and on Sunday, March 22nd, Germany implemented national-wide social distancing and contact restrictions (further referred to as the "lockdown week"). In contrast to most other European countries, the stringency of measures differs substantially between states: For example, while Bavaria banned "leaving the house without a reason", spending time outdoors was still allowed in neighboring Baden-Württemberg. The central aim of this paper is to find out if the demand for psychological assistance increased due to the general COVID-19 outbreak and lockdown measures (hypothesis H1), and second, if the effect is stronger in those states that imposed stricter measures (H2).

We test our hypotheses by using data from Germany's largest online and telephone counseling helpline, the "TelefonSeelsorge", (TS, TelefonSeelsorge 2020) for the period 01/01/2019 – 04/31/2020, combined with data on reported daily COVID-19 cases and deaths (RKI 2020a), state–wide policy measure data for Germany (Armbruster and Klotzbuecher 2020), as well as state–level unemployment (Bundesagentur fuer Arbeit 2020). After analyzing the development

[1] Parmar et al. (2016) found a strong increase in suicide after the 2008 global economic crisis; there were about 4900 excess suicides in the year 2009 alone compared with those expected based on previous trends. Yip et al. (2010) examine the case of Severe Acute Respiratory Syndrome (SARS) and suicide among older adults in Hong Kong, finding that social disengagement, mental stress, and anxiety at the time of the SARS epidemic among a certain group of older adults resulted in an exceptionally high rate of suicide deaths.

Covid Economics 22, 26 May 2020: 117-153

graphically, we take the data to an (i) event study framework to quantify the effect over time (H1) and to a (ii) Difference–in–Difference (DiD) model, where we try to disentangle the effects of the pandemic and the mitigation policies on mental health by comparing strict and less–strict lockdown states and by controlling for infection rates that differ across states (H2).

Our main findings can be summarized as follows. During the week of the lockdown, demand for counseling increased by around 25%, and started to slowly decrease again after the third week. Results for different problem issues reveal that the spike in helpline contacts is mainly driven by mental health issues, such as loneliness, fear and depression. Our results are robust to using alternative econometric approaches and different specifications. Regarding H2, preliminary evidence suggests that the effect is indeed stronger where stricter measures were implemented: We find a significantly stronger increase in helpline contacts for strict lockdown states in the week of the lockdown, in particular for contacts concerning mental health issues.

Our paper relates to several strands of interdisciplinary literature. We contribute to the current medical and psychological research on the effect of COVID-19 and mental health (Rajkumar 2020).[2] For China, Wang et al. (2020); Xiao (2020) and Liu et al. (2020) suggest that anxiety is a very common individual mental health symptom. Our study offers valuable insights into the mental health issues prevailing during the COVID-19 pandemic in Germany.

We further add to the fast growing literature analyzing the social (see, e.g. Brodeur et al. 2020; Knipe et al. 2020; Brülhart and Lalive 2020) and economic impacts of the COVID-19 outbreak (see, e.g. Alon et al. 2020). Focusing on lockdown measures, evidence shows that people's behavior towards compliance with prevention recommendations and lockdown policies can depend on media exposure and misinformation (Bursztyn et al. 2020), political leader's communication (Ajzenman et al. 2020), people's expectations about the length of the lockdown (Briscese et al. 2020) or the economic endowment of a living area (Wright et al. 2020).[3]

Closely related are Brodeur et al. (2020); Knipe et al. (2020) as well as Tubadji et al. (2020) who use Google Trends data to a analyze the consequences of COVID-19 lockdowns implemented in

[2] A further living systematic map of the evidence is online available under: COVID-19: living map of the evidence

[3] Bursztyn et al. (2020) focus on misinformation in the U.S. concerning the COVID-19 risk and find that provision of misinformation in the early stages of a pandemic affects precautionary behavior and downstream health outcomes. Ajzenman et al. (2020) show that when Brazil's president publicly dismisses the COVID-19 risks, recommended prevention practices were reduced. Briscese et al. (2020) study the role of expectation about the length of the lockdown in Italy and resulting compliance with Stay–at–home orders. If the lockdown is longer than expected, there is a lower willingness to comply. Wright et al. (2020) show that compliance with local Stay–at–Home orders depends on the economic endowments and that low income areas comply less than areas with stronger endowments.

Covid Economics 22, 26 May 2020: 117-153

Europe and America on well-being and mental health. Findings suggest that there is evidence for severe mental health implications: levels of fear are rising and searches for loneliness, worry and sadness increase substantially under lockdown. The main advantage of Google Trends over survey data is, in addition to the availability of daily data for different countries before and after the pandemic, the fact that online search intensity reveals the actual interest of the population. On the downside, older segments of the population are less likely to search online and it is not possible to distinguish individuals by age, gender or other characteristics. Tran et al. (2017) provide evidence and a review of research on using Google Trends to forecast suicide and conclude that the validity of the approach is rather low and depends very much on the specific search terms chosen.

The closest match to our approach is a preliminary analysis of Brülhart and Lalive (2020), who analyze calls to Switzerland's most popular helpline "*Die Dargebotene Hand*" during the COVID-19 outbreak. They show that anxiety did not increase substantially in response to lockdown measures, and that only calls related to the pandemic threat, i.e. elderly individuals who worry about the risk of infection, increased. They do, however, find that calls about relationship issues, as well as addiction and suicidality, have been increasing during the lockdown. Our paper provides new evidence from Germany, looking more closely into the development for different relevant topics and further uses spatial variation in lockdown measures across states to analyze the effect of the lockdown itself. Compared to Switzerland, differences in Germany seem to be more pronounced, pontentially due to the stricter social distancing measures implemented.

The remainder of this paper proceeds as follows. Section 2 provides background on the chronology of the COVID-19 outbreak in Germany and on the TS and summarizes the data and illustrates descriptive time trends. Section 3 describes the econometric approach. Section 4 presents the empirical findings. Section 5 concludes.

2 Background and Data

In this section, we provide background information on the timeline of the COVID-19 pandemic in Germany (section 2.1) as well as on Germany's largest psychological telephone and online counseling service, the "TelefonSeelsorge" (section 2.2). In section 2.3, we describe our combined dataset, followed by descriptive time trends in Section 2.4.

Covid Economics 22, 26 May 2020: 117-153

2.1 Covid-19 in Germany

In December 2019, SARS–CoV–2, a new virus from the family of corona viruses, appeared in China. The virus causes the lung disease Covid-19 with typical symptoms such as fever, cough, breathing problems, sometimes runny nose and diarrhea. The infection is usually less severe but in particularly difficult cases, life–threatening pneumonia can develop. The disease developed into an epidemic in China in January 2020 and ultimately spread worldwide.[4] On March 11, 2020, the WHO officially declared the previous epidemic a pandemic.

In Germany, which is the focus of our study, the first official case occurred on January 27, 2020. The Robert Koch Institute (RKI), the government's central scientific institution in the field of biomedicine initially rated the risk of the Covid-19 pandemic for the population in Germany on February 28, 2020 as "low to moderate", since March 17 as "high" and since March 26 as "very high", especially for risk groups. Risk groups are classified based on a higher risk of severe symptoms, which mainly occurs for individuals from about 50–60 years (87% of those who died of Covid-19 in Germany were ≥ 70 years old (median age: 82 year), for smokers (weak evidence), very obese people and individuals with certain medical conditions (RKI 2020b). On February 25, the first cases were documented in Baden-Württemberg and North Rhine-Westphalia. As of May 5th 2020, there are 166,877 confirmed cases in Germany, 132,700 recovered and 7,110 persons died with Covid-19 (RKI 2020a).

As a response to the Covid-19 pandemic, Germany enacted various mitigation policies on the national as well as on the federal state level (i.e. a large number of laws, ordinances, general directives and other regulations). As the stringency index provided by Hale et al. (2020) makes clear, these measures were relatively liberal compared to the lockdown in neighboring countries such as France or Italy. On the national level, Germany started on March 8th with a recommendation to cancel events with more than a thousand participants, followed by an entry stop for third-country nationals, a global travel warning, and restrictions to within EU travel. Most shops, as well as schools and kindergartens, were closed on March 17th. On March 22nd, Germany implemented national–wide social distancing and contact restrictions. Both the "economic lockdown" of March 17th and the "social lockdown" on the 22nd were announced roughly two days before. We further

[4] On 30 January 2020, the World Health Organization (WHO) announced the international health emergency in order to counteract the spread to countries without efficient health systems. From February 28, 2020, the WHO's reports assessed the risk at global level as "very high".

Covid Economics 22, 26 May 2020: 117-153

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Covid Economics 22, 26 May 2020: 117-153

call the week of March 16th – 23th as the "lockdown week." The goal of the social lockdown was to reduce physical contact as much as possible, requiring a minimum distance of at least 1.5 meters in public spaces. Restaurants and services in the field of personal care, e.g. hairdressers, cosmetic studios, massage practices and tattoo studios, were closed, with exceptions only for medically necessary services.

However, each of the 16 federal states in Germany regulated the lockdown details differently.[5] The different lockdown measures by each federal state are presented online and are regularly updated, see Armbruster and Klotzbuecher (2020).[6] In particular, we classify the federal states of Bavaria, Saarland, Berlin and Brandenburg and Sachsen–Anhalt as "strict lockdown states", as they implemented not only contact-restriction measures but also a stay–at–home order, not allowing individuals to leave the house "without a reason." Our data availability leaves us with Bavaria, Saarland, and Sachsen–Anhalt as the strict states, see figure 1 and section 2.3. In these states, leaving one's home was only allowed if there were good reasons. Such reasons included the way to work, to emergency care, participation in necessary appointments, as well as individual sport and exercise in fresh air. All other outside activity, however, such as resting in parks, were not permitted.

Since April 10th, a 14–day domestic quarantine requirement for returnees from abroad was implemented. Re-opening slowly started on April 28th, when the Saarland Constitutional Court overturned parts of the restrictions: encounters with family members and spending time outdoors were possible again. Around the Easter weekend, demands for further re–opening became louder and since May 4th, school started to re–open, although daycare centers remained closed. Re–opening of playgrounds, hairdressing salons, church services, museums and zoos started on May 6th on the national level. On the state level, Bavaria allowed to meet or visit a person outside of the own household and close family members since May 5th. Five people can meet again in Saxony–Anhalt, even if they do not belong to a common household and Lower Saxony decided to gradually reopen restaurants and coffee shops from May 11. National contact restrictions and mask requirements were generally extended until June 5th, but federal states are supposed to take on more responsibility and decide about the regionally appropriate level of restrictions.

[5] In Germany, authority between the federal government and the states is divided by sixteen partly–sovereign states, see Ter-Minassian (1997) for an overview on the German system of fiscal federalism.

[6] The now widley used Hale et al. (2020) data base does not contain sub–national state level data for Germany.

2.2 Psychological Counseling by the TelefonSeelsorge

With over 100 helpline–centers in Germany, the TS is by far the largest telephone and online emergency helpline in Germany. It is free, anonymous, partly government funded, and the only facility in Germany to offer telephone conversations day and night for people in crisis. The TS is a pastoral service under responsibility of the Evangelical and the Catholic Church and can be reached around the clock by telephone at the nationwide toll-free numbers +49 0800 1110 111 (Protestant), +49 800 1110 222 (Catholic), and 116 123, as well as online via webmail and a chat on the central website telefonseelsorge.de. Online search for relevant topics, such as "kill yourself" on Google lead individuals in Germany directly to the TS hotline, see figure A.1. Around 7,500 fully trained volunteers (TS counselors) with a wide range of life and professional skills are available to help those seeking advice in 105 local counseling centers.

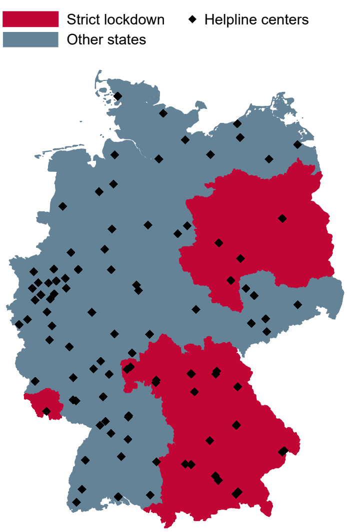


Figure 1: Lockdown stringency and helpline–centers. Black dots represent the approximate locations of TS helpline–centers, red shading indicates strict-lockdown states.

2.3 Data

Since 2019, the TS has been implementing a contact tracking system and we have access to anonymized data on contacts to the TS for the period of 01/01/2019 – 04/28/2020 (TelefonSeelsorge 2020). The dataset includes information on the date, time, and duration, and type of counseling (telephone, mail, chat, on–site), as well as the the organizational unit. Moreover, a number of individual characteristics are recorded such as gender, approximate age, occupation, living situation (living alone, in marriage / partnership, in a family, in an institution, in a shared apartment), as well as whether the contact was the first contact of the respective person or a repeated one. Further details include known psychological diagnoses, suicidal ideation, and up to three conversation topics per data record.[7] Table A.2 provides an overview over the available variables. We drop records where people hung up, as well as those that are labeled as jokes or irrelevant.

Out of the available information on conversation topics, we classify the following broader categories, which are potentially overlapping and thus non–exclusive:

- Mental and physical health: depression, grief, suicide, self-harming behavior, fears, anger, confusion, addiction, loneliness, other mental health, and physical constitution
- Violence: physical and sexual violence
- Social issues: relationships, religion, society

  → Relationships: life with partner, parenting, pregnancy, everyday relationships, family relations, separation, virtual relationships

  → Religion: Belief/values, church, religion

  → Society: Society/culture
- Economic issues: Finance and economics

  → Finances/inheritance, poverty, living situation

  → Work situation, unemployment, job search

If a person seeking advice calls the TS or makes contact via the Internet, he or she will be connected to a location that is as close as possible to one's current location.This allows us to track counseling by helpline–center, and therefore by federal state. Table A.1 gives an overview of the helpline–centers by state. After some initial cleaning, where we drop erroneous records and helpline–centers that start using the tracking system only later, we are left with 91 helpline–centers and we concentrate on mail, chat and telephone contacts. On–site contacts are dropped as they are not tracked consistently.

[7] During a contact is made, the TS counselor picks a maximum of three topics out of an available list with problem topics.

Covid Economics 22, 26 May 2020: 117-153

We combine our data set with information on state–level policy measures for Germany that we compile together with collaborators (Armbruster and Klotzbuecher 2020). The data set is regularly updated and available for download *here*. The data includes information on the federal state level about the onset of the lockdown, the social distancing policies, bans on social interaction in group settings (restaurants, movies, gymnasiums etc.), zoo, kindergarten and school closures as well as shop closures and consequently the re–openings. We use the national announcement date of the social contact restrictions on the state level as our "lockdown" date and the week of March 16th – 23th is the lockdown week.

We further complement the data set on the helpline–center level (i.e. the community of the helpline–center) with daily COVID-19 cases and deaths caused by COVID-19, provided by the RKI (RKI 2020a). Suspected COVID-19 cases and evidence of SARS-CoV-2 are reported to the responsible health authorities. The data is first transmitted electronically by the health department to the state authorities and in a second step to the RKI at the latest on the next working day where the data is validated using largely automated algorithms.[8] The cases are assigned to the federal state or county from which the case was transmitted, which usually corresponds to the place of residence or habitual residence of the cases and not the place where the person was probably infected. Note that as our main goal is to control for the fear caused by locally reported cases, which means it is not important whether the numbers reflect the actual prevalence of the disease but rather captures the alert level transported in local media. Moreover, we also use monthly unemployment rates on the state level from (Bundesagentur fuer Arbeit 2020).

2.4 Graphical Analysis of Helpline Contacts in 2020

Figure 2a shows the development of the daily number of helpline contacts around the social lockdown date (03/22/2020) in Germany. Overall, contacts sharply increased around one week before the national lockdown week, from around 1800 to almost 2400 contacts per day. After around three weeks, the number of contacts starts to decrease again, but remains elevated at around 2200 daily contacts at the end of April.

Figure 2b shows the mean number of daily contacts for a helpline–center around the same time, distinguishing strict and less–strict lockdown states. Before the lockdown, an average center

[8] Only cases in which laboratory diagnostic confirmation is available regardless of the clinical picture are published.

received about 22–25 contacts each day, with no substantial difference between the two groups. Around the lockdown date, the average number increases by around 5 contacts per day, and the increase appears to be slightly stronger in strict lockdown states.

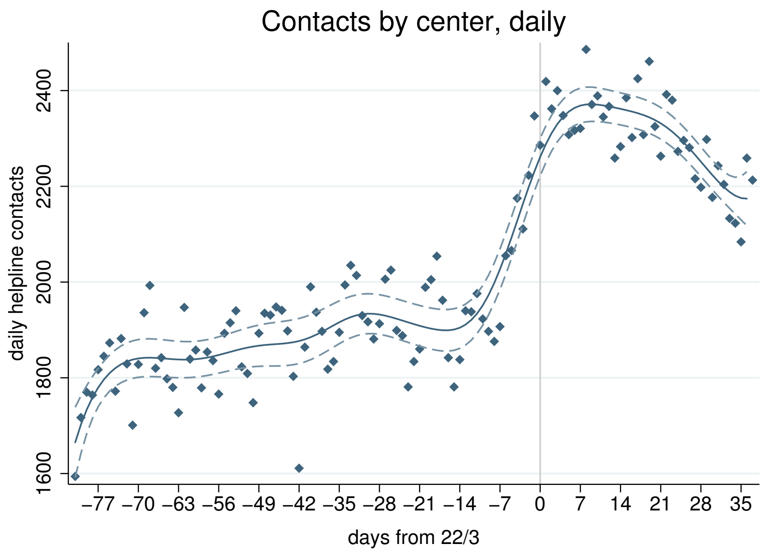
Looking into the development of contacts by topic, i.e. contacts concerning mental and physical health (figure 3a), violence (figure 3b), and social issues (figure 3c) allows us to gain a better understanding of what is behind the strong overall increase. Figure 3a illustrates that the overall rise is driven by contacts related to mental health issues, which have risen sharply from around 1400 daily contacts to around 1800. Contacts dealing with the work and financial situation remained roughly constant with a slightly decreasing trend (figure 3d). While not as strong as the increase in mental health–related contacts, we also see a light uptick in contacts who talk about physical and sexual violence. Note that the true prevalence of domestic violence might be higher than figure 3b suggests, as victims might not be able to contact the helpline while in lockdown with their tormentor.

In figure 4, we show mental health–related contacts further broken down into the subcategories loneliness, addiction, and suicidal ideation (see section 2.3 for details). Loneliness, i.e. the perceived discrepancy between desired and actually existing relationships, is as a key concern regarding the effect of social distancing policies. We see a sharp increase from around 400 to 550–600 daily contacts during the week of the national lockdown. Contacts peaked after around two weeks and started to decline again, but did not fully revert to the pre–lockdown level. Addiction–related contacts (figure 4b) seem to decrease immediately before the lockdown, from around 60 contacts to a little over 50, but then increase with a delay of around one week to around 70 daily contacts. As the COVID-19 pandemic is challenging for many people (e.g. fears of subsistence, social isolation, overwhelmed with home office and childcare), some might get used to drinking regularly, and functional addicts might further loose control without the daily routine of work. Closed borders might additionally lead to illegal drugs becoming more expensive.

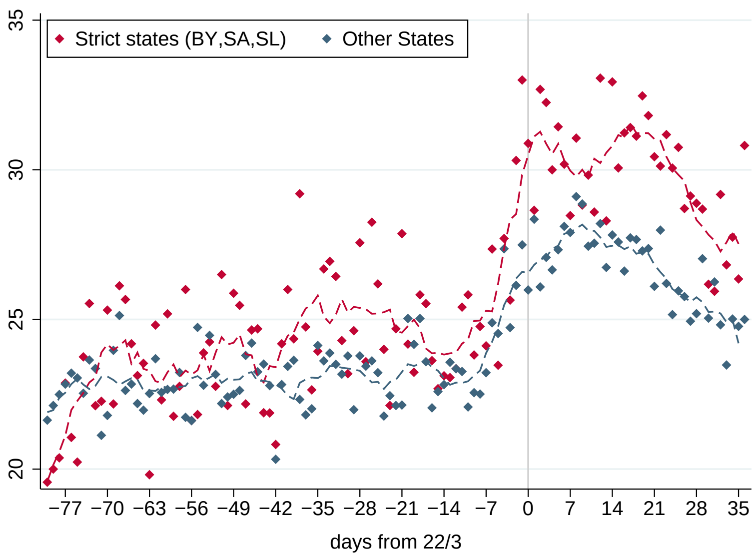
The demand for suicide counseling (i.e. contacts relating to suicidal thoughts, intentions, or even suicide attempts) shows a similar development as overall mental health, with a sharp increase in the week of the national lockdown, from around 230 to 280 contacts per day (4c). Also interesting is the development of fear–related contacts shown in figure 4d: Already four weeks before the lockdown, we see an increase from 250 to 350, probably reflecting fear of the pandemic

Covid Economics 22, 26 May 2020: 117-153

Covid Economics 22, 26 May 2020: 117-153



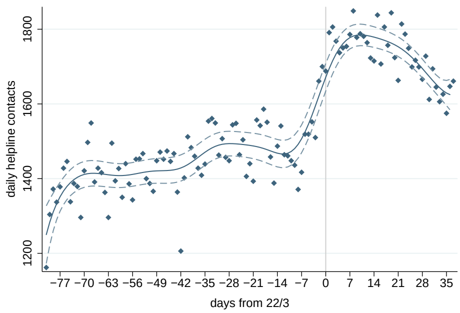
(a) Daily contacts in Germany, 2020



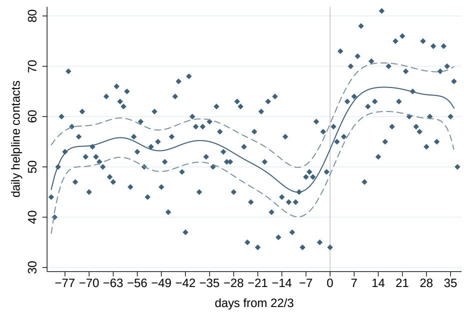
(b) Mean daily contacts per center, strict and non–strict states

Figure 2: Helpline contacts before and after lockdown. The upper graphs shows the daily number of total contacts in Germany. The solid line is fitted using kernel-weighted local polynomial regression, dashed lines represent the 95% confidence intervals. The lower graph shows the average daily contacts by helpline–center in strict lockdown states in red and in all other states in blue.

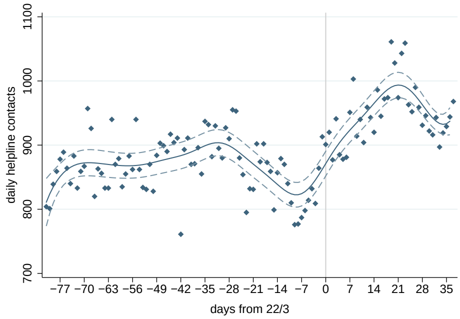
Covid Economics 22, 26 May 2020: 117-153



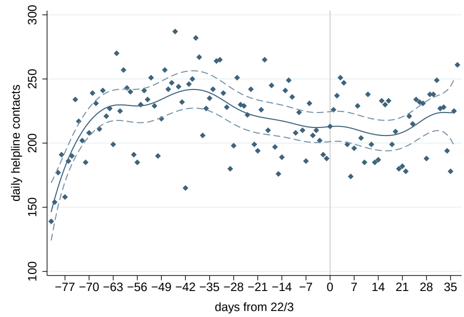
(a) Mental and physical health



(b) Violence



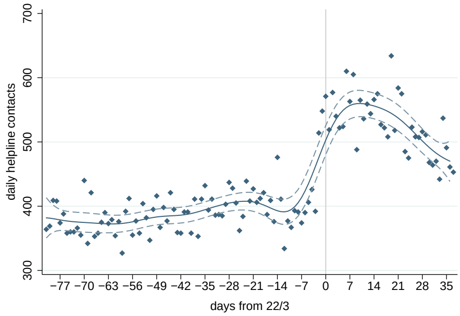
(c) Social issues



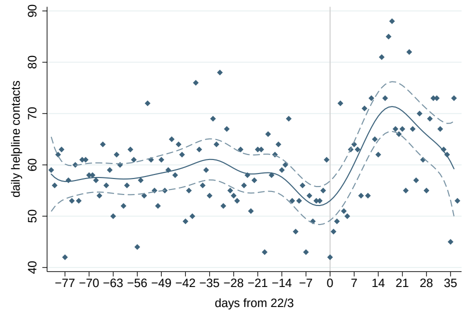
(d) Economic issues

Figure 3: Daily helpline contacts in Germany by topic, before and after lockdown. The solid line is fitted using kernel-weighted local polynomial regression, dashed lines represent the 95% confidence intervals.

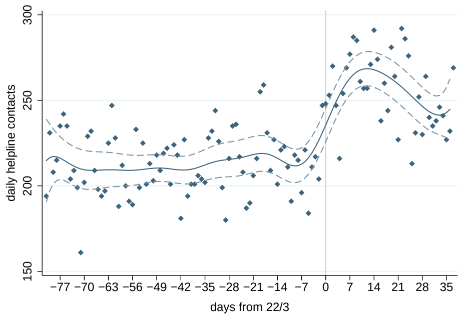
Covid Economics 22, 26 May 2020: 117-153



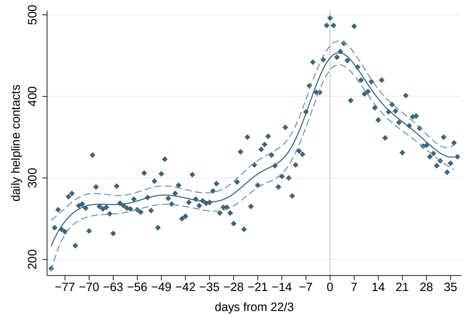
(a) Loneliness



(b) Addiction



(c) Suicide



(d) Fear

Figure 4: Daily helpline contacts in Germany, mental health–related issues, before and after lockdown. The solid line is fitted using kernel-weighted local polynomial regression, dashed lines represent the 95% confidence intervals.

itself. Around the lockdown, these contacts further increase to around 450 per day.

If we look at contacts according to individual characteristics, we see that women seek contact more often than men (figure A.2) and most contacts stem from individuals living alone (figure A.4). The data suggest that contacts of almost all age groups (except for the 10–14 year old) increase, with the greatest number of contacts from individuals between 50 – 69 (see figure A.7 – A.9).

People are not good at enduring insecurities and humans have a basic need for consistency, and the experience of coherence in our lifestyle is demonstrably related to life satisfaction. Due to the multiple uncertainties caused by the corona crisis, this cannot be guaranteed, which contributes to the individual and collective reduction in mental well-being (Grevenstein et al. 2018), which seems to be confirmed in our data.

3 Empirical Approach

In this section, we elaborate on the empirical method we use to test our main hypotheses. To quantify the magnitude and statistical significance of the previously described effects more precisely, we apply an event study design to assess the dynamic movements of helpline demand. In order to capture differences in lockdown measures and other local factors such as the locally reported number of COVID-19 infections, we analyze the effect in a daily panel of helpline–centers. In total, our panel covers 91 helpline–centers and the period from 1/1/2019 up to 28/4/2020. The baseline specification we estimate to test H1 takes the following form:

$$Contacts_{i,j,t} = \alpha + \sum_{\tau=-9}^{5} \beta^{\tau}\, week_t^{\tau} + \gamma X'_{i,t} + \delta Z'_{j,t} + \xi_i + \theta_t + \mu_t + \upsilon_t + \epsilon_{i,j,t} \qquad (1)$$

The dependent variable is the number of contacts (general and later by subcategory) per helpline–center i in the federal state j on date t. The dummies $week_t^{\tau}$ takes the value of one if date is within τ weeks before/after the lockdown week (March 16–22), and zero otherwise. $X'_{i,t}$ is a vector of community–level control variables (COVID-19 cases) and $Z'_{j,t}$ contains controls on the state level (unemployment rate). ξ_i represent helpline–center fixed effects that capture constant factors on the helpline–center and state level, e.g. the size of the helpline–center, quality of counseling service, or local culture. We also include a weekly linear time trend θ_t to capture the long-term increase in contacts, as well as year and weekday indicators, denoted μ_t and υ_t respectively. The

Covid Economics 22, 26 May 2020: 117-153

constant is represented by α and $\epsilon_{i,j,t}$ is the error term.

To learn if there is a higher demand for psychological counseling in stricter states (H2), we extend the event study and estimate the following model:

$$Contacts_{i,j,t} = \alpha + \sum_{\tau=-9}^{5} \left(\lambda^{\tau}\ week_{t}^{\tau} \times strict_{j}\right) + \gamma X'_{i,t} + \delta Z'_{j,t} + \xi_{i} + \vartheta_{t} + \epsilon_{i,j,t} \quad (2)$$

where we include again helpline–center fixed effects ξ_i and control for local COVID-19 infections and unemployment, and where $strict_j$ is defined as follows:

$$strict_j = \begin{cases} 1 \text{ if } j = \text{Bavaria/Saarland/Saxony–Anhalt} \\ 0 \text{ else} \end{cases}$$

Berlin and Brandenburg also fall under this category of strict states but are dropped from the analysis because of incomplete coverage. Importantly, in this specification we include daily date fixed effects ϑ_t that non-parametrically capture all common time effects (e.g. chancellor Merkel's speech on March 18), allowing us to isolate the differential effect in strict-lockdown states. For the ease of interpretation, we provide simple OLS estimates even though our dependent variable is the non-negative count of contacts and a count data model is therefore more appropriate (Greene 2003). We obtain qualitatively similar results when we estimate the model using a Poisson Pseudo Maximum Likelihood (PPML) estimator (Correia et al. 2019a,b).

4 Results

In this section, we present our effects estimates for H1 and H2. Our outcome of interest is the change in helpline–center contacts across different time periods and problem categories.

4.1 Helpline Contacts Before and After Lockdown

In Table 1, we show the results of model (1), estimated using OLS for helpline contacts in levels or logs, as well as PPML. As all specifications show similar results, we focus on the most simple model and plot the coefficients from column (1) in figure 5: The results confirm the interpretation from the graphical analysis, indicating that the introduction of lockdown measures is associated with a

Covid Economics 22, 26 May 2020: 117-153

significant increase in helpline contacts. H1 is confirmed. In the first four weeks of the lockdown, approximately four to five additional daily contacts were recorded at an average helpline–center: After the fourth week contacts decrease again, and although they remain elevated, the difference is not statistically significant. We find a significant time trend but no discernible effect of local infections or unemployment.

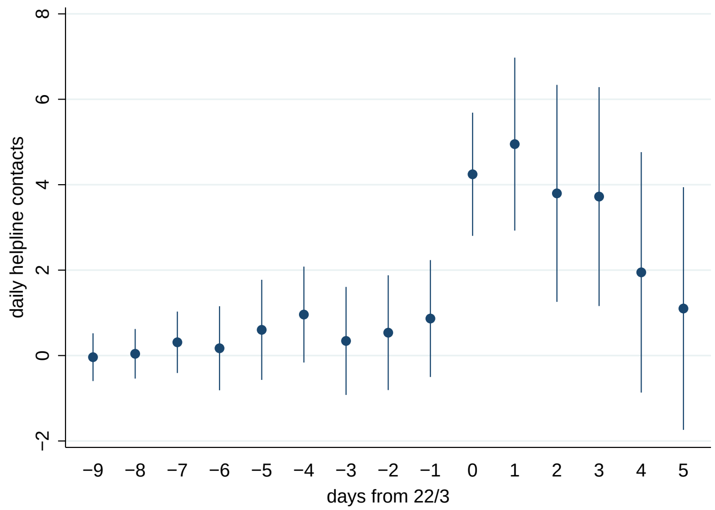


Figure 5: Event study results. The graph shows point estimates from table 1, column (1) with 95 % confidence intervals. Zero is the week of the lockdown and the coefficients are estimated relative to the time before.

Estimation results for the four main groups by problem category are presented in table 2. For ease of interpretation, we present OLS estimations with count of contacts as the dependent variable. PPML estimates are identical in terms of significance and sign (see table A.5 and A.6). The picture which is emerging in the descriptive trends can be confirmed. The effect is most pronounced for mental health–related contacts, which significantly increase starting in the first lockdown week and peak in the second week. Additional contact related to physical and sexual violence are positive and highly significant in the first week after the lockdown and then appear to flatten out. For social and economic issues, we do not find a significant increase on the demand for psychological counseling during the lockdown period.

A more detailed analysis of the increase in demand for advice on health problems reveals that the increase is driven by loneliness and fear. As the results presented in table 3 show, contacts concerning loneliness significantly increase in the lockdown week and remain high until the

Covid Economics 22, 26 May 2020: 117-153

fourth week. For fear we find a significant increase already four weeks before the lockdown, capturing the effect of the pandemic rather than the lockdown. After the lockdown, these contacts increase further, and remain significantly higher four weeks after the lockdown. Unexpected demand on suicidal ideation is most pronounced in week one after the lockdown, but flattens out more quickly in the weeks after. For addiction, we find no significant increase after the lockdown.

4.2 Differential Effect by Lockdown Stringency

Table 4 presents the estimation results for H2 specified by equation (2). We find a significant positive difference (5% level) between the strict and non–strict federal states in the week of the lockdown (*Week of the lockdown* × *strict*) of around four additional calls per helpline–center per day than in the less–strict states. Results for selected topics suggest a significantly higher increase in the demand for health related contacts as well as for violence and economic issues.

When we further break down the category of mental health–related contacts in table 5, we see a positive difference for loneliness and fear, and an even stronger difference for contacts concerning suicidal ideation. After the second lockdown week, we find no significant differential increase in stricter states for any of the topics.

While this preliminary evidence speaks in favor of H2, we can not be certain what is behind the stronger average effect in Bavaria, Saarland and Saxony-Anhalt. As a next step in our project, we will not only classify states as "strict" and "less strict", but also take a closer look at the individual measures of the federal states to assess whether there are certain measures that people find particularly difficult to cope with.

5 Concluding Remarks

In this paper, we exploit some unique design features of the COVID-19 lockdown in Germany in order to bring new evidence to bear on two important questions. First, did the demand for psychological assistance increase as a response to the outbreack of the COVID-19 pandemic and the implemented lockdown measures? Second, is the increase in demand is higher in stricter states?

We see clear evidence for substantial increase in the demand for psychological counseling

Covid Economics 22, 26 May 2020: 117-153

Covid Economics 22, 26 May 2020: 117-153

Table 1: Event Study Results – Alternative Specifications

	OLS		PPML
	Contacts	log(Contacts)	Contacts
Week -9	−0.038	0.015	−0.002
	(0.262)	(0.017)	(0.011)
Week -8	0.041	0.012	0.001
	(0.272)	(0.018)	(0.012)
Week -7	0.310	0.041*	0.013
	(0.337)	(0.021)	(0.015)
Week -6	0.171	0.032	0.006
	(0.462)	(0.033)	(0.021)
Week -5	0.602	0.047	0.024
	(0.550)	(0.043)	(0.025)
Week -4	0.960*	0.072*	0.039*
	(0.527)	(0.040)	(0.024)
Week -3	0.342	0.037	0.011
	(0.593)	(0.047)	(0.027)
Week -2	0.536	0.041	0.020
	(0.630)	(0.048)	(0.028)
Week -1	0.867	0.059	0.033
	(0.642)	(0.044)	(0.029)
Week of lockdown	4.244***	0.182***	0.167***
	(0.677)	(0.041)	(0.027)
Week 1	4.951***	0.181***	0.186***
	(0.950)	(0.056)	(0.039)
Week 2	3.797***	0.129	0.143***
	(1.192)	(0.073)	(0.049)
Week 3	3.722***	0.133	0.137***
	(1.202)	(0.079)	(0.052)
Week 4	1.948	0.067	0.069
	(1.321)	(0.085)	(0.057)
Week 5	1.101	0.031	0.034
	(1.333)	(0.085)	(0.058)
C19 cases	0.163	0.009	0.009*
	(0.119)	(0.007)	(0.005)
Unemployment	0.615	0.032	0.015
	(0.640)	(0.049)	(0.036)
Trend	0.060***	0.005***	0.003***
	(0.013)	(0.001)	(0.001)
Constant	15.805***	2.499***	3.011***
	(3.380)	(0.259)	(0.190)
Helpline center FE	✓	✓	✓
Year FE	✓	✓	✓
Weekday FE	✓	✓	✓
# Helpline centers	91	91	91
# Observations	34,199	34,199	34,199

Note: Results from estimation equation (1), standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

after the lockdown week, by around 20% relative to the time before. While contacts related to financial worries and fear of the pandemic itself increase already before, the strong increase around the lockdown date seems to be driven by heightened feelings of loneliness and other mental health problems. For contacts concerning violence we see some increase as well. Results

Table 2: Event Study Results – Main Issues

	Health	Violence	Social	Economic
Week -9	0.089	0.027	−0.152	0.408***
	(0.254)	(0.030)	(0.140)	(0.076)
Week -8	0.066	0.026	−0.059	0.377***
	(0.297)	(0.051)	(0.130)	(0.126)
Week -7	0.278	−0.044	−0.190	0.437***
	(0.311)	(0.061)	(0.145)	(0.109)
Week -6	−0.002	0.038	0.011	0.514***
	(0.408)	(0.064)	(0.273)	(0.170)
Week -5	0.661	0.003	0.022	0.587***
	(0.538)	(0.042)	(0.238)	(0.100)
Week -4	0.884*	−0.003	0.322	0.351***
	(0.416)	(0.063)	(0.292)	(0.085)
Week -3	0.617	−0.083	−0.451	0.344***
	(0.529)	(0.065)	(0.312)	(0.112)
Week -2	0.924*	−0.065**	−0.315	0.230*
	(0.493)	(0.027)	(0.272)	(0.109)
Week -1	0.199	−0.142***	−1.175***	0.195***
	(0.521)	(0.041)	(0.339)	(0.060)
Week of lockdown	2.490***	−0.078	−0.480	0.099
	(0.529)	(0.051)	(0.334)	(0.085)
Week 1	3.389***	0.129**	−0.097	0.106
	(0.765)	(0.044)	(0.388)	(0.113)
Week 2	2.554**	0.053	−0.254	−0.025
	(0.956)	(0.100)	(0.579)	(0.182)
Week 3	2.325**	0.109	0.402	−0.159
	(0.933)	(0.084)	(0.503)	(0.157)
Week 4	1.119	0.051	−0.527	0.094
	(1.101)	(0.091)	(0.643)	(0.206)
Week 5	0.387	0.052	−0.797	0.067
	(1.074)	(0.078)	(0.585)	(0.199)
C19 cases	0.141	0.005	0.083*	0.024*
	(0.095)	(0.003)	(0.045)	(0.013)
Unemployment	0.500	−0.016	0.321	0.017
	(0.444)	(0.043)	(0.217)	(0.150)
Trend	0.045***	0.001	0.027***	0.001
	(0.011)	(0.001)	(0.006)	(0.003)
Constant	11.845***	0.646**	7.436***	2.242**
	(2.373)	(0.228)	(1.180)	(0.785)
Helpline center FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓
# Helpline centers	91	91	91	91
# Observations	34, 199	34, 199	34, 199	34, 199

Note: Results from estimation equation (1), standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

are robust to using alternative estimators. Our analysis further suggests that, on average, stricter states experience a somewhat stronger increase in helpline contacts compared to less strict states.

Our findings are important as they shed light on the true extent of mental health consequences of the COVID-19 pandemic and lockdown measures in Germany. Our results support the recent warning by the United Nations: Launching the UN policy brief on COVID-19 and mental health

Covid Economics 22, 26 May 2020: 117-153

Table 3: Event Study Results – Mental Health Issues

	Loneliness	Suicide	Addiction	Fear
Week -9	−0.180	−0.022	0.004	0.052
	(0.110)	(0.092)	(0.039)	(0.122)
Week -8	−0.201	−0.184*	−0.033	0.108
	(0.167)	(0.094)	(0.044)	(0.144)
Week -7	−0.003	−0.059	0.015	0.247**
	(0.135)	(0.080)	(0.048)	(0.095)
Week -6	−0.060	−0.101	−0.010	0.133
	(0.132)	(0.129)	(0.054)	(0.109)
Week -5	0.035	−0.111	0.051	0.124
	(0.191)	(0.130)	(0.065)	(0.158)
Week -4	0.112	−0.021	0.014	0.087
	(0.161)	(0.160)	(0.063)	(0.128)
Week -3	0.146	−0.099	−0.035	0.485***
	(0.159)	(0.233)	(0.053)	(0.148)
Week -2	0.129	0.054	0.047	0.673***
	(0.137)	(0.173)	(0.066)	(0.196)
Week -1	−0.142	−0.201	−0.104**	1.049***
	(0.116)	(0.174)	(0.048)	(0.188)
Week of lockdown	1.206***	0.113	−0.110*	2.134***
	(0.226)	(0.090)	(0.056)	(0.209)
Week 1	1.639***	0.385**	−0.032	1.970***
	(0.303)	(0.141)	(0.047)	(0.182)
Week 2	1.378***	0.257	0.034	1.312***
	(0.355)	(0.286)	(0.047)	(0.241)
Week 3	1.178***	0.214	0.069	1.015***
	(0.309)	(0.248)	(0.057)	(0.318)
Week 4	0.552	−0.086	−0.043	0.668**
	(0.354)	(0.207)	(0.065)	(0.269)
Week 5	0.230	−0.124	−0.072	0.383
	(0.366)	(0.197)	(0.065)	(0.262)
C19 cases	0.037	0.019	0.009**	0.023
	(0.025)	(0.012)	(0.003)	(0.028)
Unemployment	0.322	0.157*	0.028	0.031
	(0.203)	(0.084)	(0.035)	(0.122)
Trend	0.018***	0.007**	0.002*	0.008***
	(0.004)	(0.003)	(0.001)	(0.002)
Constant	2.105*	1.376***	0.433**	2.457***
	(1.096)	(0.464)	(0.183)	(0.663)
Helpline center FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓
# Helpline centers	91	91	91	91
# Observations	34,199	34,199	34,199	34,199

Note: Results from estimation equation (1), standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

on May 13th, Secretary-General António Guterres stressed that "mental health services are an essential part of all government responses to COVID-19".[9]

This article is still work in progress as we will further analyze different groups and topics, as well as update our estimates as new data points become available, allowing us to look at the

[9] See www.un.org/en/coronavirus/mental-health-services-are-essential-part-all-government-responses-covid-19

Table 4: Event Study Results, Lockdown Stringency

	Total	Health	Violence	Social	Economic
Week -9 × strict	2.029	1.899*	0.254***	0.962	0.144
	(1.641)	(1.026)	(0.078)	(0.588)	(0.215)
Week -8 × strict	2.658	2.405*	0.099*	0.517	−0.082
	(1.673)	(1.251)	(0.048)	(0.665)	(0.262)
Week -7 × strict	2.686	2.537	0.079	0.889	0.068
	(1.957)	(1.462)	(0.052)	(0.705)	(0.260)
Week -6 × strict	2.534	2.106	0.080	0.565	0.152
	(1.822)	(1.196)	(0.067)	(0.864)	(0.405)
Week -5 × strict	3.896	2.909	0.148**	1.940**	0.629**
	(2.247)	(1.730)	(0.053)	(0.867)	(0.218)
Week -4 × strict	3.446	3.472	0.097	1.516	0.325
	(2.815)	(2.033)	(0.063)	(1.262)	(0.263)
Week -3 × strict	3.048	2.561	0.109	0.671	0.284
	(2.815)	(2.232)	(0.097)	(1.280)	(0.349)
Week -2 × strict	2.534	2.616	0.222***	0.950	0.334
	(2.509)	(1.672)	(0.068)	(1.073)	(0.195)
Week -1 × strict	3.542*	2.613**	0.147	1.615	0.420**
	(1.709)	(1.068)	(0.091)	(1.019)	(0.147)
Week of lockdown × strict	4.378**	3.134**	0.296***	0.971	0.723**
	(1.923)	(1.303)	(0.066)	(1.048)	(0.298)
Week 1 × strict	3.258	2.475	0.269***	0.936	0.712**
	(2.705)	(2.090)	(0.062)	(1.115)	(0.305)
Week 2 × strict	3.674	3.274*	−0.005	0.508	0.359
	(2.714)	(1.834)	(0.083)	(1.410)	(0.437)
Week 3 × strict	3.896	2.971	0.047	1.113	0.470*
	(3.720)	(2.379)	(0.054)	(1.458)	(0.218)
Week 4 × strict	2.870	2.593	−0.018	−0.141	0.103
	(3.523)	(2.595)	(0.132)	(1.660)	(0.423)
Week 5 × strict	2.840	2.168	0.107	0.413	0.171
	(3.590)	(2.530)	(0.102)	(1.555)	(0.373)
C19 cases	0.239**	0.202***	0.007**	0.120***	0.030**
	(0.085)	(0.065)	(0.003)	(0.032)	(0.013)
Unemployment	1.696***	1.120***	−0.021	0.731***	0.166
	(0.311)	(0.222)	(0.050)	(0.228)	(0.154)
Constant	12.147***	10.031***	0.706**	5.949***	1.563*
	(1.661)	(1.183)	(0.255)	(1.188)	(0.793)
Helpline center FE	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓
# Helpline centers	88	88	88	88	88
# Observations	32,914	32,914	32,914	32,914	32,914

Note: Results from estimation equation (1), standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

development in May 2020. Given that the lockdown measures in Germany were far less strict than in other countries, future research should look more closely into the mental health effects in stricter countries such as France or Italy.

Table 5: Event Study Results, Lockdown Stringency by Mental Health Issues

	Loneliness	Suicide	Addiction	Fear
Week -9 × strict	0.552	−0.128	−0.005	0.738***
	(0.458)	(0.174)	(0.078)	(0.209)
Week -8 × strict	1.400***	−0.005	0.074	0.893**
	(0.435)	(0.199)	(0.108)	(0.335)
Week -7 × strict	0.988	−0.207	0.138	0.303
	(0.736)	(0.141)	(0.080)	(0.281)
Week -6 × strict	1.094**	0.004	0.158*	0.594**
	(0.449)	(0.176)	(0.079)	(0.259)
Week -5 × strict	1.429*	−0.110	−0.059	0.883
	(0.669)	(0.183)	(0.120)	(0.531)
Week -4 × strict	1.439	−0.251	0.335***	0.737
	(0.895)	(0.391)	(0.074)	(0.443)
Week -3 × strict	1.020	0.030	0.265***	0.716
	(0.697)	(0.293)	(0.087)	(0.476)
Week -2 × strict	0.851	−0.066	0.249	0.291
	(0.545)	(0.305)	(0.171)	(0.368)
Week -1 × strict	0.836**	0.617***	−0.149**	0.433
	(0.358)	(0.161)	(0.061)	(0.308)
Week of lockdown × strict	0.863*	0.302*	0.033	1.128**
	(0.443)	(0.156)	(0.111)	(0.377)
Week 1 × strict	0.890	0.515***	−0.155	0.615*
	(1.034)	(0.127)	(0.089)	(0.306)
Week 2 × strict	1.634**	0.653**	0.094	1.197*
	(0.713)	(0.289)	(0.076)	(0.638)
Week 3 × strict	1.399	0.268	−0.022	0.812
	(0.863)	(0.290)	(0.170)	(0.744)
Week 4 × strict	1.036	−0.176	−0.013	1.047*
	(0.789)	(0.247)	(0.084)	(0.576)
Week 5 × strict	1.306	−0.010	−0.096	0.679
	(0.821)	(0.237)	(0.119)	(0.633)
C19 cases	0.050***	0.030***	0.012***	0.038*
	(0.012)	(0.009)	(0.003)	(0.020)
Unemployment	0.421**	0.183	0.084**	0.137
	(0.146)	(0.137)	(0.038)	(0.103)
Constant	2.104**	1.440*	0.181	2.276***
	(0.754)	(0.707)	(0.196)	(0.537)
Helpline center FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
# Helpline centers	88	88	88	88
# Observations	32,914	32,914	32,914	32,914

Note: Results from estimation equation (1), standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

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Covid Economics 22, 26 May 2020: 117-153

Appendix

A.1 Additional figures and tables

Table A.1: List of Helpline–centers by State

Baden-Württemberg: Freiburg (485), Heilbronn (134), Karlsruhe (89), Konstanz (484), Lörrach (480), Mannheim (482), Offenburg (484), Pforzheim (481), Ravensburg (326), Stuttgart (913), Tübingen (404), Ulm (485)
Bavaria: Aschaffenburg (485), Augsburg (297), Bamberg (302), Bayreuth (478), Erlangen (472), Ingolstadt (452), München (897), Passau (334), Regensburg (443), Rosenheim (483), Weiden (485), Würzburg (484)
Berlin: Berlin (822)
Brandenburg: Potsdam (1)

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Bremen: Bremen (451)
Hamburg: Hamburg (908)
Hesse: Darmstadt (484), Frankfurt (880), Fulda (120), Gießen (441), Hanau (485), Kassel (480), Mainz (182), Trier (126)
Mecklenburg-Vorpommern: Greifswald (459), Neubrandenburg (466), Rostock (485), Schwerin (485)
Lower Saxony: Bad Bederkesa (394), Braunschweig (337), Hannover (416), Meppen (59), Oldenburg (274), Soltau (1), Wolfsburg (485)
North Rhine-Westphalia: Aachen (484), Bad Neuenahr (31), Bad Oeynhausen (485), Bielefeld (474), Bochum (485), Bonn (454), Dortmund (469), Duisburg (312), Düren (479), Düsseldorf (362), Essen (883), Hagen (485), Hamm (485), Krefeld (485), Köln (519), Meschede (1), Münster (485), Neuss (316), Paderborn (484), Recklinghausen (484), Siegen (485), Solingen (470), Wesel (318), Wuppertal (485)
Rhineland-Palatinate: Bad Kreuznach (120), Kaiserslautern (484), Koblenz (136)
Saarland: Saarbrücken (397)
Saxony: Auerbach (468), Chemnitz (188), Dresden (151), Leipzig (191), Zwickau (114)
Saxony-Anhalt: Dessau (485), Halle/Saale (326), Magdeburg (124)
Schleswig-Holstein: Kiel (119), Lübeck (35), Sylt (302)
Thuringia: Erfurt (129), Jena/Gera (1)

Note: The table shows the helpline–centers by federal state, number of daily observations in parentheses. Stuttgart, München, Berlin, Hamburg, Frankfurt, Essen, and Köln each have two separate centers.

Table A.2: Summary Statistics – Individual and Contact Characteristics

	Mean	S.D.	Min.	Max.	N
Chat contacts	0.045	0.208	0	1	715,227
Mail contacts	0.070	0.255	0	1	715,227
Phone contacts	0.885	0.319	0	1	715,227
Duration in minutes	22.693	29.046	0	17312	715,227
First contacts	0.199	0.400	0	1	540,657
Recurring contacts	0.801	0.400	0	1	540,657
Female	0.683	0.465	0	1	697,929
Male	0.315	0.464	0	1	697,929
Other gender	0.002	0.049	0	1	697,929
Living alone	0.642	0.479	0	1	622,869
Living in institution	0.052	0.222	0	1	622,869

Covid Economics 22, 26 May 2020: 117-153

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	Mean	S.D.	Min.	Max.	N
Living with family	0.137	0.344	0	1	622,869
Living with partner	0.143	0.351	0	1	622,869
Living in shared flat	0.025	0.157	0	1	622,869
Searching job	0.061	0.240	0	1	555,418
Employed	0.280	0.449	0	1	555,418
Disability	0.278	0.448	0	1	555,418
Not searching job	0.058	0.234	0	1	555,418
Retired	0.234	0.423	0	1	555,418
In education	0.088	0.284	0	1	555,418
Suicide of others	0.013	0.112	0	1	714,959
Suicidal thoughts	0.086	0.281	0	1	714,959
Suicidal intentions	0.014	0.119	0	1	714,959
Suicide attempts	0.012	0.109	0	1	714,959
Psych. diagnosis	0.326	0.469	0	1	714,968

Table A.3: Summary Statistics – Topics

	Mean	S.D.	Min.	Max.	N
Physical constitution	0.165	0.371	0	1	702,351
Depressive mood	0.178	0.383	0	1	702,351
Grief	0.044	0.206	0	1	702,351
Fears	0.146	0.353	0	1	702,351
Stress, emotional fatigue	0.091	0.288	0	1	702,351
Anger, agression	0.073	0.260	0	1	702,351
Self-harming behaviour	0.014	0.115	0	1	702,351
Confusion	0.023	0.150	0	1	702,351
Addiction	0.030	0.171	0	1	702,351
Low confidence, shame	0.068	0.252	0	1	702,351
Loneliness, isolation	0.211	0.408	0	1	702,351
Positive feeling	0.013	0.113	0	1	702,351
Suicidal self	0.031	0.174	0	1	702,351
Suicidal other	0.011	0.104	0	1	702,351
Sexuality	0.027	0.162	0	1	702,351

Covid Economics 22, 26 May 2020: 117-153

	Mean	S.D.	Min.	Max.	N
Other mental issues	0.075	0.263	0	1	702,351
Partner search or choice	0.056	0.230	0	1	702,351
Life with partner	0.076	0.265	0	1	702,351
Parenting	0.025	0.157	0	1	702,351
Pregnancy, childwish	0.004	0.063	0	1	702,351
Family relations	0.167	0.373	0	1	702,351
Everyday relationships	0.109	0.311	0	1	702,351
Public institutions	0.024	0.154	0	1	702,351
Care, therapy	0.071	0.257	0	1	702,351
Separation	0.034	0.181	0	1	702,351
Mortality, death	0.028	0.165	0	1	702,351
Virtual relationships	0.002	0.046	0	1	702,351
Migration, integration	0.002	0.048	0	1	702,351
Physical violence	0.018	0.133	0	1	702,351
Sexual violence	0.012	0.110	0	1	702,351
School, education	0.018	0.131	0	1	702,351
Work situation	0.047	0.211	0	1	702,351
Unemployment, job search	0.017	0.128	0	1	702,351
Daily routines	0.053	0.224	0	1	702,351
Volunteering	0.003	0.055	0	1	702,351
Poverty	0.014	0.117	0	1	702,351
Finances, inheritance	0.023	0.148	0	1	702,351
Housing situation	0.027	0.162	0	1	702,351
Belief, values	0.028	0.165	0	1	702,351
Church, religion	0.006	0.079	0	1	702,351
Society, culture	0.012	0.109	0	1	702,351
TS: positive feedback	0.018	0.133	0	1	702,351
TS: negative feedback	0.003	0.057	0	1	702,351
TS: agreed feedback	0.001	0.035	0	1	702,351
TS: other feedback	0.003	0.053	0	1	702,351
Further information	0.006	0.078	0	1	702,351
Other topic	0.014	0.116	0	1	702,351
Current topic	0.049	0.216	0	1	702,351

Covid Economics 22, 26 May 2020: 117-153

Table A.4: Summary Statistics – Age groups

	Mean	S.D.	Min.	Max.	N
Age: 0-9	0.000	0.011	0	1	653,683
Age: 10-14	0.009	0.096	0	1	653,683
Age: 15-19	0.041	0.199	0	1	653,683
Age: 20-29	0.103	0.305	0	1	653,683
Age: 30-39	0.133	0.340	0	1	653,683
Age: 40-49	0.170	0.376	0	1	653,683
Age: 50-59	0.249	0.433	0	1	653,683
Age: 60-69	0.196	0.397	0	1	653,683
Age: 70-79	0.075	0.263	0	1	653,683
Age: 80 and above	0.023	0.149	0	1	653,683

Covid Economics 22, 26 May 2020: 117-153

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Covid Economics 22, 26 May 2020: 117-153

Table A.5: Event Study Results – Issues (PPML)

	Health	Violence	Social	Economic
Week -9	0.005	0.041	−0.015	0.158***
	(0.014)	(0.046)	(0.013)	(0.025)
Week -8	0.003	0.038	−0.007	0.146***
	(0.017)	(0.079)	(0.013)	(0.044)
Week -7	0.015	−0.070	−0.019	0.169***
	(0.018)	(0.094)	(0.014)	(0.036)
Week -6	−0.002	0.055	−0.001	0.196***
	(0.025)	(0.098)	(0.026)	(0.057)
Week -5	0.036	0.003	0.000	0.221***
	(0.031)	(0.066)	(0.023)	(0.034)
Week -4	0.048**	−0.006	0.028	0.139***
	(0.024)	(0.098)	(0.028)	(0.034)
Week -3	0.031	−0.137	−0.046	0.136***
	(0.031)	(0.100)	(0.031)	(0.041)
Week -2	0.049*	−0.106**	−0.033	0.094**
	(0.028)	(0.042)	(0.027)	(0.042)
Week -1	0.007	−0.246***	−0.120***	0.080***
	(0.031)	(0.068)	(0.034)	(0.024)
Week of lockdown	0.131***	−0.124	−0.049	0.041
	(0.028)	(0.079)	(0.032)	(0.035)
Week 1	0.169***	0.180**	−0.016	0.042
	(0.041)	(0.070)	(0.038)	(0.045)
Week 2	0.127**	0.097	−0.029	−0.012
	(0.051)	(0.151)	(0.055)	(0.073)
Week 3	0.113**	0.173	0.026	−0.069
	(0.052)	(0.130)	(0.049)	(0.064)
Week 4	0.053	0.099	−0.056	0.032
	(0.061)	(0.140)	(0.063)	(0.082)
Week 5	0.013	0.101	−0.082	0.020
	(0.060)	(0.123)	(0.058)	(0.080)
C19 cases	0.009**	0.004	0.009**	0.010**
	(0.004)	(0.005)	(0.004)	(0.005)
Unemployment	0.019	−0.041	0.023	0.006
	(0.032)	(0.067)	(0.024)	(0.064)
Trend	0.003***	0.002	0.003***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.712***	−0.184	2.231***	0.979***
	(0.170)	(0.349)	(0.127)	(0.336)
Helpline center FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓
# Helpline centers	91	90	91	91
# Observations	34,199	34,169	34,199	34,199

Note: Results from estimation equation (1) using PPML, standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

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Covid Economics 22, 26 May 2020: 117-153

Table A.6: Event Study Results – Issues (PPML)

	Loneliness	Suicide	Addiction	Fear
Week -9	−0.040	−0.009	0.005	0.016
	(0.024)	(0.035)	(0.055)	(0.037)
Week -8	−0.045	−0.073**	−0.049	0.033
	(0.037)	(0.036)	(0.065)	(0.043)
Week -7	−0.003	−0.023	0.019	0.074***
	(0.030)	(0.031)	(0.069)	(0.028)
Week -6	−0.017	−0.040	−0.016	0.038
	(0.028)	(0.052)	(0.075)	(0.034)
Week -5	0.003	−0.044	0.068	0.035
	(0.040)	(0.052)	(0.085)	(0.048)
Week -4	0.018	−0.009	0.018	0.023
	(0.034)	(0.062)	(0.086)	(0.040)
Week -3	0.023	−0.040	−0.054	0.135***
	(0.034)	(0.093)	(0.076)	(0.041)
Week -2	0.020	0.018	0.062	0.186***
	(0.029)	(0.064)	(0.089)	(0.050)
Week -1	−0.040	−0.080	−0.161**	0.278***
	(0.027)	(0.072)	(0.080)	(0.046)
Week of lockdown	0.214***	0.043	−0.168*	0.506***
	(0.039)	(0.034)	(0.089)	(0.043)
Week 1	0.272***	0.137**	−0.047	0.468***
	(0.056)	(0.054)	(0.070)	(0.037)
Week 2	0.217***	0.088	0.036	0.337***
	(0.066)	(0.099)	(0.067)	(0.059)
Week 3	0.179***	0.076	0.075	0.270***
	(0.066)	(0.082)	(0.077)	(0.078)
Week 4	0.073	−0.023	−0.066	0.189***
	(0.075)	(0.072)	(0.094)	(0.066)
Week 5	0.012	−0.037	−0.107	0.115*
	(0.078)	(0.071)	(0.096)	(0.061)
C19 cases	0.011*	0.005**	0.011**	0.005
	(0.006)	(0.002)	(0.005)	(0.004)
Unemployment	0.055	0.063*	0.040	−0.002
	(0.052)	(0.034)	(0.054)	(0.038)
Trend	0.004***	0.003**	0.003*	0.003***
	(0.001)	(0.001)	(0.002)	(0.001)
Constant	1.214***	0.581***	−0.596**	1.110***
	(0.277)	(0.191)	(0.291)	(0.207)
Helpline center FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓
# Helpline centers	91	91	90	91
# Observations	34,199	34,199	34,164	34,199

Note: Results from estimation equation (1) using PPML, standard errors in parentheses are clustered at the state level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

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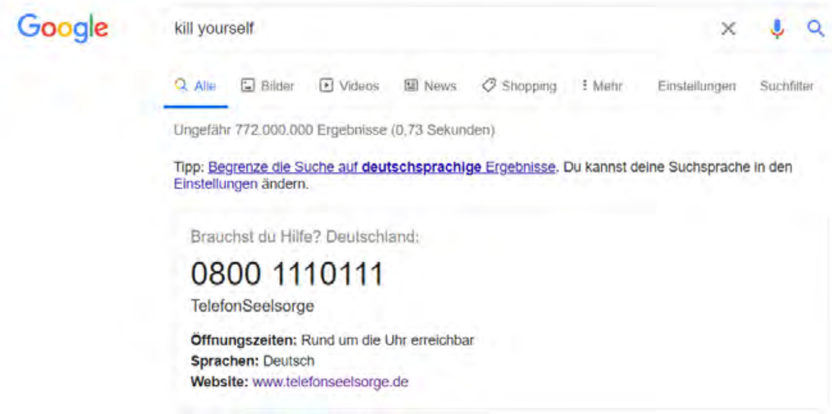

Figure A.1: Searching for help

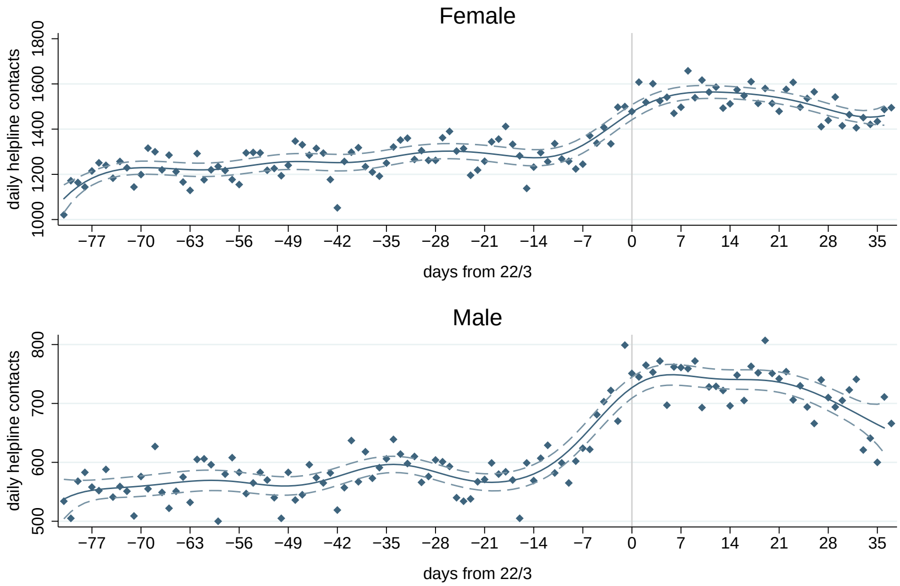

Figure A.2: Daily helpline contacts, by gender

Covid Economics 22, 26 May 2020: 117-153

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Figure A.3: Daily helpline contacts, repeated and first contacts

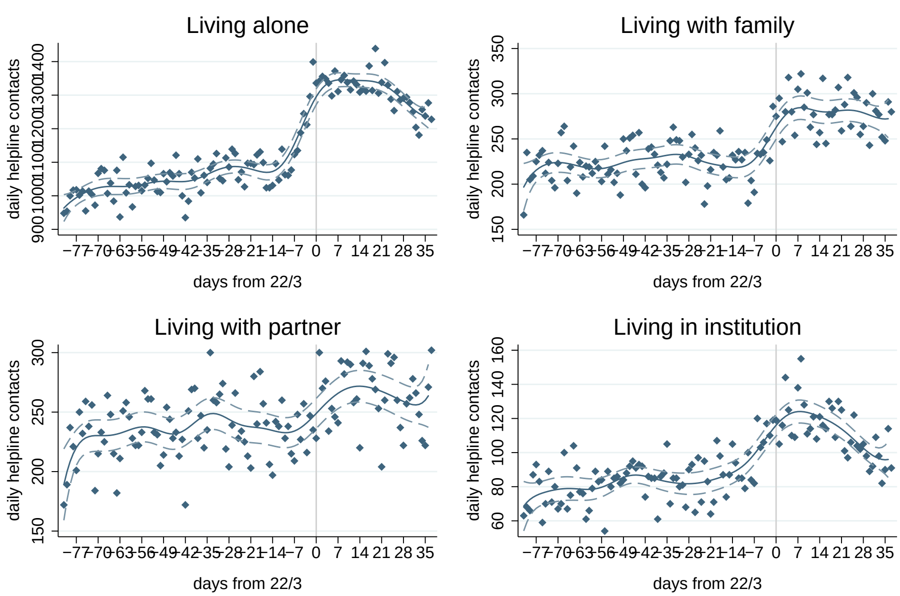

Figure A.4: Daily helpline contacts, by living situation

Covid Economics 22, 26 May 2020: 117-153

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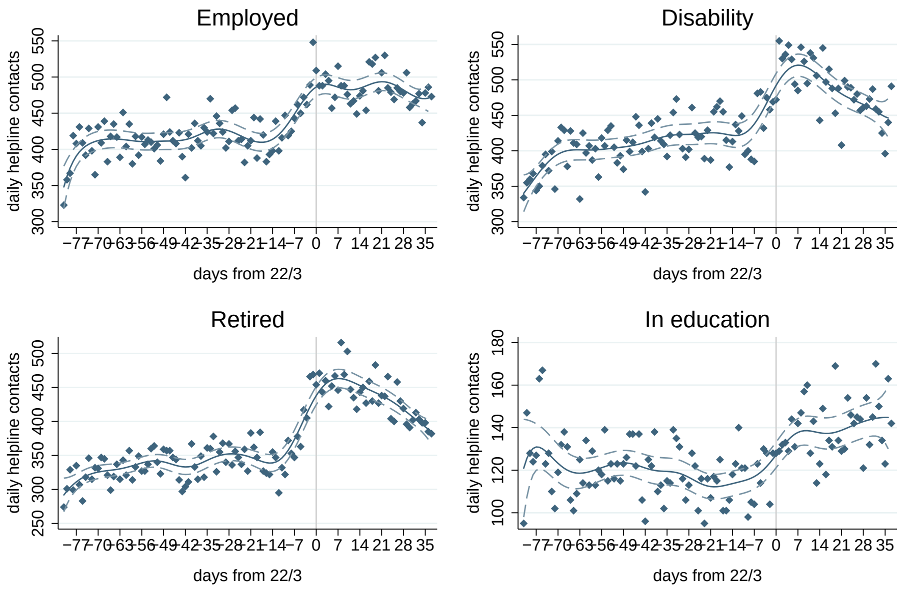

Figure A.5: Daily helpline contacts, by occupation status

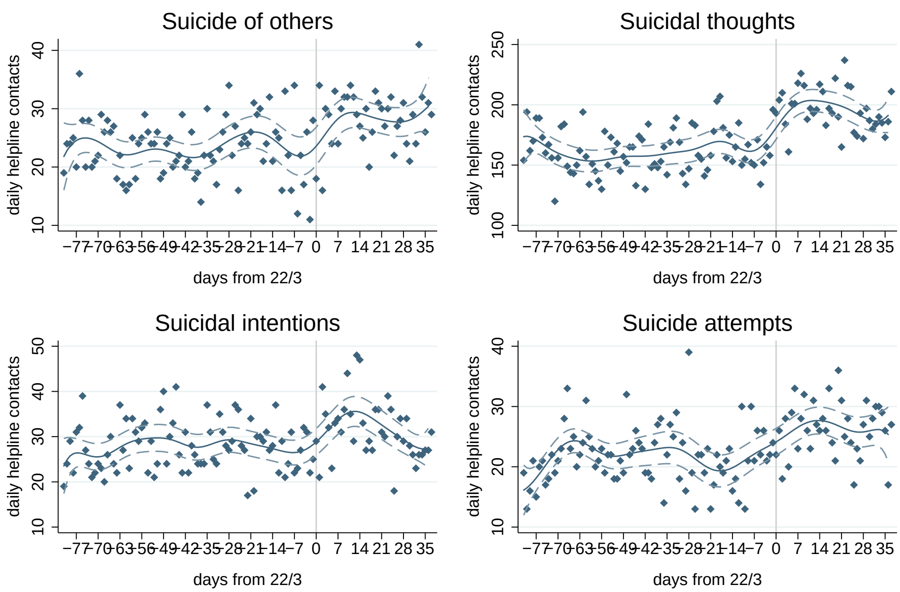

Figure A.6: Daily helpline contacts, different degrees of suicidal ideation

Covid Economics 22, 26 May 2020: 117-153

Covid Economics 22, 26 May 2020: 117-153

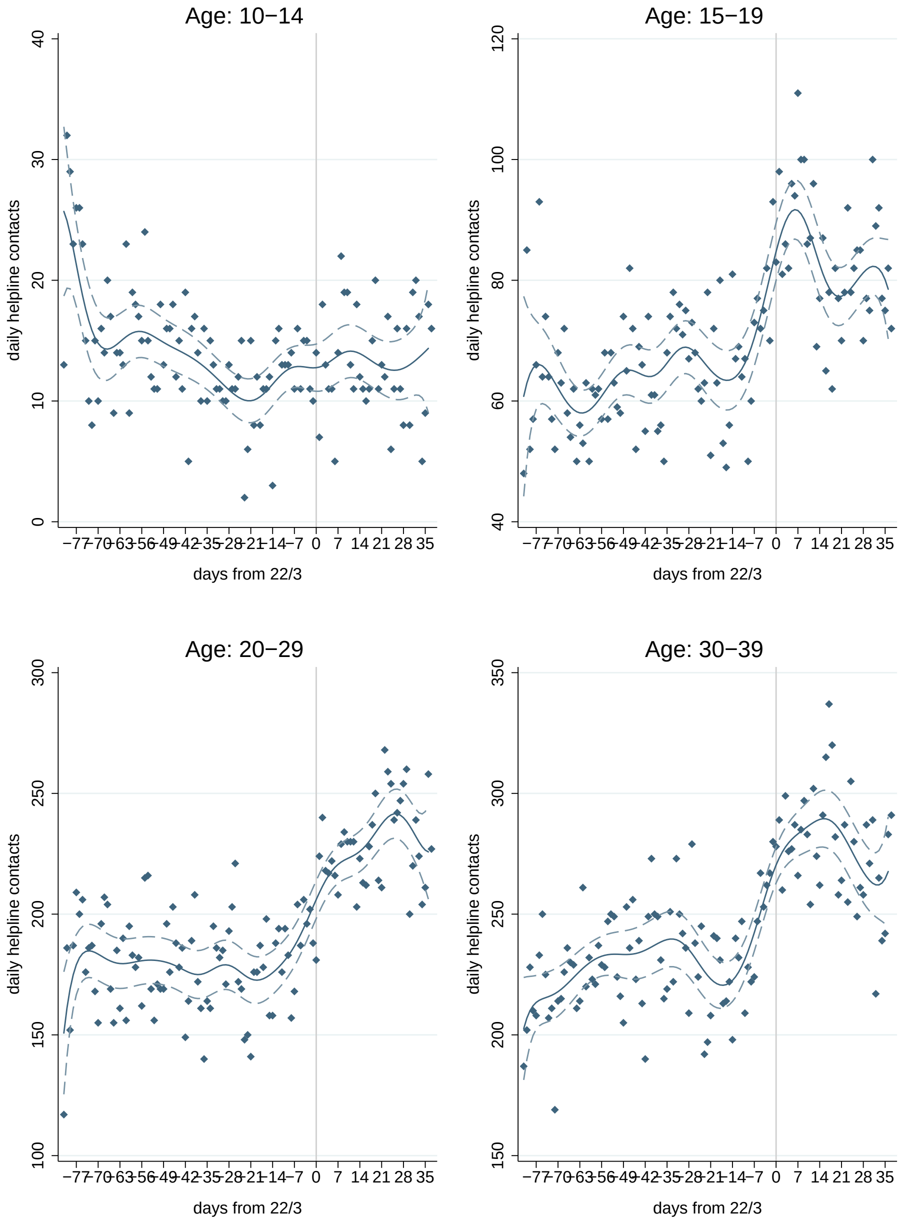

Figure A.7: Daily helpline contacts, by age group

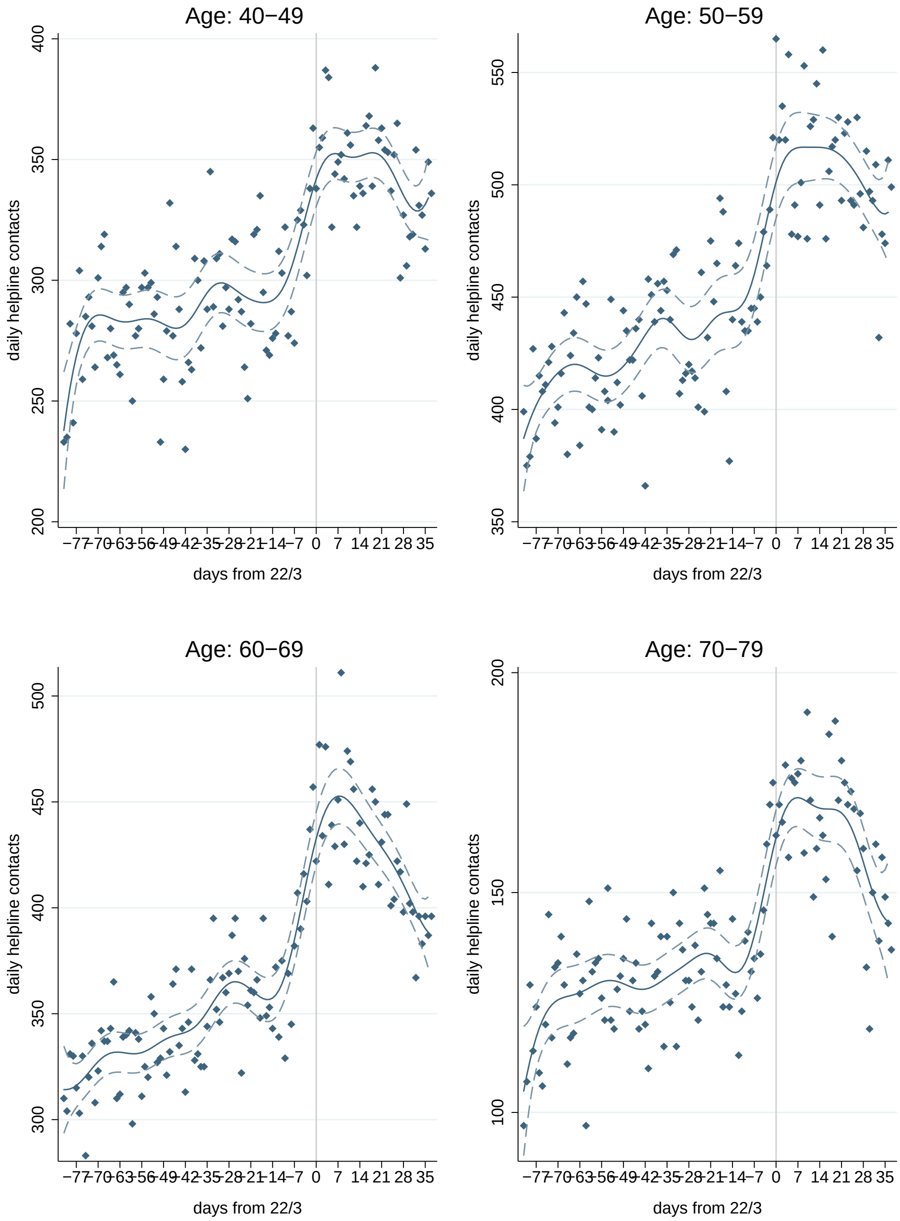

Figure A.8: Daily helpline contacts, by age group (continued)

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Covid Economics 22, 26 May 2020: 117-153

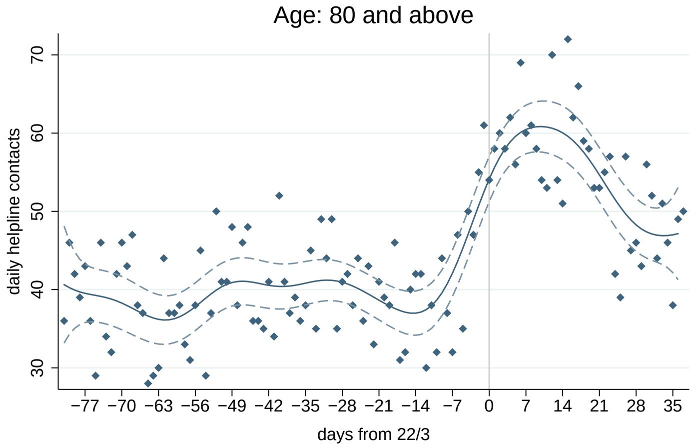

Figure A.9: Daily helpline contacts, by age group (continued)

Covid Economics Issue 22, 26 May 2020

How did the 2003 SARS epidemic shape Chinese trade?[1]

Ana Fernandes[2] and Heiwai Tang[3]

Date submitted: 18 May 2020; **Date accepted:** 21 May 2020

This paper examines the impact of the Severe Acute Respiratory Syndrome (SARS) epidemic on China's trade. Using quarterly transaction-level trade data of all Chinese firms, we find that firms in regions with local transmission of SARS experienced lower import and export growth at both the intensive and extensive margins, compared to those in the unaffected regions. The affected firms' trade growth remained lower two years after SARS. Products that are more capital-intensive, skill-intensive, upstream in the supply chains, and differentiated experienced a smaller export decline but a stronger recovery. Small exporters were more likely to exit, slowing down trade recovery.

Covid Economics 22, 26 May 2020: 154-176

1 We thank the participants at the online conference hosted by the Luohan Academy. All errors are our own.
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Covid Economics 22, 26 May 2020: 154-176

1 Introduction

The Covid-19 pandemic has disrupted the global economy and supply chains. The World Trade Organization (WTO) forecasts a global trade decline of up to 32% in 2020, more than double the magnitude of the "Great Trade Collapse" during the 2008-2009 global financial crisis (WTO, 2020). While the pandemic is still evolving and its end remains uncertain, there should be important lessons that one can draw from a similar episode in the past to shed light on the upcoming trade slump and eventual recovery. How severe is the 2020 trade collapse likely to be? How long will it take to recover? Which sectors will be most affected? What types of firms will be most impacted?

This paper exploits the 2003 Severe Acute Respiratory Syndrome (SARS) epidemic that hit various regions in China to shed light on these questions. Using a standard difference-in-differences research design, we assess the impact of SARS on firms' export and import performance in the affected regions in China, relative to those in the unaffected regions. Despite the apparent differences, there are clear advantages from using the SARS epidemic to shed light on the trade outcomes of the Covid-19 pandemic. First, the sudden and abrupt travel and trade disruption triggered by the unexpected outbreak of SARS, similar to the situations during the Covid-19 pandemic, offer a unique opportunity for an event study on the effect of a health crisis on global trade. Second, the fact that the outbreaks of SARS are clustered mostly in China, unlike Covid-19 which is a global crisis, allows us to clearly categorize Chinese firms into the treatment and control groups. Third, the relatively short duration of the SARS epidemic permits an analysis on the recovery path of trade when it is eventually over.

It is worth noting that despite the much weaker impact on global health, SARS serves as a relevant benchmark to draw lessons for Covid-19 in terms of the impact on trade. Because of the high death rate,[1] the fear created by SARS among consumers, investors, and businesses in the affected regions, together with the policy responses that disrupted travel and trade, could have resulted in local economic losses comparable in size to those triggered by Covid-19. Most importantly, SARS has halted business travels and activities for about half of 2003 in the affected parts of China, potentially impacting Chinese trade in the medium run.

[1] When the SARS epidemic ended and concluded in the third quarter of 2003, the global death rate, defined as the ratio between the cumulative number of SARS-related death to that of infections, is 9.2%. It is much higher than the death rates of the evolving Covid-19, according to the official statistics reported by all countries.

Covid Economics 22, 26 May 2020: 154-176

Using quarterly transaction-level trade data of all Chinese firms, we find that during the quarters of 2003 SARS epidemic, firms in regions (provinces and municipality cities) with local transmission experienced significant declines in both import and export growth, at both the intensive and extensive margins, relative to those in the unaffected regions. Both aggregate exports and imports started to recover by the fourth quarter of 2003, right after the end of the SARS epidemic, which was officially announced by the World Health Organization (WHO) in July 2003. That said, by the end of 2005, two years after SARS was over, firms' average export and import growth in the affected regions were still 4 and 6 percentage-points below the pre-SARS trend, respectively, relative to those in the unaffected regions. In other words, SARS had a medium-term effect on Chinese trade, contrasting the conventional view.

Moreover, we unveil the heterogeneous effects of SARS on trade performance across firms and products. Large and processing exporters, many of them being foreign-owned, are more likely to survive; and conditional on survival, large and processing exporters contributed to slower export growth during the post-SARS recovery in the affected regions. Products that are more capital-intensive, skill-intensive, upstream in the supply chains, and differentiated were more resilient to the export disruption caused by SARS, and drove export recovery afterwards. These findings are consistent with the hypothesis that products that are highly substitutable and widely available in other countries, such as mass-produced consumption goods and downstream low-tech products, could have replaced some Chinese exports permanently despite a temporary disruption of trade. Firms' imports in the affected regions also declined significantly during the epidemic and then rebounded right after the end of it, partly related to the dominance of processing trade in China in the early 2000s, in which firms' exports and imports are more interconnected.

With China's moving up the value chains in the past two decades and a more global and uncertain nature of Covid-19, the outcomes this time may well be different. China is now less dependent on processing exports, commanding a lot more in the upstream of various sophisticated supply chains, and more specialized in skill- and capital-intensive products. Based on our results, China may experience a smaller disruption or a faster recovery in both exports and imports due to the supply shocks caused by Covid-19, all else equal, as foreign buyers may not be able to find substitutes easily. However, the low substitutability of Chinese products can imply a larger disruption of the supply chains, especially given the increased interdependence between firms and

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Covid Economics 22, 26 May 2020: 154-176

countries through global production sharing. Moreover, given that the pandemic is global, the propagation of demand or supply shocks when economies were shut down sequentially imply larger and prolonged effects of the pandemic on global trade.

This paper relates to several strands of literature. It adds to the large literature on trade fluctuations caused by economic recessions, in particular the 2008-2009 financial crisis (e.g., Baldwin, 2009; Bems, Johnson, Yi, 2010; Levchenko, Lewis, and Tesar, 2010; Chor and Manova, 2012).[2] It is also related to the quantitative analysis of the propagation of supply shocks originating from natural disasters (Barrot and Sauvagnat, 2017; Carvalho et al. 2017; Boehm et al., 2020). Of note, Huang (2019) also examines the SARS epidemic on firms' input sourcing, focusing on firms' supply chain resilience based on their pre-crisis supplier diversification. Our paper has a more straightforward goal, which is to examine both the short-term and medium-term effects of SARS on firms' trade performance, as well as the potential heterogeneous effects across firms and products. These facts are important for understanding the pattern of the post-pandemic recovery of global trade, in the absence of escalating trade tension between countries. Finally, our work naturally contributes to the rapidly growing literature on the macroeconomic impact of the current coronavirus pandemic, by shedding light from the trade angle on which sectors and firms may be more affected or contribute to an eventual recovery.

2 Background of SARS

SARS was the first infectious coronavirus in the 21st century.[3] It infected over 8000 people and killed 774 globally (Chan-Yeung and Xu, 2003). It emerged in late 2002 from an outbreak of atypical pneumonia in Guangdong Province in China, and subsequently spread to 29 countries on five continents (Heymann et al., 2003). The majority of the infections and deaths were recorded in mainland China and Hong Kong, which together accounted for 87.5% and 80.0% of infections and deaths, respectively (WHO, 2004). Within China, the places that were hit the hardest are Guangdong, Beijing, Inner Mongolia, and Shanxi. In addition, all SARS epidemic outbreaks in

[2] See Bem, Johnson and Yi (2013) for a review of the literature on the determinants of the Great Trade Collapse in 2008-2009. The main determinants of the trade collapse and the slow recovery were attributed to the collapse in global demand and the deteriorated trade financing. The rise of protectionist policies was still not the main cause of the collapse or the slow recovery afterwards (Kee, Neagu, and Nicita, 2013).

[3] The second one is Middle East respiratory syndrome (MERS) in 2012. The third one is the Covid-19 pandemic in 2020.

Chinese regions ended in the third quarter of 2003, while most regions in China had the start of local transmission in the first half of 2003, with the exception of Guangdong. In short, SARS is a lot more local and short-lived than Covid-19. As discussed in the introduction, the geographic concentration and short duration of SARS actually make it more appealing as a natural experiment for an empirical study.

It is worth emphasizing that despite the smaller number of global infections and deaths, SARS remains a relevant benchmark to shed light on the potential disruptions of Covid-19 in trade and the macroeconomy. First, the SARS death rate, which was concluded to be 9.2% when the epidemic ended, is much higher than the death rates of the evolving Covid-19 reported in almost all countries. Hence, the fear among consumers, investors, and businesses in the affected regions, together with the policy reactions that disrupt travel and trade, could create losses in local economies that are comparable in size to those triggered by Covid-19. Second, it is important to note that the smaller geographic scope of SARS does not mean that it has an insignificant economic impact on the affected regions. According to Hanna and Huang (2004), China's GDP was estimated to contract by over 5% in the second quarter of 2003 on a seasonally adjusted annualized basis, which is equivalent to a 0.5% reduction in China's 2003 GDP.

Third, and probably most relevant for a study on trade, SARS has halted business travels and activities for two quarters in 2003 in the affected parts of China, potentially impacting Chinese trade in the medium run. Like the consequence of Covid-19, SARS has significantly disrupted domestic and international travels for the affected regions. On April 2, 2003, the WHO issued a travel advice to recommend people to postpone all non-essential travel to Hong Kong and Guangdong province. The same advice was extended to cover Beijing on April 23 and Tianjin and Inner Mongolia on May 8 in the same year. While air passenger travel data were not publicly available for individual cities in mainland China for that period, the 65% and 68% declines in international passenger arrivals in Hong Kong in April and May in 2003 respectively can serve as a reliable inference for the extent of air travel disruption in the affected Chinese cities (Noy and Shields, 2019).

These disruptions in air travel could have medium and even long-term impacts on Chinese global trade. Research has shown that international business travels are highly correlated with the volume and composition of differentiated goods' trade (Cristea, 2011). An abrupt and sharp reduction in international travels and cancellation of business meetings, even for a few months, will have an

Covid Economics 22, 26 May 2020: 154-176

impact on trade over a longer period. For instance, hundreds of thousands of buyers from around the world would travel to Guangzhou, the epicenter of SARS in 2003, to attend the annual Canton Fair to meet the Chinese sellers since 1957. Many long-term business relationships and trade orders were created in the fair. In April 2003, due to the WHO travel alerts and the fear among business travellers, only about 23,000 buyers attended the fair, a roughly 80% downturn from the previous year.[4] It is also widely believed that SARS, which caused major disruption of both domestic and foreign trade, contributed to the rapid rise of the Alibaba Group, an E-Commerce giant in China.[5] A temporary shift in business transactions from offline to online may have triggered a more long-run structural change in economic activities.

3 Data and Identification

We use micro trade data sets from China's Customs Office. It covers monthly export and import transactions of all Chinese firms. For this paper, we use data between 2001 and 2005, which cover the period before and after the SARS epidemic in 2003. For each transaction, the data set contains information about the value (in US dollars) and quantity of each product (over 7000 HS 8-digit categories) exported (imported) to (from) each country (over 200 destination and source countries) by each firm. We also have information on the ownership type (domestic private, foreign, and state-owned) and trade regime (processing versus non-processing) of each trading firm, as well as the province or municipality city in China where the firm trades. We aggregate the data to the HS 6-digit product level. To average out noise due to infrequent trade and seasonality (e.g., the factory shutdown during the Lunar New Year can happen in January or February depending on the year), we aggregate the monthly observations to the quarterly level. See Table A1 in the appendix for the summary statistics of the variables of interest used in the regressions.

To identify the effects of the epidemic on firms' trade patterns, we exploit the timing of the outbreak of local transmission of SARS across Chinese regions (provinces or municipality cities) as quasi-natural experiments. We use the announcement by the WHO about which region in China

[4] "The Trade Show of Everything' *The Atlantic* MAY 23, 2016. (Source: https://www.theatlantic.com/business/archive/2016/05/canton-fair-guangzhou-everything/483545/)

[5] "The SARS epidemic threatened Alibaba's survival in 2003—here's how it made it through to become a $470 billion company" CNBC March 26, 2020. (Source: https://www.cnbc.com/2020/03/26/chinas-2002-2003-sars-outbreak-helped-alibaba-become-e-commerce-giant.html)

Covid Economics 22, 26 May 2020: 154-176

Covid Economics 22, 26 May 2020: 154-176

had a local outbreak, which gives us both spatial and time variation in the shocks to firms. Table A2 in the appendix lists the start and end quarters for the regions that had a SARS outbreak in 2002-2003. 8 provinces and 2 municipality cities (Beijing and Tianjin) had local outbreaks during the epidemic. Guangdong was the first region that experienced the outbreak in the fourth quarter of 2002, followed by Beijing, Inner Mongolia and Shanxi which had an outbreak in the first quarter of 2003. The remaining regions had their outbreak started in the second quarter of 2003. All regions had the epidemic ended in the third quarter of 2003, according to the WHO.

We exploit the nature of the shocks to obtain difference-in-differences estimates across time and regions. Firms in the affected regions during the SARS epidemic belong to the treatment group, while those from regions that never had a local outbreak belong to the control group. In our empirical specifications, the treatment variable, $SARS_{rt}$, takes the value 1 from the quarter (t) (inclusive) when region r reported the first local transmission of SARS until the end of the epidemic (i.e., the third quarter of 2003), and zero otherwise.[6]

We first examine the impact of SARS on firms' exports and imports by estimating the following specification at the firm level:

$$\Delta \ln X_{frt} = \beta_1 SARS_{rt} + \delta \ln X_{fr,t-1} + d_t + \epsilon_{frt}. \tag{1}$$

The dependent variable is the change in firm f's log quarterly (t) trade (export or import) value from the same quarter in the previous year ($\ln X_{frt} - \ln X_{frt-4}$). Since the SARS epidemic was active in China during the first three quarters of 2003, we use data for the first three quarters of both 2002 and 2003. Year-to-year changes for each quarter in 2001-2002 correspond to the pre-treatment period, while those in 2002-2003 correspond to the treatment period for the affected firms. We also use as dependent variables the number of products exported (imported), number of destination (origin) countries and the dummy for exit from exporting (importing). Time (year-quarter) fixed effects (d_t) are always included to take aggregate shocks into account, as well as the firms' (log) lagged quarterly trade value ($\ln X_{fr,t-1}$, exports or imports). Since the equation is estimated in differences, unobserved firm-specific characteristics are already absorbed. The coefficient β_1 identifies the differential effect of SARS on trade for firms in the affected regions, relative to the

[6]Source: https://www.who.int/csr/sars/areas/areas2003_11_21/en/

Covid Economics 22, 26 May 2020: 154-176

pre-SARS period and to firms in the unaffected regions. This allows us to infer whether the epidemic contributes to a differential loss in trade growth, controlling for prior trends. ϵ_{frt} is a disturbance term. Standard errors are clustered by firm. We will also estimate a variant of (1) by using as a dependent variable the dummy indicating whether a firm exits from trade (exporting or importing) in quarter t.

To study which firms or products were more vulnerable to the SARS shock, we estimate the following specification at a more disaggregated level:

$$\Delta \ln X_{frsct} = \gamma_1 SARS_{rt} + \gamma_2 (SARS_{rt} \times Z_{fs}) + \gamma_3 Z_{frs} + \alpha \ln X_{fr,t-1} + d_t + \epsilon_{frsct}. \tag{2}$$

Here, the dependent variable, $\Delta \ln X_{fsrt}$, is the change in the log export (import) value of firm f (in province r), for product s, to (or from) country c, relative to the same quarter in the previous year ($\ln X_{frsct} - \ln X_{frsct-4}$). Estimation is therefore based on continuing triplets (i.e., a firm continued to trade in a country-product market). Time fixed effects and (log) firm lagged quarterly exports ($\ln X_{fr,t-1}$) are always included. Since the equation is estimated in differences, it accounts for unobserved characteristics at the firm-product-country level. Standard errors are clustered by firm. ϵ_{frsct} is a disturbance term. Z_{frs} is a vector of firm and product characteristics to explain the trade decline and the eventual recovery. These characteristics are measured based on the data in 2002, prior to SARS, to avoid changes induced by SARS that will bias the estimates. The coefficient γ_2 captures the differential changes induced by SARS according to those characteristics.

To study the recovery period after the SARS epidemic was announced to be over by the WHO in the third quarter of 2003, we estimate a specification similar to equation (2) but for growth in every quarter in 2004 and 2005 (relative to the previous year) as the post-SARS period, compared to their corresponding growth in the four quarters in 2002 (relative to 2001). In that specification the SARS dummy takes the value 1 for regions that had a SARS outbreak in all quarters of 2004 and 2005 and zero for 2002 and for the unaffected firms. The estimated coefficients will inform us about the potential medium-term effects of SARS on firms' trade growth, and whether there is any heterogeneity.

Covid Economics 22, 26 May 2020: 154-176

4 Results

4.1 Trade Performance During SARS

We start by providing a graphical illustration of the differential export and import growth in the affected (the treatment group) regions, relative to the unaffected regions (the control group), before and after the SARS outbreak. Figure 1 plots the dynamic treatments from three quarters before the outbreak in a region ($t = -3$ in the graph) to the last quarter in 2005 ($t = 12$). $t = 0$ is the reference quarter when a Chinese region started to have its local transmission of SARS.[7] Specifically, it plots the point estimates from estimating a slightly adjusted version of specification (2), where the dependent variable is still the log difference in export (import) values at the firm-product-country level from the same quarter a year ago, but the independent variables of interest are a set of quarter indicators that take the value 1 for the affected firms, in each lead and lag quarter from the SARS shock, relative to the start of the SARS outbreak in a region, and zero otherwise, allowing estimation of a time-varying effect of the disruption. The regressions control for the pre-trend by including a post-2003 dummy. The vertical bars around each point estimate show the 95 percent confidence intervals.

The figure shows a short dip during the SARS quarters, and then a rapid recovery right after the end of the epidemic, which gradually dissipated into the negative territory by the end of 2004, about a year after SARS ended. In particular, the coefficients for the exposed firms' import and export growth are both positive in the 2 lead quarters prior to the outbreak. There is also no negative trend for the affected firms. If anything, the growth rate of imports for the firms in the affected regions was actually increasing in the 3 quarters leading to the outbreak. These results collectively suggest no pre-trend among the treated firms. The coefficients become negative and statistically significant for the firms in the affected regions after the epidemic began, and both of their export and import growth remained lower than those of the unaffected firms' in the three quarters since the outbreak started. Specifically, during the epidemic, firms in the affected regions experienced a -1.4 percentage-point relative decline in annualized growth in both exports and imports for three consecutive quarters.

[7] As mentioned above, different regions had their $t = 0$ in different quarters. It is the first quarter of 2002 for Guangdong and the first or second quarter of 2003 for other regions.

Covid Economics 22, 26 May 2020: 154-176

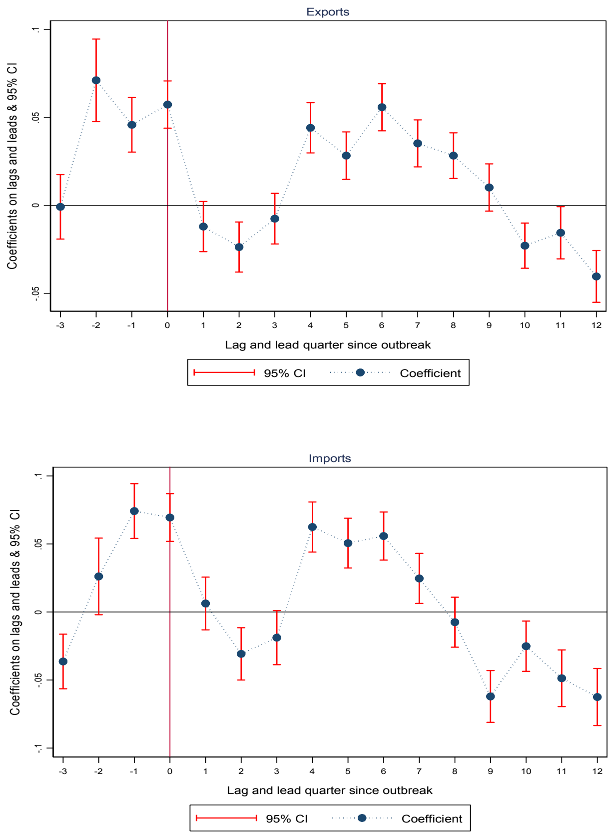

Figure 1: Dynamic treatments over time, quarterly 2002-2005

Firms in the affected regions, conditional on survival, experienced a significant recovery starting from the quarter right after SARS ended. Firms' annualized growth was higher for exports in 5 consecutive quarters and for imports in 4 consecutive quarters among the affected firms from the quarter right after the epidemic ended ($t = 4$). This finding of a rebound may be specific to the short duration of the epidemic, when the WHO officially announced in the third quarter of 2003 that the epidemic was under control globally. As shown in Table A2 in the appendix, the epidemic lasted for less than 2 quarters in 6 out of 10 affected regions.

Despite the immediate and sharp trade recovery, the rebound ended in about a year. The affected firms' export growth was lower in the last 3 quarters in 2005 than the unaffected counterparts, while their import growth was lower since the last quarter of 2014 to the end of 2015. In particular, in the last quarter of 2015, the affected firms had a 4 and 6 percentage-point lower export and import growth, respectively, relative to the unaffected firms. This shows that SARS had a medium-term effect on Chinese trade, in contrast to the conventional view.

Table 1 reports the estimates of equation (1). We estimate the regressions separately for firms' exports and imports. In Panel A, we find that controlling for time fixed effects and firms' lagged total export values, firms in the regions (provinces and municipality cities) that had a SARS outbreak in 2002-2003 had a roughly 11 percentage-point lower export growth on average relative to the pre-SARS period and to the non-exposed firms (column 1). The difference-in-differences estimates account for potential differences in growth trends between the treated and the non-treated firms before the SARS outbreak. Columns (2) and (3) of Table 1 show that the SARS epidemic also contributed to an average 4 percentage-point lower growth in the number of exported products and destination markets respectively among the exposed firms.

In the last column, we gauge the impact of the SARS outbreak on the likelihood of firms' exit from exporting.[8] Exploiting the firms' quarterly export data, we find that firms in the affected regions have about 0.6 percentage-point higher probability of exit from exporting during the SARS outbreak, relative to the unaffected firms and the pre-SARS period.

In Panel B of Table 1, we find consistent results that firms in the affected regions experience a larger decline in imports, at both the intensive and extensive margins. Specifically, firms in the regions that had an outbreak experienced a roughly 6 percentage-point lower import growth relative to the pre-SARS period (2001-2002) and to the non-exposed firms. Firms in the affected regions tend to drop products and source countries, relative to those that did not experience an outbreak. The affected importers have an 8 percentage-point *lower* probability of exit from importing, implying that when domestic supply was disrupted, consumers and firms might have switched input sources from domestic to foreign suppliers.

As the first analysis of the heterogeneous effects of SARS on firms' trade outcomes, in Panels C and D of Table 1, we show the estimates of (2) with the dummy for exit from exporting (or importing) as the dependent variable. In column (1), we add as a regressor an interaction term

[8] A firm's trade (import or export) exit dummy is set to 1 if a firm traded for the last time in the current quarter, and is zero in all previous quarters.

Covid Economics 22, 26 May 2020: 154-176

Covid Economics 22, 26 May 2020: 154-176

Table 1: Firm-level Export and Import growth, 2002-2003

	(1)	(2)	(3)	(4)
	Panel A: Export Performance			
Dependent variable:	Δln(volume)	Δln(no. hs6)	Δln(no. countries)	Exit
SARS	-0.112***	-0.0376***	-0.0384***	0.00573***
	(0.00815)	(0.00408)	(0.00400)	(0.00118)
N	279255	279255	279255	400227
R2	.11	.017	.0216	.00698
	Panel B: Import Performance			
Dependent variable:	Δln(volume)	Δln(no. hs6)	Δln(no. countries)	Exit
SARS	-0.0573***	-0.0612***	-0.0226***	-0.0809***
	(0.0111)	(0.00558)	(0.00415)	(0.00160)
N	220578	220578	220578	336713
R2	.115	.0272	.0164	.0232
	Panel C: Exit from Exporting			
Dependent variable:	Exit Dummy			
Firm characteristic (Z):	size	EP firm	foreign	SOEs
SARS	0.00840***	0.0162***	0.0792***	0.00397***
	(0.00187)	(0.00182)	(0.00338)	(0.00119)
SARS*dz	-0.00926***	-0.0161***	-0.0847***	0.0640***
	(0.00204)	(0.00210)	(0.00350)	(0.00609)
N	400227	400227	400227	400227
R2	.0331	.00513	.0126	.00826
	Panel D: Exit from Importing			
Dependent variable:	Exit Dummy			
Firm characteristic (Z):	size	EP firm	foreign	SOEs
SARS	-0.0987***	-0.0349***	-0.00980*	-0.0873***
	(0.00273)	(0.00298)	(0.00556)	(0.00164)
SARS*dz	0.0472***	0.0107***	-0.0682***	0.0809***
	(0.00284)	(0.00317)	(0.00567)	(0.00775)
N	220578	220578	220578	220578
R2	.0283	.0275	.0277	.0277

Observations are by firm-quarter. Data are for each of the first three quarters of 2002 and 2003. In Panel A and B, dependent variables in the first 3 columns are the log difference in the variable of interest from the same quarter a year ago. SARS takes the value 1 for region (provinces or municipality cities) with local transmission of SARS since its outbreak, and zero otherwise. Changes between 2002-2001 correspond to the pre-treatment period, and between 2003-2002 to the treatment period after a SARS outbreak was announced by the WHO. Time fixed effects are always included as controls. Lagged quarterly firm exports (imports) are always included in columns (1)-(3) of Panels A and B. In Panels C and D, dZ is a dummy variable that takes the value 1 if the firm is above the median size across firms in an industry (HS2) in column (1); if the firms' processing exports (imports) account for over 50 percent in column (2); or if the a firm is foreign or a SOE in the remaining columns, respectively, and zero otherwise. The dZ terms are always included, but they are not reported for space consideration. Standard errors clustered by firm are reported in parenthesis. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

between the SARS dummy and a dummy that takes the value 1 if the firm's export (import) volume is above the median of the firms' main industry (defined as the HS2), and zero otherwise. We find that larger firms are less likely to exit from exporting, consistent with the conventional wisdom that larger firms are more capitalized and thus less budget-constrained. We also find that foreign and processing exporters (if processing exports account for over 50% of the firms' exports) are less likely to exit from exporting. To the extent that many processing firms are foreign-invested enterprises, which tend to have access to internal capital markets in foreign countries (Manova, Wei, and Zhang, 2015), their lower likelihood of exiting from trade is expected. We also find that state-owned enterprises (SOEs) are more likely to exit. While SOEs are generally expected to have soft budget constraints (Qian and Roland, 1998), the Chinese government intended to use trade liberalization to foster privatization in the early 2000s (Khandelwal, Schott, and Wei, 2013; Hsieh and Song, 2015). It is therefore possible that during the SARS epidemic, the Chinese governments did not provide extra support to SOEs to survive exporting.

We repeat the same analysis on firms' exits from importing, and find that despite a relatively lower probability of firms' exits (or higher probability of survival) from importing, larger, processing, and state-owned firms are relatively more likely to exit from importing, while foreign firms are more likely to continue to import. These results are largely consistent with the results about the extensive margins on the export side.

In Table 2, we examine the potential heterogeneous effects of the epidemic on firms' intensive margin of import and export growth, depending on firm characteristics. To this end, we estimate equation (2) at the firm-product-country level. In column (1), we estimate the average treatment effect across firms; the difference-in-differences coefficient implies that the exposed firms (those in the affected regions) experience a roughly 3 percentage-point lower average export growth across markets (country-product pairs) during the outbreak period, relative to the pre-SARS period and to the non-exposed firms. In the subsequent columns, we estimate the triple difference effects according to firm characteristics. In column (2) we interact the $SARS_{rt}$ variable with the dummy variable for whether the firm is above the median size across firms in the same industry (the HS2 of the firms' main line of business). We find that larger firms had a significantly bigger decline in exports. Together with the evidence that smaller firms are more likely to exit, our findings suggest that the shock induces smaller firms to exit, while larger firms tended to survive by adjusting their

Covid Economics 22, 26 May 2020: 154-176

Table 2: Firm-product Export and Import Growth and Firm Characteristics, 2002-2003

	(1)	(2)	(3)	(4)	(5)
Firm characteristic (Z):		size	EP firm	foreign	SOEs
Dependent variable:	export growth: $\Delta\ln(X_{fcp})$				
SARS	-0.0274***	0.106***	-0.00578	-0.0533***	-0.0266***
	(0.00721)	(0.0121)	(0.0130)	(0.0160)	(0.00694)
SARS*dz		-0.149***	-0.0438***	0.0291*	-0.0746***
		(0.0126)	(0.0169)	(0.0170)	(0.0235)
N	1899930	1899930	1899930	1899930	1899930
R2	.00216	.0029	.0022	.00217	.00223
Dependent variable:	import growth: $\Delta\ln(M_{fcp})$				
SARS	-0.0543***	0.0987***	0.0865***	-0.105***	-0.0429***
	(0.0104)	(0.0183)	(0.0184)	(0.0211)	(0.0115)
SARS*dz		-0.170***	-0.134***	0.0647***	-0.0847***
		(0.0183)	(0.0190)	(0.0233)	(0.0266)
N	1721900	1721900	1721900	1721900	1721900
R2	.00199	.00297	.00311	.00203	.00203

Observations are by firm-product(HS6)-country-quarter. Data are for each of the first three quarters of 2002 and 2003. Dependent variables are the log difference in the variable of interest from the same quarter a year ago. Changes between 2002-2001 correspond to the pre-treatment period, and between 2003-2002 to the treatment period, after the SARS outbreak began in the affected regions. dZ is a dummy variable that takes the value 1 if the firm is above the median size across firms in an industry (HS2) in column (1); if the firms' processing exports (imports) account for over 50 percent in column (2); if the firm is a foreign or a SOE in columns (3)-(4), respectively; and zero otherwise. Time fixed effects and lagged quarterly firm exports (imports) are always included. The dZ terms, when the corresponding interaction terms are added, are always included. They are not reported for space consideration. Standard errors clustered by firm in parenthesis. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

export growth instead.

In columns (3) and (4) we find that processing exporters in the affected regions experienced a relatively larger drop in export growth, while foreign firms appeared to be more resilient and had a smaller decline in export growth. Column (5) shows that SOEs experienced a significantly larger decline in export growth. All these results are consistent with our earlier explanations for the patterns of the adjustments on the extensive margin.

In the lower panel of Table 2, we report similar results for imports. Specifically, we find that surviving importers in the affected regions experienced a slower annualized import growth, and larger firms, processing exporters, and SOEs all experienced an even larger decline, relative to those in the unaffected regions. The fact that larger and processing firms experience a relatively slower import growth in the affected regions are consistent with the trend during the sample period,

Covid Economics 22, 26 May 2020: 154-176

as documented by Kee and Tang (2016), that Chinese exporters in general become less dependent on foreign inputs. Those that had their global supply disrupted for a short period of time may have decided to either reorient input sources from foreign to domestic suppliers. Foreign firms, once again, seemed to be more resilient to the epidemic shocks, in terms of maintaining a solid import growth (column (4)).

Table 3 reports the estimates of (2) by exploring the potential heterogeneous effects of the epidemic on firms' intensive margin of import and export growth, according to product characteristics. In column (1), we interact the $SARS_{rt}$ treatment variable with an indicator variable that takes the value of 1 if the import demand elasticity, provided by Broda and Weistein (2006), is above the median across HS3-digit tariff.[9] We find that goods that are more substitutable experienced a larger fall in exports. In particular, the export growth of the high-elasticity goods drop by an additional 2 percentage-points on average during the epidemic. These results are consistent with Furusawa et al. (2018), who find that sourcing of differentiated inputs are less vulnerable to external shocks on trade.

In columns (2)-(4), we examine the potential differential effects between intermediate inputs and final goods, as well as those between consumption goods and capital goods.[10] As is shown, the export growth of consumption goods is more negatively affected by SARS, while capital goods were less negatively impacted. Intermediate inputs did not exhibit a different response to the outbreak, compared to final goods. In column (5), we find that products that are produced in the relatively more upstream position in the global supply chains, as defined by the upstreamness index proposed by Antras et al. (2012), were less negatively affected by the epidemic.[11] In other words, goods that are closer to the consumers, which tend to be more substitutable by goods from other countries, were more negatively affected by the epidemic. In the last two columns, we find that capital- and skill-intensive goods are also less affected by SARS.[12] In sum, the heterogeneous effects across products we document reveal that less substitutable and more sophisticated products are naturally

[9] We use Broda and Weistein (2006) import demand elasticity for the US for the exports regressions and for China for imports regressions.

[10] We use the UN-BEC classification to classify each HS6 product as an input, consumer good, or capital good.

[11] Specifically, we add as a regressor an interaction term between the SARS dummy and a dummy that takes the value 1 if the firm's main industry (HS2) upstreamness index is above the median of all HS2 categories.

[12] Specifically, we add as a regressor an interaction term between the SARS dummy and a dummy that takes the value 1 if the firm's main product (HS6) capital or skill intensity measure, provided by Ma et al. (2014), is above the median of all HS6 categories.

Covid Economics 22, 26 May 2020: 154-176

Table 3: Firm-product-country level Export and Import Growth and Product Characteristics, 2002-2003

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Product characteristic (Z):	high elasticity	input	cons. goods	capital goods	upstreamness	capital int.	skill int.
Dependent variable:				export growth: $\Delta\ln(X_{fcp})$			
SARS	-0.0187**	-0.0284***	-0.0165**	-0.0337***	-0.0522***	-0.111***	0.0172
	(0.00798)	(0.00784)	(0.00809)	(0.00751)	(0.0147)	(0.0291)	(0.0131)
SARS*dZ	-0.0208**	0.00655	-0.0224**	0.0565***	0.0136**	0.0200***	0.0510***
	(0.00925)	(0.00950)	(0.00957)	(0.0138)	(0.00683)	(0.00655)	(0.0135)
N	1866556	1899930	1899930	1899930	1899199	1883799	1880414
R2	.00229	.00222	.00231	.00224	.00218	.00245	.00252
Dependent variable:				import growth: $\Delta\ln(M_{fcp})$			
SARS	-0.0299**	-0.0226	-0.0555***	-0.0547***	0.00800	-0.0582	-0.0483***
	(0.0131)	(0.0146)	(0.0104)	(0.0102)	(0.0262)	(0.0363)	(0.0136)
SARS*dZ	-0.0406***	-0.0403***	0.00662	0.00923	-0.0256***	0.000187	0.0175
	(0.00985)	(0.0105)	(0.0154)	(0.0165)	(0.00850)	(0.00666)	(0.0135)
N	1713047	1721900	1721900	1721900	1721855	1702030	1687630
R2	.00205	.00201	.00203	.00201	.002	.00225	.00261

Observations are by firm-product(HS6)-country-quarter. Data are for each of the first three quarters of 2002 and 2003. Dependent variables are the log difference in the variable of interest from the same quarter a year ago. Changes between 2002-2001 correspond to the pre-treatment period, and between 2003-2002 to the treatment period, during SARS. dZ is a dummy variable that takes the value 1 if the import demand elasticity, provided by Broda and Weistein (2006), for the US for exports and for China for imports, is above the median across HS3-digit categories in column (1), or if the HS6-digit product is an input, consumer good, or capital good in columns (2)-(4), respectively, according to the UN BEC list; or if the upstreamness index, provided by Antras et al. (2012), is above the median across HS2-digit categories in column (5); or if the capital and skill intensity, provided by Ma et al. (2014), is above the median across HS6-digit categories in columns (6) and (7), and zero otherwise. Time fixed effects and lagged quarterly firm exports (imports) are always included. The dZ terms are always included. They are not reported for space consideration. Standard errors clustered by firm in parenthesis. ***, **, * indicate significance at the 1, 5 and 10 percent levels, respectively.

Covid Economics 22, 26 May 2020: 154-176

more resilient to the supply shocks caused by an epidemic.

In the lower panel of Table 3, we repeat the same empirical exercises for annualized import growth for each quarter in 2002-2003. We find that firms' imports of the more substitutable goods (column (1)) are relatively more affected by the epidemic. These results are consistent with our expectation, based on the findings that more substitutable exports experienced a more significant growth slowdown. We also find, as reported in columns (2) and (3), that imports of intermediate inputs and goods produced in upstream sectors experienced a sharper decline in import growth. While these findings seem to contrast with their relatively more resilient export performance, they are consistent with the notion that imports of inputs will be first affected, when reduced export demand in the months ahead is anticipated.

4.2 Trade Performance After SARS

In the rest of the paper, we will document some new facts about the recovery of Chinese trade after the SARS epidemic. To this end, we estimate specification (2), but using the panel of 2004-2005 (relative to the previous year) as the post-SARS period, compared to their corresponding growth in the four quarters in 2002 (relative to 2001). In that specification, the SARS dummy takes the value 1 for regions that had a SARS outbreak in all quarters of 2004 and 2005 and zero for 2002 and for the unaffected firms.

Before reporting any heterogeneous effects, in column (1) of Table 4, we show that firms' average annualized export growth across the 8 quarters in 2004-2005 is on average around 3 percentage-point lower than that of the unaffected firms and the pre-trend. Column (2) shows that the slower growth was largely driven by larger firms having slower growth compared to smaller firms after the epidemic. Together with the above finding that small and medium enterprises were more likely to exit during SARS, the fact that exports grow slower in the affected regions in the medium run may be related to the reallocation of resources from small to large firms. We also find that processing firms' exports (column (4)) tend to grow even slower during the recovery period in the affected regions in post-SARS China.

In Panel B, we report no difference in average import growth between the exposed and unexposed firms. That said, large firms (column (2)), processing exporters (column (4)), and SOEs (column (6)) tend to experience slower import growth in the affected regions, while foreign firms tended to

Table 4: Firm-product-country level Export and Import Growth and Firm Characteristics, 2004-2005, compared to 2002

	Panel A: Dependent Variable = export growth: $\Delta\ln(X_{fcp})$						
	(1)	(2)	(3)	(4)	(5)	(6)	
Firm characteristic (z):	-	size	new	EP firm	foreign	SOEs	
SARS	-0.0278***	0.0502***	-0.0276***	0.00609	-0.0304**	-0.0337***	
	(0.00521)	(0.00841)	(0.00521)	(0.00799)	(0.0123)	(0.00516)	
SARS*dz		-0.0871***	0.0166	-0.0483***	-0.00131	-0.00873	
		(0.00934)	(0.0138)	(0.0102)	(0.0130)	(0.0197)	
	Panel B: Dependent Variable = import growth: $\Delta\ln(M_{fcp})$						
SARS	-0.00426	0.0986***	-0.00223	0.0535***	-0.0551***	0.00806	
	(0.00748)	(0.0123)	(0.00799)	(0.0105)	(0.0175)	(0.00752)	
SARS*dz		-0.114***	-0.000446	-0.0452***	0.0645***	-0.0849***	
		(0.0135)	(0.0174)	(0.0126)	(0.0184)	(0.0209)	
	Panel C: Dependent variable = export growth: Δln(Xfcp)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Product characteristic (Z):	high elasticity	input	cons. goods	capital goods	upstreamness	capital int.	skill int.
SARS	-0.0194***	-0.0351***	-0.0178***	-0.0293***	-0.0675***	-0.109***	0.0301**
	(0.00607)	(0.00605)	(0.00584)	(0.00528)	(0.0105)	(0.0228)	(0.0146)
SARS*dZ	-0.0188***	0.0239***	-0.0248***	0.0102	0.0236***	0.0198***	0.0223***
	(0.00633)	(0.00677)	(0.00680)	(0.0114)	(0.00448)	(0.00501)	(0.00591)
	Panel D: Dependent variable = import growth: $\Delta\ln(M_{fcp})$						
SARS	0.00821	0.00140	-0.00176	-0.00559	-0.00306	-0.0848***	0.0142
	(0.00964)	(0.0110)	(0.00749)	(0.00726)	(0.0175)	(0.0241)	(0.00929)
SARS*dZ	-0.0220***	-0.00711	-0.0492***	0.0147	-0.00130	0.0152***	0.0421***
	(0.00705)	(0.00751)	(0.0117)	(0.0102)	(0.00558)	(0.00443)	(0.00898)

Observations are by firm-product(HS6)-country-quarter. Data are for all quarters of 2002 and 2004-2005. Dependent variables are the log difference in the variable of interest from the same quarter a year ago. SARS takes the value 1 for all quarters of 2004 and 2005 for the firms in regions that are affected by SARS (in 2002-2003), and zero otherwise. Changes for 2004-2005 correspond to the post-epidemic period, and for 2002 to the pre-epidemic period. In Panels A and B, dZ is a dummy variable that takes the value 1 if the firm is above the median size across firms in an industry (HS2) in column (1); if the firms' processing exports (imports) account for over 50 percent in column (2); if the firm is a foreign or a SOE in columns (3)-(4), respectively; and zero otherwise. In Panels C and D, dZ is a dummy variable that takes the value 1 if the import demand elasticity, provided by Broda and Weistein (2006), for the US for exports and for China for imports, is above the median across HS3-digit categories in column (1), or if the HS6-digit product is an input, consumer good, or capital good in columns (2)-(4), respectively, according to the UN BEC list; or if the upstreamness index, provided by Antras et al. (2012), is above the median across HS2-digit categories in column (5); or if the capital and skill intensity, provided by Ma et al. (2014), is above the median across HS6-digit categories in columns (6) and (7), and zero otherwise. In all specifications, time fixed effects and lagged quarterly firm exports (imports) are always included. The dZ terms are always included in when its interaction terms are included. They are not reported for space consideration. Standard errors clustered by firm in parenthesis. ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

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have faster import growth (column (5)).

We next show the estimates of (2) to examine whether firms' import and export recovery vary across different types of products. As shown in Panel C, we find that export growth of the highly substitutable products (column (1)) and consumption goods (column (3)) respectively remained significantly lower for firms in the affected regions in the post-SARS period. Exports of intermediate (column 2), more upstream (column 5), capital-intensive (column 6), and skill-intensive goods (column 7) all experience a relatively more robust recovery. These findings are consistent with the hypothesis that widely available substitutes in foreign countries, including mass-produced consumption goods and downstream low-tech products, could have replaced some Chinese exports permanently, despite a temporary disruption of trade.

Finally, we repeat the same set of regressions for import recovery. As reported in Panel D of Table 4, despite no significant relationship between firms' import recovery and the SARS outbreak, we find that the affected firms experienced a lower recovery than the unaffected firms for the highly substitutable products (column 1) and consumption goods (column 3), consistent with our earlier findings that the more substitutable exports experienced a sharper decline and a slower recovery.

5 Concluding Remarks

This paper studies the impact of the SARS epidemic on China's trade in 2003-2005. Based on the quarterly transaction-level trade data of all Chinese firms, we find that firms in regions with local transmission of SARS experience lower import and export growth at both the intensive and extensive margins, compared to those without. The affected firms' trade growth remains significantly lower 2 years after the end of SARS. Products that are more capital-intensive, skill-intensive, upstream in the supply chains, and differentiated experienced a smaller decline in exports but a stronger recovery. Small exporters are more likely to exit. The surviving large firms, which tended to grow slower, dragged down the affected regions' export recovery.

With China's moving up the value chains and a more global and uncertain nature of Covid-19, the outcomes this time may well be different. China is now less dependent on processing exports and more specialized in skill- and capital-intensive products. It commands a lot more in the upstream of the various sophisticated supply chains. The good news, according to our research, is that China

Covid Economics 22, 26 May 2020: 154-176

may experience a smaller decline in exports due to the pandemic, all else equal, as foreign buyers may not be able to find substitutes easily. The bad news is that the low substitutability of Chinese products implies a larger disruption of the supply chains. The increased interconnections between firms and countries in global production sharing since 2003 also implies that the propagation of demand or supply shocks will tend to have larger effects on other connected firms and economies.

Covid Economics 22, 26 May 2020: 154-176

Covid Economics 22, 26 May 2020: 154-176

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Covid Economics 22, 26 May 2020: 154-176

Après-ski: The Spread of Coronavirus from Ischgl through Germany[1]

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Covid Economics 22, 26 May 2020L 177-204

The Austrian ski resort of Ischgl is commonly claimed to be ground zero for the diffusion of the SARS-CoV-2 virus across Germany. Drawing on data for 401 German counties, we find that conditional on geographical latitude and testing behavior by health authorities, road distance to Ischgl is indeed an important predictor of infection cases, but — in line with expectations — not of fatality rates. Were all German counties located as far from Ischgl as the most distant county of Vorpommern-Rügen, Germany would have seen about 48% fewer COVID-19 cases. A simple diffusion model predicts that the absolute value of the distance-to-Ischgl elasticity should fall over time when inter- and intra-county mobility are unrestricted. We test this hypothesis and conclude that the German lockdown measures have halted the spread of the virus.

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1 Introduction

By mid May 2020, the highly contagious SARS-CoV-2 virus infected about 4.5 million people worldwide and led to almost 300,000 fatalities.[1] The outbreak prompted governments to impose lockdowns affecting nearly 3 billion people world-wide, in an unprecedented attempt to 'flatten the curve' of infections so that healthcare systems are not overwhelmed. In Germany, despite restrictions phased in from March 9th to 23rd, the number of confirmed cases increased to approximately 175,000 with almost 8,000 deaths by mid May 2020.[2] However, the spread *within* Germany is far from homogeneous — the two southernmost states, Bayern and Baden-Württemberg, are amongst the most affected, and even within these states there is a lot of variation.

Figure 1 depicts the spatial distribution of confirmed COVID-19 cases per 100,000 inhabitants in each of the 401 'Kreise' (counties)[3] using data provided by the Robert-Koch Institute, the German federal government agency and research institute responsible for disease control and prevention.[4] The left-hand side map indicates that as early as March 13th, 356 out of 401 counties already reported some confirmed cases. By May 9th, infections had increased across the country with counties in southern and eastern Germany experiencing significantly higher case burdens, as shown by the histogram on the right-hand side.

The county with the lowest case incidence rate (CIR) is Mansfeld-Südhartz in North-Eastern Saxony-Anhalt (0.03%). Tirschenreuth in Bavaria, the most affected county, has a CIR 52 times higher (1.53%).[5] Across counties, the standard deviation of the CIR is almost as large as its mean. A similar dispersion is observable for the case fatality rate (CFR), which has been reported zero for 26 counties.[6]

Which factors explain this spatial distribution? In this paper we explore whether tourists visiting super-spreader locations, in particular the resort town of Ischgl in neighbouring Austria, brought home the virus from trips in February and March, as hypothesized by German and international media outlets.[7] Another earlier hotspot in Germany, the county of Heinsberg, located in the Carneval-celebrating Rhineland region, likely contributed to the diffusion of the virus, as did the highly affected French border region of 'Grand Est'.

[1] See e.g. https://ourworldindata.org/coronavirus-data.

[2] See https://experience.arcgis.com/experience/478220a4c454480e823b17327b2bf1d4/page/page_1/.

[3] Strictly speaking, in Germany there are 294 so called 'Landkreise' (rural counties) and 107 'kreisfreie Städte' (cities not belonging to any 'Kreis').

[4] See https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Fallzahlen.html.

[5] Case incidence rate (CIR) is defined as the number of infected individuals divided by population size.

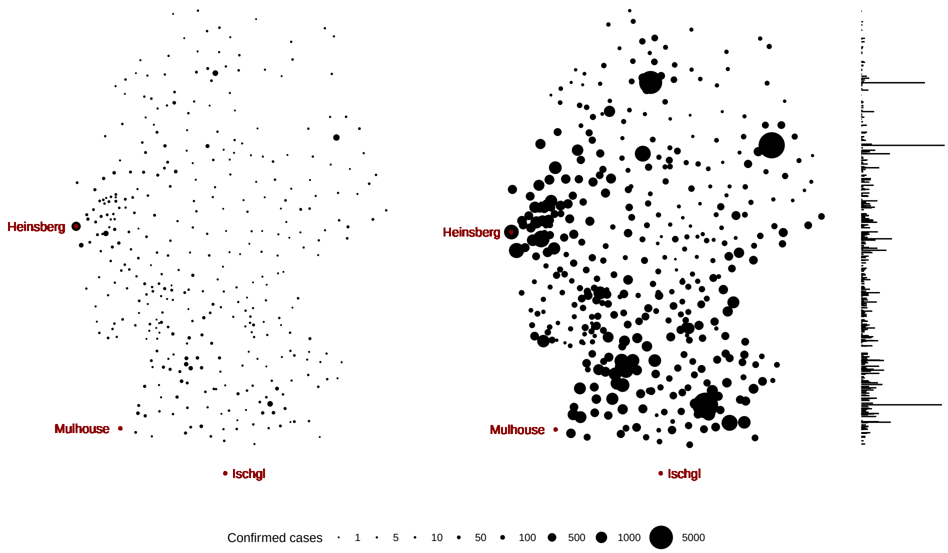
[6] Case fatality rate (CFR) is defined as the number of confirmed deaths divided by the number of confirmed cases.

[7] See e.g. "A Corona Hotspot in the Alps Spread Virus Across Europe", March 31st, 2020, Der Spiegel (https://www.spiegel.de/international/world/ischgl-austria-a-corona-hotspot-in-the-alps-spread-virus-across-europe-a-32b17b76-14df-4f37-bfcf-39d2ceee92ec).

Covid Economics 22, 26 May 2020L 177-204

Covid Economics 22, 26 May 2020L 177-204

Figure 1: Confirmed cases in Germany on March 13th and May 9th, 2020



Note: Map on the left-hand side shows confirmed cases on March 13th, map on the right-hand side shows those on May 9th. The histogram to the very right shows the change by latitude, binned by county.

We evaluate these claims by exploiting the exogenous variation in the road distances of German counties from these three important clusters of infections — Ischgl, Heinsberg and Grand Est. By estimating negative binomial regressions, we compute the elasticity of cases and mortality from COVID-19 with respect to distance from these initial European hotspots. The primary aim of our analysis is to explain the substantial spatial heterogeneity in infections across German counties. By observing the spatial heterogeneity over time, we indirectly evaluate the efficacy of the lockdown measures in halting the diffusion of the virus.

To guide our empirical analysis, we present a two period model where the mobility of persons drives infection transmissions. This simple model yields an insightful and testable proposition: The (absolute value of the) elasticity of COVID-19 cases with respect to distance from a super-spreader location is lower (higher) when individuals are more (less) mobile. We evaluate this proposition by examining the evolution of estimated distance elasticities over time. Finally, we demonstrate the significance of Ischgl as 'Ground Zero' for the outbreak in Germany by performing a back-of-the-envelope counterfactual scenario with a hypothetical location for the town.

Crucially, all our regressions control for a host of possible confounding variables — including the relative latitude of a county. Hence, our results do not simply capture general effects of distance to, e.g. Lombardy in Northern Italy, the European region hit hardest and earliest by the pandemic. We also control for testing by health authorities to account for the spatial pattern in the likelihood of detecting COVID-19 cases.

Our results paint a clear picture: Cases increase strictly proportionally with population, but the share of the population infected is, amongst other factors, a function of the road distance to the major Austrian ski resort Ischgl. Were all German counties as far away from Ischgl as Vorpommern-Rügen, Germany would have 48% fewer COVID-19 cases. In contrast, distance to other hotspots is unimportant. Catholic culture appears to increase the number of cases — likely through Carnival celebrations in late February.[8] We fail to find evidence for a host of socio-demographic determinants such as trade exposure to China, the share of foreigners, the age structure, or a work-from-home index. In line with expectations, fatality rates however do not depend on distance to Ischgl. Case fatality rates increase, however, strongly in the share of population above 65 years and tend to fall in the number of available hospital beds. Finally, distance to Ischgl does not become irrelevant over time for observed cases, suggesting that lockdown measures have been effective in reducing mobility and avoiding further diffusion of the virus across German counties.

Studying the diffusion of the virus across space is of utmost importance to guide the pandemic response which has so far largely been framed and implemented at national levels. Yet, with substantial heterogeneities in the number of infections — both in absolute and per capita numbers — a more fine-grained approach may be required that can take into consideration the specificity of the diffusion. Our analysis also highlights that international tourism is a powerful channel for the spread of contagious diseases. Timely travel bans can therefore limit transmission paths and control the cross-border spillover of infections. Popular destinations such as Ischgl have a critical role to play in such containment strategies since they can rapidly turn into super-spreader locations.

Declared a global pandemic by the WHO on March 11th 2020, the SARS-CoV-2 virus and its associated disease COVID-19 present an enormous challenge to the world economy. Outside of China where the virus was first detected, several European countries such as Italy, Spain and the UK have been hit particularly hard by the outbreak. Within Europe, Germany is treated as an exception due to its low case fatality rates (4.4%) in comparison to Italy (13.9%), Spain (10.1%) and the UK (14.8%).[9]

The absence of proven treatments and vaccines necessitate quarantine measures which have curtailed human mobility and halted economic activity such as industrial production, retail sales and tourism. Although there is a great degree of uncertainty, the economic costs are expected

[8]Carnival is a typical Catholic tradition. The German South and South-West are predominantly Catholic, the North and North-East predominantly Protestant, but there is substantial variation within those regions as well.

[9]Figures as of May 8th, 2020

Covid Economics 22, 26 May 2020L 177-204

CEPR PRESS

Covid Economics 22, 26 May 2020L 177-204

to be high. For 2020, the International Monetary Fund expects global GDP to fall by 3%, more than in the world economic and financial crisis of 2009.[10] In the Eurozone, the Fund expects an output contraction of 7.5%. The World Trade Organization (WTO) expects international trade to fall by by 13-32% in 2020, a collapse that exceeds the trade slump which followed the financial recession of 2008-09.

Since the outbreak of disease, economists have worked on several strands of research. The literature is moving fast; here we present only a few characteristic papers. Macroeconomists have introduced optimizing behavior by economic agents into the basic epidemiological SIER (Susceptible-Infected-Exposed-Recovered) model to examine the economic consequences of pandemics under different policy choices (Eichenbaum, Rebelo, and Trabandt, 2020; Farboodi, Jarosch, and Shimer, 2020; Krueger, Uhlig, and Xie, 2020). Behavioral economists have started to examine the long-run effects of this crisis on preferences (Kozlowski, Veldkamp, and Venkateswaran, 2020). Trade economists are studying the diffusion of health-related shocks through trade networks (Sforza and Steininger, 2020). Economic historians are investigating past pandemics to search for patterns that may inform current policy making (Barro, Ursua, and Weng, 2020), whereas econometricians are working to fill data gaps in order to properly calibrate macroeconomic models (Stock, 2020).

Our paper is most closely linked to the emerging literature on the geographical dispersion of the SARS-CoV-2 virus. Harris (2020) shows how the subway system was critical for the propagation of infections in New York City and identifies several distinct hotspot zip codes from where the virus subsequently spread. Jia et al. (2020) also examine the geographical distribution of COVID-19 cases by using detailed mobile phone geo-location data to compute population outflows from Wuhan to other prefectures in China. Cuñat and Zymek (2020) combine the SIR model with a structural gravity framework to simulate the spread of contagion in the UK.

Our work contributes to the literature by (i) using exogenous variation in the distance to a super-spreader location to identify the role of tourism in the spatial diffusion of COVID-19 and by (ii) providing a very simple test for the effectiveness of lockdown measures.

The remainder of this paper is structured as follows. Section 2 provides the relevant context to this analysis by describing the circumstances of the outbreak in Ischgl, Heinsberg and the French region of Grand Est. Section 3 outlines a simple theoretical model which underpins our empirical analysis. In Section 4, we describe our empirical strategy, the datasets used and the construction of key variables. Section 5 presents the main regression results followed by a counterfactual analysis in Section 6. Finally, Section 7 concludes.

[10]World Economic Outlook, April 2020.

2 Context

By mid May 2020, there were around 16,000 confirmed cases of COVID-19 in Austria. The largest cluster of infections, comprising more than 20% of total cases, is located in the alpine province of Tyrol that is home to approximately 8% of Austria's population. The province's capital city, Innsbruck, was the first to report COVID-19 infections in the country, on February 25th, 2020. In Tyrol, the ski resort town of Ischgl is considered to be one of the epicentres, where the virus spread within après-ski bars, restaurants and shared accommodation.

A highly popular destination for international tourists, Ischgl was first flagged as a risk zone by Iceland on March 5th after infection tracing revealed it as an important origin for COVID-19 cases. By March 8th, Norway's testing results also revealed that 491 of its 1198 cases had acquired the infection in Tyrol.[11] Despite these early warnings, skiing in Ischgl continued for nine more days. It was only on March 13th that the town was placed under quarantine measures. On the same day, Germany's leading centre for epidemiological research, Robert Koch Institute (RKI), also designated Ischgl as a high risk area — alongside Italy, Iran, Hubei Province in China, North Gyeongsang Province in South Korea, and the Grand Est region in France.

As the caseload of infections increased, Austrian authorities finally announced a lockdown in Tyrol on March 19th, 2020. This substantial delay in response is likely to have exacerbated the spread of the pandemic in Austria and other European countries, given the timing of the ski season and the location of the province which is bordered by Italy, Germany and Switzerland. As of March 20th, one-third of all cases in Denmark and one-sixth of those in Sweden were traced to Ischgl.[12]

In Germany, the states of Bavaria, Baden-Württemberg and North Rhine-Westphalia (NRW) report the highest number of confirmed cases of the disease. Together, they accounted for about two thirds of Germany's total 175,000 COVID-19 cases as of mid May 2020. Besides Ischgl, the district of Heinsberg in NRW has emerged as another important cluster that may have intensified the outbreak in Germany. The virus was reported to have spread there through Carnival celebrations, with an attendant testing positive on February 25th, 2020.

The northeastern French region of Grand Est is also heavily affected by the pandemic. Close to France's border with Germany, the spread of infections in the area have largely been traced to a mass church gathering in Mulhouse.[13] Given the region's proximity to the hard-hit German state

[11] See "How an Austrian ski paradise became a COVID-19 hotspot", March 20th, 2020, Euractiv,(https://www.euractiv.com/section/coronavirus/news/ischgl-oesterreichisches-skiparadies-als-corona-hotspot/)

[12] See "Austrian Ski Region Global Hotspot for Epidemic", March 19th, 2020, Financial Times, (https://www.ft.com/content/e5130f06-6910-11ea-800d-da70cff6e4d3)

[13] See e.g. "Special Report: Five days of worship that set a virus time bomb in France", March 30th, 2020, Reuters, (https://www.reuters.com/article/us-health-coronavirus-france-church-spec/special-report-five-days-of-worship-that-set-a-virus-time-bomb-in-france-idUSKBN21H0Q2)

Covid Economics 22, 26 May 2020L 177-204

Covid Economics 22, 26 May 2020L 177-204

of Baden-Württemberg and the regular cross-border movement of German and French workers, we incorporate the town of Mulhouse in the Grand Est region into our analysis. Therefore, these three locations — Ischgl, Heinsberg and Mulhouse — constitute interesting candidates as 'super-spreader locations' for studying the transmission of infections within Germany.

3 Theoretical Model

In this section, we sketch a stylized model where the virus is transmitted through the mobility of population.

Let there be two rounds of infections. In the first round, people can be infected by visiting a super-spreader location such as Ischgl. Let P_i be the (time-invariant) population of county i and I_i^0 the number of infected individuals at the end of period 0. Let $f\left(D_i^0\right)$ denote the likelihood that an individual from county i has visited the super-spreader location in period 0 and has become infected, with f being a function of county i's distance to the super-spreader location. Let $f:[1,\infty)\rightarrow[0,1]$ be a continuous and twice differentiable function with $f'<0$ and $f''<0$.[14]

Hence,

$$\begin{aligned} & I_i^0 = P_i f\left(D_i^0\right) \\ \Leftrightarrow \quad & \iota_i^0 = I_i^0/P_i = f\left(D_i^0\right), \end{aligned}$$

with $\iota_i^0 \in [0,1]$ being the initial infection rate in county i.

In the second round, individuals randomly meet within Germany. If an infected person comes into contact with a susceptible person, the latter is also infected. Thus, in the absence of outside mobility between counties, new infections in period 1 would be given by

$$\begin{aligned} & \iota_i^1 - \iota_i^0 = \gamma\iota_i^0(1-\iota_i^0) \\ \Leftrightarrow \quad & I_i^1 = I_i^0 + \gamma P_i \iota_i^0(1-\iota_i^0), \end{aligned}$$

where $\gamma \in [0,1]$ is the probability that an infection occurs when a susceptible individual meets an infected one.

However, individuals tend to move — within and across counties.[15] Let M_{ij} denote those individuals from county i that meet other individuals from county j, with $\sum_j M_{ij} = P_i$.[16]

[14] The underlying intuition being that a person is less likely to visit Ischgl when the road distance is greater.
[15] For simplicity we assume there is no mobility outside of Germany.
[16] Note that one could assume gravity-type micro-foundations with frictions to interactions between i and j, e.g. à la Anderson (2011).

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Assuming symmetry in mobility between counties, i.e. $M_{ij} = M_{ji}$, we have

$$I_i^1 = I_i^0 + \gamma M_{ii} \left(1 - \iota_i^0\right) \iota_i^0 + 2\gamma \sum_{j \neq i} M_{ji} \left(1 - \iota_i^0\right) \iota_j^0. \tag{1}$$

The elasticity of the infection rate with respect to the distance to the super-spreader location is given by $\delta^t \equiv \frac{\partial I_i^t}{\partial D_i^0} \frac{D_i^0}{I_i^t}$. Assuming $\frac{\partial M_{ii}}{\partial D_i^0} = 0$, it can be shown that

Proposition. *If any* $M_{ij} > 0 \; \forall \; i, j$, *then* $\delta^0 < \delta^1$.

Proof. See appendix A.

As both δ^0 and δ^1 are negative, we expect the elasticity of infections with respect to distance from the super-spreader location to be greater (i.e. closer to zero) with mobility than without mobility. When there is no inter-county geographical mobility after period 0, then $M_{ij} = 0$ for all $j \neq i$, the elasticity is larger in absolute terms than when mobility is allowed; when even intra-county mobility is not permitted, then the elasticity is time invariant: $\delta^1 = \delta^0$ as $I_i^1 = I_i^0$.

The intuition for this result is simple: as mobility between and within counties spreads the virus further over time, the role of distance to Ischgl in explaining the spatial variation of infections goes down. We assume mobility between counties i and j, M_{ij}, to be exogenous to i's and j's distance to Ischgl, believing this to be a rather innocuous assumption.[17]

4 Empirical Model and Data

4.1 Model and Hypotheses

As reflected in our theoretical model, we are interested in understanding the number of COVID-19 patients (I_i^0 and I_i^1) and fatalities registered in a county. For this reason, the appropriate econometric strategy is to estimate a count data model, such as a Poisson or negative binomial model. In this context, we expect the variation of our dependent variable to exceed that of a true Poisson since (i) counts will not be independent in a pandemic; and (ii) there may be unobserved heterogeneity. Therefore, we employ a negative binomial model in which the variance is assumed to be a function of the mean (NB-2 model; see Cameron and Trivedi, 2013). Since the NB-2 model nests the simple Poisson model, one can test for over-dispersion.[18] One handy feature of the negative binomial model is that its coefficients can be interpreted exactly as in a linear

[17] Essentially, the spatial distribution of counties, mobility costs between them, and their population sizes are assumed to be independent of the counties' distance to Ischgl.

[18] As frequently observed with negative binomial models, as in our exercise, it does not matter substantially whether dispersion is assumed constant across observations (NB-1 model) or is a function of the expected mean (NB-2 model).

Covid Economics 22, 26 May 2020L 177-204

CEPR PRESS

model in which the dependent variable is logarithmic.

We exploit the variation in cases and deaths across the numerous counties as of May 9th, 2020, and estimate elasticities with respect to road distances from Ischgl, Heinsberg, and Mulhouse. We run cross-sectional regressions which are specified as follows:

$$\text{cases}_i = exp(\alpha + \sum_{k\in\{0,1,2\}} \delta_k \log(D_i^k) + \boldsymbol{\gamma}\mathbf{Z}_i + \varepsilon_i) \tag{2}$$

$$\text{deaths}_i = exp(\alpha + \rho \log(\text{lagged cases}_i) + \sum_{k\in\{0,1,2\}} \delta_k \log(D_i^k) + \boldsymbol{\gamma}\mathbf{Z}_i + \varepsilon_i) \tag{3}$$

The main coefficients of interest in the above regressions are δ_0, δ_1 and δ_2 which capture the elasticity of COVID-19 cases or deaths with respect to the road distance of any given county i from Ischgl, Heinsberg, and Mulhouse respectively. In equation (2), these distance elasticities enable us to test our first hypothesis — namely, that COVID-19 cases decay as distance from an infection cluster increases. Therefore, as per our theoretical model, we expect the coefficients δ_0, δ_1 and δ_2 to be negative.

Equation (3) takes the number of COVID-19 deaths as the dependent variable and introduces log cases lagged by 18 days as an additional explanatory variable. We control for cases with a lag since mean time between onset of symptoms and death is estimated at 17.8 days (Verity et al., 2020). This allows us to test our second hypothesis — that distance to super-spreader locations should not matter for the number of deaths in a county, controlling for the number of infections in a county. Proximity to any of the hotspots may have affected the incidence rate, but should not determine the medical severity of cases and therefore the fatalities.

Our third and final hypothesis is that the distance of a county from these towns is more crucial for spreading infections in the initial phase of the epidemic — in the absence of restrictions on the movement of people. With time, COVID-19 expands its reach to more locations and the role of these initial clusters may become less relevant. A test of this hypothesis can be conducted by introducing time variation in the number of cases and deaths at the county-level. By repeatedly estimating equation (2) for each day within this period, we obtain a time series of coefficients for the distance variables. These time series can then be examined graphically in order to determine when and for how long distance to initial infection clusters mattered in the propagation of COVID-19.

Clearly, distance to Ischgl correlates with other potential determinants of infections. Hence, while we trivially have no issues with reverse causality, our exercise is potentially subject to substantial omitted variable bias. In our exercise, we have no other way to deal with this problem than to load the vector $\mathbf{Z_i}$ with a rich and well-design array of control variables. The most

Covid Economics 22, 26 May 2020L 177-204

important is geographical latitude, relative to the southernmost point of Germany. This rules out that the coefficient δ_0 simply captures proximity to Italy. The control also captures climatic variation, as well as other, e.g. cultural factors, that tend to have a north-south gradient and may influence infection rates. Moreover, we add further county-specific characteristics such as population and population density, GDP per capita, share of population that is older than 65 years, shares of Protestants and Catholics, share of foreigners, a work-from-home index that captures the prevalence of home office work, exposure to trade with China and the number of hospital beds in a county. All these controls may exhibit non-zero correlation with distance to Ischgl. For example, the share of Catholics is much higher in the South than in the North and Catholic festivities, e.g. Carnival, may propagate infections.

The $cases_i$ variable in equations (2) and (3) refer to diagnosed cases rather than to a full count of the infected population, or a random draw. There could be many more undetected cases in the German population than diagnosed ones. For instance, Li et al. (2020) find that in early stages of pandemics, six times more people were infected than official statistics revealed. To deal with this issue, we control for the number of tests per county. Interestingly, there is substantial variation across counties in the share of population tested.

Despite these efforts to contain omitted variable bias, we adopt a cautious reading of our results and refrain from interpreting them as causal. Nonetheless, our evidence on the spatial determinants of the COVID-19 spread in Germany reveals interesting correlations and strong indications of a link between the COVID-19 burden of a county and its distance from a super-spreader location.

Finally, in Appendix B we analyse the sensitivity of our results to the choice of distance measures by switching from road distance to travel time and great circle distances. Note that by simply subtracting the log of population from both sides of equation (2) and the log of lagged number of cases from both sides of equation (3), one can interpret the estimated coefficients as elasticities (or semi-elasticities) of case incidence rates (CIRs) or of case fatality rates (CFRs), respectively. Therefore, as an additional robustness check, we estimate models with CIR and CFR as dependent variables using OLS.

4.2 Data

We exploit publicly available data on COVID-19 cases provided by the Robert Koch Institute (RKI). The RKI database reports confirmed cases as well as fatalities from COVID-19, although it should be noted that these numbers may under-represent the actual spread of infections due to limitations in testing. A valuable feature of the RKI dataset for our purposes is its level of geographic disaggregation. Information is available not just at the country-wide or Bundesländer (state) level, but at the county-level in Germany. The data spans from March 10th to May 9th,

Covid Economics 22, 26 May 2020L 177-204

Table 1: Summary statistics

Variable	Mean	Std. dev.	Median	Max	Min
Number of confirmed cases, current	421.91	587.63	279.00	6258.00	13.00
Number of confirmed cases, 18 day lag	369.24	518.21	242.00	5365.00	13.00
Case incidence rate (CIR), in %	0.21	0.16	0.17	1.53	0.03
Number of deaths	18.44	25.25	10.00	204.00	0.00
Case fatality rate (CFR), in %	4.65	3.19	4.18	19.64	0.00
Population (in thousands)	201.23	231.06	149.07	3421.83	34.08
Number of tests (in thousands)*	257.18	175.50	208.19	497.28	25.03
Road distance to Ischgl (in km)	609.75	237.28	610.95	1134.26	138.69
Road distance to Heinsberg (in km)	428.40	184.31	433.05	805.37	0.27
Road distance to Mulhouse (in km)	521.01	211.44	507.22	1069.63	56.81
Population / Area	517.74	676.47	195.78	4531.17	36.47
Log of relative latitude	3.35	1.75	3.32	7.51	0.22
GDP per capita (in thousand Euros)	37.16	16.14	33.11	172.44	16.40
Share of foreigners	0.07	0.05	0.06	0.31	0.01
Share of 65+	0.21	0.02	0.21	0.29	0.15
Share of Catholics	0.32	0.24	0.29	0.88	0.02
Share of Protestants	0.30	0.17	0.26	0.72	0.04
Work-from-Home Index	0.53	0.04	0.52	0.67	0.46
Trade with China measure	6338.35	4079.31	5321.70	30228.97	470.53
Number of hospital beds	1255.41	1598.54	851.50	20390.00	42.00

Note: Epidemological data refer to May 9, 2020; other data to year of 2019 or latest available year. Case fatality rate calculated on the basis of reported cases 18 days earlier. *All variables are measured at the county level except the number of tests (at state level).

2020.[19] In this paper, we work with cumulative confirmed cases and COVID-19 related deaths as of May 9th, 2020.

We merge this database with information on the county-level from the Regionaldatenbank Deutschland. We include data on the local population,[20] which allows us to control for the demographic structure of each county, given the higher risk of hospitalisation and fatalities from COVID-19 amongst older populations. We also control for another population characteristic, namely religious affiliation, that may indicate whether Carnival gatherings — largely a Catholic festival — may have contributed to the spread.

To control for the levels of economic activity, we utilize GDP per capita at the county level for the latest available year, 2018. We further include a variable that describes the regional intensity of jobs that can be performed from home, the "work-from-home" index at the county level computed by Alipour, Falck, and Schüller (2020). Ability to work from home, and thus avoid public spaces and offices, may have played an important role in determining the local spread of the virus (Fadinger and Schymik, 2020). As another possible channel for the transmission of the

[19]The RKI data have been criticized for inaccurate timing of reported cases. For example, there are differences between weekends and weekdays. Since we do not exploit daily variation in cases, our estimations should be largely free from this problem. Besides these issues, German administrative data are generally perceived as being of high quality.

[20]As of December 31st, 2017.

Covid Economics 22, 26 May 2020L 177-204

CEPR PRESS
Covid Economics 22, 26 May 2020L 177-204

virus within Germany, we incorporate the exposure of counties to international trade with China, where the outbreak was first reported. The trade (export and import) exposure measures are taken from Dauth et al. (2017).[21]

The number of confirmed cases may also be dependent on the testing capacity and healthcare infrastructure of the county. However, there is no reliable data available as of the time of writing on the number of tests conducted daily in each county. Given this limitation, we use the number of tests performed in each of the 16 German Bundesländer. This information is provided by the RKI. For healthcare capacity, which may impact the prevalence of testing and the possibility of adequate treatment, we use the number of hospital beds in each county as an indicator. This is again drawn from Regionaldatenbank Deutschland database for the year 2018.

In order to examine the impact the three hotspots had on the spread of the virus, we exploit each of the county administrative centers' distance to the towns of Ischgl, Heinsberg and Mulhouse. We compute road distance and travel times based on the the shortest path in road networks with data from the OpenStreetMap project. In a robustness exercise we additionally use the great circle distance between the respective locations; see Table 4 in Appendix B.

5 Regression Results

In this section, we analyse regression results based on specifications described in equations (2) and (3) and assess the evolution of estimated coefficients such as distance elasticities over time.

5.1 COVID-19 Cases

Table 2 reports results for confirmed COVID-19 cases, where we introduce a richer set of controls with each successive regression. Starting with Column (1), we find that the coefficient on population is statistically identical to 1, implying that cases rise proportionately with population size.[22] Counties with bigger populations do not have higher case rates (infections per number of inhabitants). This finding is robust across all our specifications.

The coefficient for the number of tests is positive and statistically significant — i.e. counties located in states that conducted more tests have reported more confirmed cases. The estimated coefficient is large; it suggests that an increase in the number of tests by 1% correlates with an increase in the number of cases by 0.441%. This implies that increasing the number of tests by

[21]The measure is constructed from national sector-level import and export data and regional sector-level employment shares.

[22]For this reason, we can interpret the coefficients in our regressions as also measuring the effect on the log CIR of counties.

Covid Economics 22, 26 May 2020L 177-204

Table 2: Count of Confirmed Cases: Negative Binomial Regressions

	Dependent variable:				
	Number of confirmed cases				
	(1)	(2)	(3)	(4)	(5)
log(Population)	0.995***	1.078***	1.056***	1.075***	1.074***
	(0.048)	(0.053)	(0.054)	(0.053)	(0.053)
log(Number of tests)	0.441***	0.285***	0.254***	0.185***	0.183***
	(0.040)	(0.045)	(0.041)	(0.043)	(0.044)
log(Distance to Ischgl)		−0.682***	−0.923***	−0.887***	−0.877***
		(0.076)	(0.254)	(0.278)	(0.296)
log(Distance to Heinsberg)			−0.143***	−0.069	−0.081
			(0.048)	(0.093)	(0.092)
log(Distance to Mulhouse)			−0.109	−0.085	−0.088
			(0.082)	(0.106)	(0.112)
log(Latitude)			0.139	0.211	0.208
			(0.192)	(0.224)	(0.235)
log(Population / Area)				0.034	−0.004
				(0.046)	(0.047)
Share of Catholics				0.723**	0.747**
				(0.298)	(0.295)
Share of Protestants				0.165	0.183
				(0.261)	(0.253)
Share of 65+				−1.207	−0.752
				(2.344)	(2.227)
Share of Foreigners				−0.538	−0.783
				(1.126)	(1.151)
log(GDP p.c.)					0.062
					(0.122)
Work-from-Home Index					1.168
					(1.205)
log(China Trade)					−0.004
					(0.069)
Pseudo R2	0.66	0.72	0.74	0.75	0.76
Observations	401	401	401	401	401
θ	3.174***	3.892***	4.093***	4.353***	4.378***
	(0.217)	(0.270)	(0.285)	(0.304)	(0.306)

Note: Constant not reported. Robust standard errors: *p<0.1; **p<0.05; ***p<0.01.

Covid Economics 22, 26 May 2020L 177-204

10% reveals about 12 more cases of infected persons in the median county.[23] This emphasises the vital importance of testing in understanding the spread of infections and its role in the policy response. In all columns of Table 1 we also report the θ parameter which indicates the extent of over-dispersion in the data. If the θ parameter were to approach infinity, the negative binomial distribution would approach a Poisson distribution. However, the parameter is seen to be finite across specifications. Hence, our choice of negative binomial regressions over Poisson estimation is indeed valid. Not surprisingly, infection data exhibits over-dispersion.

In column (2), we introduce road distance to Ischgl as an additional explanatory variable. In doing so, we find that the pseudo-R^2 increases by 6 percentage points or 9%, indicating the relevance of this variable for the overall fit of the model. The resulting coefficient implies that a county whose road distance to Ischgl is by 1% lower than that of another county has a count of infections that is higher by 0.68%. However, Ischgl may not be the only cluster from where the virus may have spread through Germany. To examine this possibility, column (3) introduces the road distances to other clusters — Heinsberg and Mulhouse — as controls. By additionally controlling for the latitude of each county, we exploit precisely the variation in road distance and not the geographical location of a county on the North-South axis. As such, latitude has no measurable effect on the case load.[24] The coefficient on the distance to Ischgl remains statistically significant and increases to -0.923. Proximity to Ischgl also appears to be far more important than proximity to Heinsberg and Mulhouse. For the purpose of illustration, compare the city of Munich, that is about 190 km away from Ischgl, to Hamburg, 935 km away. Everything else equal, Hamburg should have 77% fewer COVID-19 cases than Munich.[25] The high elasticity implies a fast decay of infections as one moves away from Ischgl.

In column (4), we control for a wide range of county-level variables that could also predict infections. Notably, the distance elasticity for Heinsberg is no longer statistically significant whereas the distance elasticity to Ischgl is remarkably stable. Examining the demographic characteristics, factors such as population density, share of the elderly (65 years and older) and foreign residents in total population are not significant determinants of the spread. In contrast, a 1% point increase in the share of Catholics is associated with a 0.723% increase in cases — probably attesting to the role of carnival celebrations in February, which are typical for Catholic regions but not for Protestant ones, in propagating the virus. To illustrate the importance of this correlation: increasing the share of Catholics in the county with the smallest share (0.02, county of Weimar in Thuringia) to the share observed in the most Catholic county (share of 0.88, county

[23] $(1.1^{0.441} - 1) \times 279 = 11.98$; adding further covariates reduces the importance of tests by about half.

[24] If latitude is included in specification (1), its coefficient is observed to be negative (coefficient of -0.45) and highly statistically significant; if distance to Ischgl is added (without the distances to other super-spreader locations, the coefficient on latitude remains negative but turns statistically insignificant while distance to Ischgl appears significant (with a coefficient of -0.40).

[25] $100\% \times [(935/190)^{-0.923} - 1] = -77\%$. In fact, Hamburg has about 20% fewer infections, but 24% more population.

of Freyung-Grafenau in Bavaria) almost doubles the case count in a county.[26]

Our baseline specification additionally controls for economic factors and is reported in column (5). In comparison to the minimalist specification reported in column (2), controlling for demographic and economic factors increases rather than decreases the distance elasticity to Ischgl; adding additional socio-economic controls keeps it approximately constant. A 1% reduction in road distance to Ischgl corresponds to a 0.88% increase in the number of confirmed cases.[27]

Looking at the coefficient on a county's trade exposure to China, where the virus first appeared, we observe that the transmission of virus in Germany was not driven by the strength of economic ties to China. Our results therefore undermine possible claims that the participation of local firms in global production chains involving China may have led to the import of the virus and therefore propagated contagion. We also find that the 'Work-from-Home' (WFH) Index is not a significant factor in the diffusion process. This runs counter to the results reported by Fadinger and Schymik (2020) – possibly because we control for WFH at the more disaggregated county (NUTS-3) level as opposed to the NUTS-2 level. Rather, infections are seen to be dependent on population size and the proximity to local hotspots. All together, the models have relatively high values for pseudo-R^2, which offers a rough measure of the variation in infection rates that our models are able to explain.

For the sake of checking robustness, Table 5 in the Appendix reports regressions analogous to those in Table 2, but with the dependent variable being the case incidence rate and the estimation method being OLS. This regression design is more restrictive than our preferred one, but we generally find that our findings are confirmed. In our most comprehensive regression, Hamburg is predicted to have a CIR that is 0.23 percentage points lower than Munich's (in the data, Hamburg's CIR is 0.27% and Munich's 0.46%).

5.2 COVID-19 Fatalities

Having examined confirmed infection cases, in Table 3 we address the observed spatial heterogeneity in COVID-19 deaths across counties. All regressions contain the log of confirmed infections 18 days prior as a major predictor of the death count.[28] As in Table 2, regressions also include the log of the number of tests conducted in a county and the log of population.

[26] $[\exp(0.723 \times 0.86) - 1] \times 100\% = 86\%$. The case incidence rate is 0.10% in Weimar and 0.24% in Freyung-Grafenau.

[27] Table 4 column (2) in the Appendix uses travel time instead of road distance as a measure of distance; the pseudo -R^2 goes down slightly, but our main results remain intact. Importantly, when distance variables are constructed using great circle distances, distance to Ischgl is no longer statistically significant, but log latitude changes sign and becomes large in absolute value. This is not surprising, as latitude almost perfectly predicts geodesic distance to Ischgl (coefficient of correlation $\rho = 0.989$); latitude highly correlates to travel time, too, but the ρ is somewhat lower at 0.972. We view this as supportive of our identification strategy which relies on road distance conditional on latitude.

[28] As noted above, Verity et al., 2020 find that the average time between a confirmed infection and a death is approximately 18 days.

Covid Economics 22, 26 May 2020L 177-204

Covid Economics 22, 26 May 2020L 177-204

In all specifications, the coefficient on log lagged cases is observed to be statistically significant and greater than 1, implying that deaths are increasing more than proportionately to the number of reported cases in a county. An underlying issue of congestion in healthcare facilities may explain this relationship. Importantly this relation is not driven by population: across all specifications, we find that more populous counties tend to have lower number of fatalities, holding the case load constant. But note that the two variables are strongly correlated, as the previous section has shown. The number of tests has no measurable influence on death counts.

Without adding the controls introduced in column (1), distance to Ischgl has a large, negative effect on the dependent variable; however, this would be a meaningless result as it only reflects the geography of case counts. Once we control for confirmed cases, distances to the super-spreader locations cease to have a negative effect; if at all, there is a positive effect which is, however, only marginally statistically significant. This is reasonable since health outcomes are likely to depend more on the individual case or county's demographic and economic characteristics than on the distance to a ski resort in the Alps.[29] However, mortality rises sharply with the share of the elderly in county populations (see columns (4) and (5)), conforming with medical findings that case fatality ratios are higher for older age groups (Verity et al. (2020)). For the purpose of illustration, comparing the county with the smallest share of elderly (0.15, county of Vechta, Lower Saxony) to the county with the greatest (0.29, county of Dessau-Roßlau in Saxony-Anhalt), model (5) predicts more than a doubling of the death count.[30]

Variables such as the share of Catholics that had an important effect in Table 2, are no longer significant. This is comforting: the capacity of the health system does not depend on a county's predominant religious group. Also, the share of foreigners is not significant, albeit the coefficient of the variable is positive. In contrast, healthcare infrastructure, as proxied by the number of hospital beds, turns out as a statistically significant predictor of COVID-19 morbidity. A 10% increase in number of beds in a county lowers deaths by approximately 1.29%.[31] Access to quality medical care is imperative for minimising the loss of human life due to the pandemic. While this finding warrants further investigation, we would like to stress that the number of beds is predetermined in our specification, so we do not face the issue of reverse causality. Moreover, the effect is estimated conditional on a number of variables that explain both fatalities and the number of hospital beds, such as density (population per area, capturing the urban/rural divide) or GDP per capita. Also note that mobility from counties with few beds to others with more beds would attenuate the effect; hence, we are likely to identify a lower bound of the true effect.

For robustness, Table 6 in the Appendix reports regressions analogous to those in Table 3, but with CFR as the dependent variable and OLS as the estimation method. Results are broadly

[29]Note that, in the robustness checks (CFR model) presented in Table 6 distance to Ischgl is never statistically significant.

[30]$\exp[6.882 \times (0.29 - 0.15)] - 1$.

[31]$1.1^{-0.136} - 1$.

CEPR PRESS

Covid Economics 22, 26 May 2020L 177-204

Table 3: Count of Deaths: Negative Binomial Regressions

	Dependent variable:				
	Number of deaths				
	(1)	(2)	(3)	(4)	(5)
log(Lagged number of confirmed cases)	1.353***	1.445***	1.446***	1.485***	1.480***
	(0.054)	(0.061)	(0.061)	(0.063)	(0.063)
log(Population)	−0.411***	−0.528***	−0.528***	−0.512***	−0.409***
	(0.068)	(0.077)	(0.078)	(0.086)	(0.095)
log(Number of tests)	−0.039	0.020	0.020	0.060	0.039
	(0.041)	(0.046)	(0.045)	(0.049)	(0.049)
log(Distance to Ischgl)		0.514*	0.512*	0.404	0.549*
		(0.278)	(0.287)	(0.281)	(0.287)
log(Distance to Heinsberg)		0.105***	0.105***	0.086*	0.083*
		(0.041)	(0.041)	(0.045)	(0.046)
log(Distance to Mulhouse)		−0.071	−0.072	−0.129	−0.096
		(0.081)	(0.085)	(0.094)	(0.099)
log(Latitude)		−0.076	−0.075	0.042	−0.063
		(0.190)	(0.192)	(0.195)	(0.201)
log(GDP p.c.)			−0.006	0.083	0.168
			(0.136)	(0.169)	(0.164)
log(Population / Area)				−0.108**	−0.072
				(0.052)	(0.052)
Share Catholics				−0.020	0.014
				(0.237)	(0.238)
Share Protestants				0.042	0.052
				(0.294)	(0.298)
Share population 65+				6.882***	7.406***
				(1.610)	(1.618)
Share foreigners				2.296	2.175
				(1.702)	(1.732)
log(Number of hospital beds)					−0.136***
					(0.052)
Pseudo R2	0.78	0.78	0.78	0.8	0.8
Observations	401	401	401	401	396
θ	4.521***	4.879***	4.879***	5.294***	5.441***
	(0.482)	(0.538)	(0.538)	(0.594)	(0.616)

Note: Constant not reported. Robust standard errors: *p<0.1; **p<0.05; ***p<0.01.

robust. For example, increasing the number of beds by 10% in a county, lowers the case fatality rate by 0.074% points;[32] the median CFR being 4.18%.

5.3 Super-spreader Effects Over Time

So far, we have focused on examining a cross-section of the RKI database by running regressions on a snapshot of COVID-19's impact across counties as of May 9th, 2020. Now, we move towards analysing the time dimension as well. Our question here is: Did the role of super-spreader locations like Ischgl diminish over time? This is addressed clearly by Figure 2. It depicts the evolution of the 'daily distance elasticities' that are computed by repeatedly estimating our baseline specification for confirmed cases. To the extent that tourists returning from Ischgl explain an initial distribution of infections but subsequent mobility spreads the virus further, one would expect the measured elasticity to decline in absolute value. This corresponds to the proposition of our theoretical model. If the lockdown (phased in from March 9th to March 23rd) has been effective in restricting mobility, our model predicts that distance elasticity will remain highly negative as initial exposure continues to be important.

Strikingly, we observe distinct phases in the behaviour of the Ischgl elasticity that broadly corresponds with the timeline of Germany's lockdown. Over the initial period, this elasticity reduces in absolute value as individuals continue to be mobile. Once mobility is severely restricted with the imposition of a lockdown, it remains significantly different from zero, strongly negative and grows in absolute terms. Thus, distance from Ischgl is a relevant predictor of cases not just over varying specifications as pointed out in Table 2, but also over time.[33]

The same exercise is carried out for other control variables that were observed to be significant in Table 2 to construct Figure 3. It shows that the positive relationship between cases and testing capacity is consistent and statistically significant over time. In the case of population size, results are in alignment with the cross-sectional regression as elasticities remain close to 1. How well does the baseline model explain the variation in cases across counties? As shown in Figure 4, the pseudo-R^2 is high and improves substantially with time up to 0.80 on March 25th, and has only slightly fallen from there. Again, if the infection would have spread geographically after the containment measures, we would expect a sizeable decline in R^2 from our model; however, we do not observe this pattern.

We conclude that restrictions in mobility after March 23rd have helped contain the virus imported from Ischgl in those counties where it first arrived.

[32] $-0.778 \times \ln(1.1)$.

[33] The Mulhouse elasticity is never statistically significant whereas the Heinsberg elasticity becomes statistically insignificant by March 28th.

Covid Economics 22, 26 May 2020L 177-204

Covid Economics 22, 26 May 2020L 177-204

Figure 2: Distance coefficents

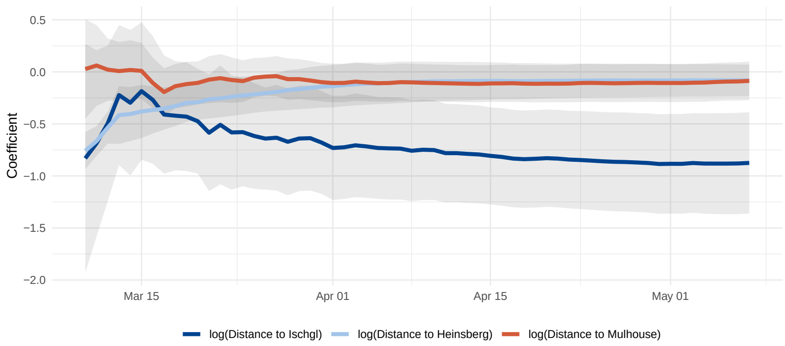


Figure 3: Control variable coefficients

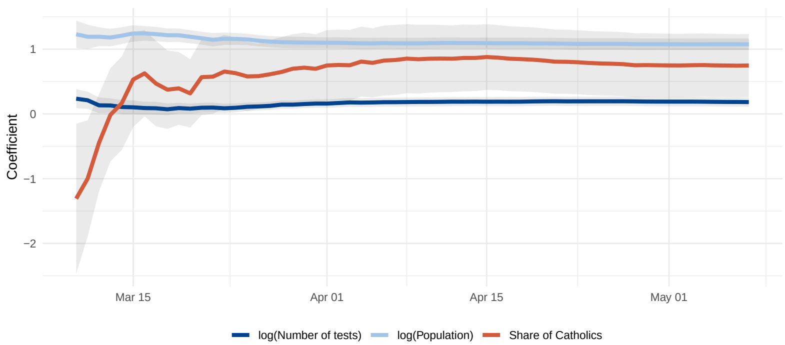
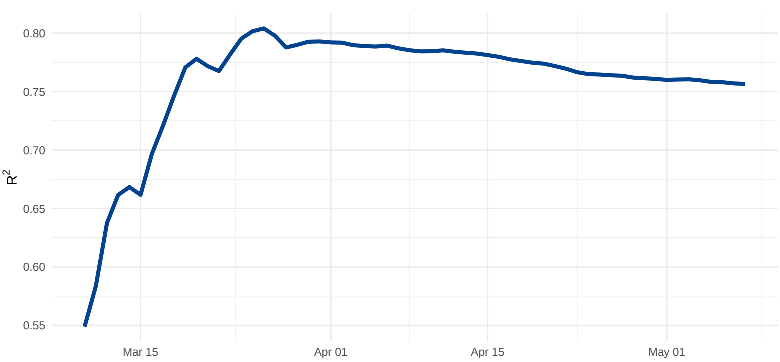


Figure 4: Pseudo-R^2 by date of data



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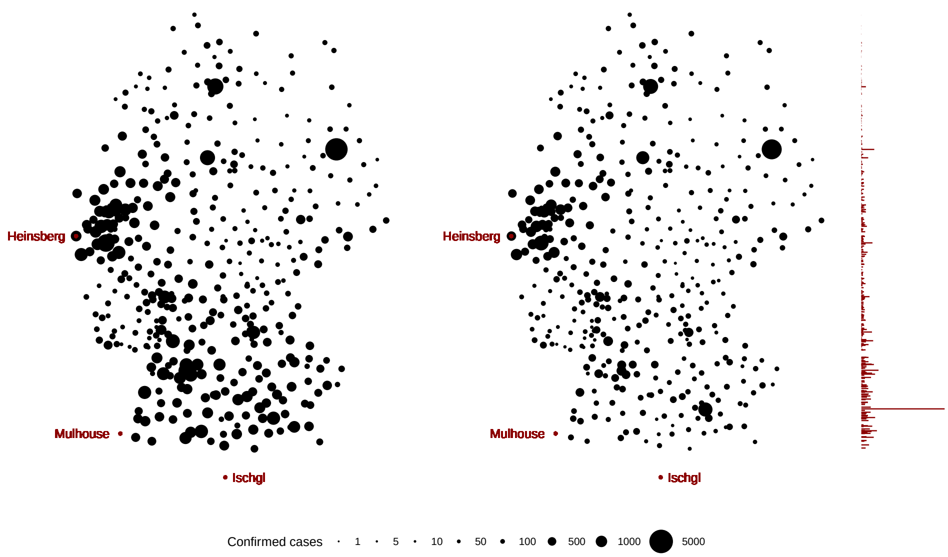
6 Counterfactual Scenario

The previous section described how the prevalence of infections in Germany is related to counties' geographic proximity to a super-spreader location such as Ischgl. To further gauge the impact of proximity to Ischgl on case counts, we now perform a simple back-of-the-envolope counterfactual exercise. We predict the number of confirmed cases were Ischgl located 1,134 km away from all counties, the distance at which the Kreis Vorpommern-Rügen, the northeastern-most county, is actually located from Ischgl. This assumes a situation in which no county is located close to the resort town, and hence simulates a situation in which fewer German tourists may have returned from their ski trip infected with the virus.

Figure 5: Predicted confirmed cases on May 9th vs. back-of-the-envelope counterfactual



Note: Map on the left-hand side shows predicted confirmed cases on May 9th, map on the right-hand side shows those predicted in counterfactual scenario for May 9th. The histogram to the very right shows the difference by latitude, binned by county.

Using the baseline negative binomial regression, we compare the predicted number of confirmed cases against the number of cases with the new, hypothetical location of Ischgl. The experiment leads to the total number of cases in Germany (as of May 9th) dropping from the predicted level of 172,135 to the counterfactual level of 89,261 i.e. a 48 % reduction. This back-of-the-envelope calculation validates our prior findings and offers a compelling demonstration of the spatial aspects of virus transmission. Figure 5 below presents maps for the predicted and counterfactual scenarios, with a histogram that captures the differences in number of cases by latitude. The south, in reality located relatively closely to Ischgl, would have seen far fewer cases.

7 Conclusion

This paper studies the geographical distribution of COVID-19 cases and fatalities across the 401 German counties. It tests the hypothesis that returning visitors from super-spreader locations like Ischgl, a popular ski resort in Tyrol, Austria, have played a major role in spreading the disease. Indeed, distance to Ischgl turns out to be an important predictor for case incidence rates, but not for case fatality rates. Were all German counties situated as far from Ischgl as the most distant county of Vorpommern-Rügen, Germany would have 48% fewer COVID-19 cases. Distance to Ischgl does not become irrelevant over time, suggesting that lockdown measures have avoided further diffusion of the virus across German counties. In contrast, distances to other hotspots are unimportant.

Catholic culture, likely capturing local Carnival festivities in late February, appears to increase the number of cases while other socio-demographic determinants such as trade exposure to China, the share of foreigners, the age structure, GDP per capita, or a work-from-home index do not add any explanatory power. Case fatality rates increase strongly in the share of population above 65 years and fall in the number of available hospital beds.

We view our results as first evidence towards confirming the role of super-spreader locations for the diffusion of a pandemic. Additionally, we find evidence for the efficacy of the lockdown measures put in place in reducing the spread of the virus. Further improvements of the analysis will be possible as more data become available, for example on testing strategies at the county-level.

Covid Economics 22, 26 May 2020L 177-204

Covid Economics 22, 26 May 2020L 177-204

A Proof of proposition

Consider

$$\begin{aligned} & \delta^0 < \delta 1 \\ \Leftrightarrow \quad & \frac{\partial I_i^0}{\partial D_i}\frac{D_i}{I_i^0} < \frac{\partial I_i^1}{\partial D_i}\frac{D_i}{I_i^1}. \end{aligned}$$

Cancelling D_i, and applying the chain rule yields

$$\frac{\partial I_i^0}{\partial D_i}\frac{1}{I_i^0} < \frac{\partial I_i^1}{\partial I_i^0}\frac{\partial I_i^0}{\partial D_i}\frac{1}{I_i^1}.$$

Dividing by $\frac{\partial I_i^0}{\partial D_i}$ flips the sign because it is negative, yielding

$$\frac{I_i^1}{I_i^0} > \frac{\partial I_i^1}{\partial I_i^0}. \tag{4}$$

We now turn to equation (1) that describes the number of new infections in county i in period 1:

$$I_i^1 = I_i^0 + (1-\iota_i^0)M_{ii}\iota_i^0 + 2\left(1-\iota_i^0\right)\sum_{j\neq i} M_{ji}\iota_j^0 \tag{5}$$

Dividing by I_i^0 gives us the left-hand side of condition (4)

$$\frac{I_i^1}{I_i^0} = 1 + (1-\iota_i^0)\frac{M_{ii}}{P_i} + 2\frac{1-\iota_i^0}{P_i}\sum_{j\neq i}\frac{M_{ij}}{P_i}\iota_j^0 \tag{6}$$

Taking the derivative of (5) with respect to I_i^0 yields

$$\frac{\partial I_i^1}{\partial I_i^0} = 1 + (1-\iota_i^0)\frac{M_{ii}}{P_i} - \frac{M_{ii}}{P_i}\iota_i^0 - 2\sum_{j\neq i}\frac{M_{ij}}{P_i}\iota_j^0 \tag{7}$$

Inserting equations (7) and (6) into condition (4) and rearranging yields

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$$1 + (1 - \iota_i^0)\frac{M_{ii}}{P_i} + 2\frac{1-\iota_i^0}{\iota_i^0}\sum_{j\neq i}\frac{M_{ij}}{P_i}\iota_j^0 > 1 + (1-\iota_i^0)\frac{M_{ii}}{P_i} - \frac{M_{ii}}{P_i}\iota_i^0 - 2\sum_{j\neq i}\frac{M_{ij}}{P_i}\iota_j^0$$

$$2\frac{1-\iota_i^0}{\iota_i^0}\sum_{j\neq i} M_{ij}\iota_j^0 > -M_{ii}\iota_i^0 - 2\sum_{j\neq i} M_{ij}\iota_j^0$$

$$2\frac{1}{I_i^0}\sum_{j\neq i} M_{ij}\iota_j^0 > -\frac{M_{ii}}{P_i}\iota_i^0$$

Since the left side is always positive, and the right side is always negative, this proves that $\delta^0 < \delta^1$.

■

B Robustness checks

In this appendix, we perform a number of robustness checks to determine whether distance elasticities are sensitive to variable definitions or model choice. In all prior regressions, we used continuous measures of distance. However, we can divide the measure into bins in order to test whether the relationship between case counts and distance from Ischgl is non-linear. We therefore alter our baseline specification by introducing a series of dummies for the various deciles of road distance to Ischgl. The estimated coefficients then capture cases relative to the first decile i.e. relative to counties that are nearest to Ischgl. Figure 6 below plots this sequence of coefficients and reveals a close to linear relationship. To explain with an example, counties belonging to the 10th decile that are farthest away from Ischgl have approximately 0.5% fewer cases in comparison to the reference group of counties closest to Ischgl.

Table 4 below compares our baseline negative binomial specification for confirmed cases in column (1) with regressions that employ alternative measures of distance. We find that Ischgl dominates over Heinsberg and Mulhouse as a super-spreader location even when switching from road distance to travel time. The results for other controls closely follow the pattern observed in Table 2. While the elasticities on population size, testing and share of Catholics are highly significant and comparable across specifications, the coefficients on other demographic and economic factors remain largely insignificant. There in no marked improvement in the model's Pseudo R^2 either when estimating with alternative definitions of distance. Switching to a great circle distance, which should not matter for the spread of the disease, yields a much smaller and statistically insignificant elasticity. Note that now relative latitude to Ischgl has a negative, albeit statistically insignificant coefficient, as it is highly collinear to the great circle distance. All other coefficients remain largely unchanged.

Covid Economics 22, 26 May 2020L 177-204

CEPR PRESS

Table 4: Robustness check: Distance measure

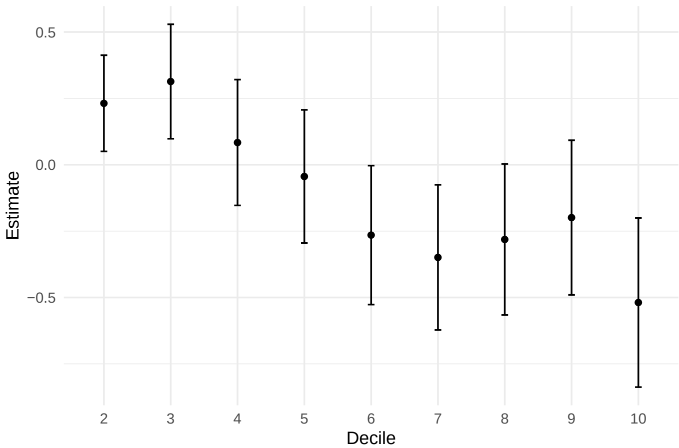
	Dependent variable:		
	Number of confirmed cases		
	(1)	(2)	(3)
log(Population)	1.074***	1.076***	1.050***
	(0.053)	(0.055)	(0.054)
log(Number of tests)	0.183***	0.189***	0.204***
	(0.044)	(0.045)	(0.045)
log(Distance to Ischgl)	−0.877***	−0.815***	−0.150
	(0.296)	(0.250)	(0.208)
log(Distance to Heinsberg)	−0.081	−0.043	−0.037
	(0.092)	(0.155)	(0.109)
log(Distance to Mulhouse)	−0.088	−0.092	0.001
	(0.112)	(0.128)	(0.108)
log(Latitude)	0.208	0.081	−0.239
	(0.235)	(0.179)	(0.194)
log(Population / Area)	−0.004	0.0001	−0.003
	(0.047)	(0.048)	(0.049)
Share of Catholics	0.747**	0.825**	0.767**
	(0.295)	(0.336)	(0.323)
Share of Protestants	0.183	0.164	0.207
	(0.253)	(0.263)	(0.263)
Share of 65+	−0.752	−0.570	−1.161
	(2.227)	(2.253)	(2.313)
Share of Foreigners	−0.783	−0.652	−0.770
	(1.151)	(1.192)	(1.196)
log(GDP p.c.)	0.062	0.043	0.061
	(0.122)	(0.122)	(0.121)
Work-from-Home Index	1.168	1.015	1.351
	(1.205)	(1.205)	(1.246)
log(China Trade)	−0.004	0.005	0.039
	(0.069)	(0.069)	(0.068)
Distance measure	Road	Travel time	Great circle
Pseudo R2	0.76	0.75	0.75
Observations	401	401	401
θ	4.378***	4.322***	4.237***
	(0.306)	(0.302)	(0.296)

Note: Constant not reported. Robust standard errors: *p<0.1; **p<0.05; ***p<0.01

Covid Economics 22, 26 May 2020L 177-204

CEPR PRESS

Figure 6: Robustness check: Distance coefficient by decile



The following robustness checks relate to the choice of the dependent variable and the estimation strategy. In Table 5, we move towards analysing CIR as opposed to the number of cases. With CIR as our outcome variable, we are now no longer in a count-model and can estimate regressions with simple OLS. Consistent with prior findings, we observe that distance to Ischgl is a significant predictor for infections. In a similar vein, we move from count models for fatalities in Table 3 to estimating OLS regressions for CFR in Table 6. This change does not undermine our main results. While testing capacity and share of the elderly influence CFR, distances of counties from super-spreader locales do not.

Covid Economics 22, 26 May 2020L 177-204

Covid Economics 22, 26 May 2020L 177-204

Table 5: Case Incidence Rate, OLS Regressions

	Dependent variable:				
	Number of confirmed cases / Population x 100.000				
	(1)	(2)	(3)	(4)	(5)
Number of tests	0.090***	0.056***	0.050***	0.043***	0.042***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
log(Distance to Ischgl)		−0.134***	−0.158**	−0.148**	−0.146*
		(0.018)	(0.073)	(0.075)	(0.081)
log(Distance to Heinsberg)			−0.025	−0.013	−0.016
			(0.021)	(0.030)	(0.030)
log(Distance to Mulhouse)			0.015	0.010	0.010
			(0.029)	(0.034)	(0.036)
log(Latitude)			−0.003	0.021	0.019
			(0.058)	(0.069)	(0.074)
log(Population / Area)				−0.011	−0.019*
				(0.009)	(0.011)
Share of Catholics				0.103	0.111
				(0.076)	(0.078)
Share of Protestants				−0.024	−0.018
				(0.045)	(0.044)
Share of 65+				−0.174	−0.074
				(0.465)	(0.489)
Share of Foreigners				0.164	0.100
				(0.219)	(0.234)
log(GDP p.c.)					0.012
					(0.029)
Work-from-Home Index					0.273
					(0.245)
log(China Trade)					−0.001
					(0.016)
Observations	401	401	401	401	401
R^2	0.247	0.354	0.361	0.382	0.385

Note: Constant not reported. Robust standard errors: *p<0.1; **p<0.05; ***p<0.01.

CEPR PRESS

Covid Economics 22, 26 May 2020L 177-204

Table 6: Case Fatality Rate, OLS Regressions

	Dependent variable:				
	Number of deaths / Confirmed cases 18 days ago				
	(1)	(2)	(3)	(4)	(5)
Log(Lagged Number of confirmed cases)	1.355***	1.825***	1.825***	2.120***	2.089***
	(0.319)	(0.371)	(0.368)	(0.366)	(0.361)
log(Population)	−1.737***	−2.295***	−2.295***	−2.378***	−1.807***
	(0.383)	(0.442)	(0.445)	(0.479)	(0.522)
log(Number of tests)	−0.028	0.176	0.176	0.403	0.274
	(0.223)	(0.244)	(0.245)	(0.279)	(0.279)
log(Distance to Ischgl)		1.572	1.572	1.056	1.777
		(1.515)	(1.561)	(1.562)	(1.612)
log(Distance to Heinsberg)		0.533**	0.533**	0.435*	0.377
		(0.216)	(0.216)	(0.241)	(0.249)
log(Distance to Mulhouse)		−0.281	−0.281	−0.660	−0.517
		(0.452)	(0.473)	(0.571)	(0.592)
log(Latitude)		0.114	0.114	0.827	0.279
		(1.019)	(1.037)	(1.108)	(1.141)
log(GDP p.c.)			0.0004	0.437	1.034
			(0.738)	(0.958)	(1.033)
log(Population / Area)				−0.574**	−0.389
				(0.279)	(0.264)
Share catholics				−0.607	−0.619
				(1.201)	(1.221)
Share protestants				−0.481	−0.531
				(1.491)	(1.514)
Share population 65+				38.036***	40.848***
				(9.454)	(9.650)
Share foreigners				14.963	13.939
				(9.478)	(9.580)
log(Number of hospital beds)					−0.778**
					(0.314)
Observations	401	401	401	401	396
R^2	0.097	0.119	0.119	0.175	0.183

Note: Constant not reported. Robust standard errors: *p<0.1; **p<0.05; ***p<0.01.

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Covid Economics Issue 22, 26 May 2020

A first look at the impact of COVID-19 on commercial real estate prices: Asset-level evidence[1]

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This paper examines the impact of the COVID-19 pandemic on commercial real estate prices. We construct a novel measure of listed commercial real estate (CRE) portfolios' exposure to the growth in COVID-19 cases using a large, granular sample of firms' individual commercial property holdings. We document a negative relationship between this geographically weighted case growth and risk-adjusted returns. However, there is substantial variation across property types: the retail and hospitality sectors react the most negatively while technology sector reacts positively to the exposure of their portfolios to growth in COVID-19 cases. After conditioning on the property type focus of a firm, days since the beginning of the portfolio's exposure to the outbreak, the weighted-average population density of the counties in which the portfolio manager is invested, and the extent to which the portfolio is concentrated by property type and geography, other firm characteristics have little effect on the negative stock price impact of the pandemic. Despite negative short-term market reactions, our findings suggest that the sensitivity of CRE returns to increases in reported COVID-19 cases is reduced after announcements of stay-at-

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Covid Economics 22, 26 May 2020: 205-260

COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

home orders and state of emergency declarations. We argue that the effects of COVID-19 that we observe in highly liquid stock markets are indicative of pricing effects occurring in private CRE markets.

Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

1. Introduction

The COVID-19 pandemic is having a devastating impact on economic activity. This has produced a rapidly growing literature that examines its economic consequences, some of which focuses on how stock returns have responded to changes in investors' information and expectations (e.g., Alfaro, Chari, Greenland, and Schott, 2020; Gormsen and Koijen, 2020; Ramelli and Wagner, 2020). Most of these studies provide evidence at the *index*-level or *firm*-level. However, movements in a firm's stock price are largely driven by the perceived current and future productivity of the firm's *underlying assets*; therefore, it is important to understand how the COVID-19 shock transmits to the equity markets from a firm's asset base. The goal of this paper is to help fill this gap in the literature.

We focus on the commercial real estate (CRE) assets owned by listed U.S. equity real estate investment trusts (REITs). This setting is advantageous to the study of the impact of COVID-19 at the level of the firm's assets for several reasons. First, the prices of liquid stocks quickly capitalize information about investors' short-run and long-run expectations of the future cash flows likely to be generated by the underlying asset portfolio, as well as the riskiness of those future cash flows. In addition, REITs are subject to a set of restrictive conditions that ensure that equity REITs invest primarily in income-producing real estate and distribute a large percentage of their cash flow in the form of dividends.[1] Also, listed REITs, with a total stock market capitalization of approximately $2 trillion, typically acquire and dispose of CRE in an illiquid, highly segmented, parallel private market, in which valuations of comparable properties are frequently observed. Thus, the CRE assets owned by REITs are relatively easier to locate and value than the tangible (e.g., plant and equipment) and intangible assets (e.g., intellectual property) owned by many conventional firms. Although the illiquidity and opaqueness of private CRE markets limit our ability to detect rent and (especially) price movements in "real time," we argue that the effects of COVID-19 that we observe in highly liquid stock markets are indicative of the effects occurring in the $12 to $14 trillion private CRE market (e.g., Barkham and Geltner, 1995).[2]

[1] A "qualified" REIT may deduct dividends paid from corporate taxable income if they satisfy a set of restrictive conditions on an ongoing basis. Fully 75% of the value of the REIT's assets must consist of real estate assets, cash and government securities. Moreover, at least 75% of the REIT's gross income must be derived from real estate assets. REITs must pay out 90% of annual taxable income in dividends.

[2] The estimated market value of the investible CRE market in the U.S. are from the National Association of Real Estate Investment Trusts (www.nareit.com).

The COVID-19 crisis is undeniably causing pain for many CRE owners. Real-estate advisers, property managers, and lawyers are fielding inquiries from tenants, landlords, and lenders about strategies for rent and mortgage relief given the closures of nonessential stores and the resulting economic downturn. Various large retailers have stopped paying rent or warned they plan to withhold payments to conserve cash. As of April 17, 2020, approximately 50% of retail tenants had paid their April rent, compared with the 85% who had paid their March rent, according to data from real-estate business-intelligence company Datex Property Solutions (Al-Muslim, 2020). Many nonpaying tenants argue they are excused from making rent payments under their leases because the pandemic is a force majeure—an event outside their control--that prevents them from fulfilling the terms of their lease contracts. The degree of pain forthcoming in some property sectors, both in the short-run and the long-run, in the form of rent deferral, rent relief, tenant bankruptcies, and financial distress is likely to be unprecedented (Green Street Advisors, 2020). In mid-May, the U.S. Federal Reserve issued a grim warning that asset prices remain vulnerable to significant price declines; in particular, CRE prices. According to the Fed, "The vulnerability stemming from elevated CRE valuation pressures, coupled with a dim outlook for the sector as indicated by recent declines in equity REIT prices, suggests that CRE may undergo a substantial repricing in response to disruptions generated by the COVID-19 pandemic."[3]

Initial comparisons using index-level returns for the S&P 500, Russell 2000, and the FTSE-NAREIT All Equity REITs Index, as well as the FTSE-NAREIT property type sub-indices (office, industrial, retail, residential, health care, and lodging/resort) reveal that the total return index of the S&P 500 declined 16% in March of 2020; the corresponding decline on the FTSE-NAREIT equity REIT index was 23%.[4] This decline in REIT share prices far exceeds the decline that can be explained by a temporary loss in rental income.[5] We also find increasing return co-movement between the broader stock market and the FTSE-NAREIT equity REIT index during the early stages of the pandemic. In addition, returns varied substantially by the property-type focus of the REIT. However, even property type indices

[3] See the Fed's bi-annual Financial Stability Report: www.federalreserve.gov/publications/files/financial-stabilitiy-report-20200515.pdf. May 15, 2020.
[4] The Russell 2000 index is a market-capitalization weighted index measuring the performance of approximately 2,000 small-cap U.S companies. The FTSE Nareit All Equity REITs Index is a free-float adjusted, market capitalization-weighted index of U.S. equity REITs. Constituents of the index include all tax-qualified REITs with more than 50 percent of total assets in qualifying real estate assets other than mortgages secured by real property.
[5] Green Street Advisors estimates that a typical property that experiences a loss of all of its operating income in the next year would decline in market value by just 5 to 6% (Green Street Advisors, 2020)

mask significant variation across REITs in the exposure of their CRE portfolios to the COVID-19 pandemic. This motivates our firm and asset level study.

To examine how the growth rates of COVID-19 cases affect firms differently through their asset holdings, we construct a novel measure of geographically weighted COVID-19 growth (*GeoCOVID*) that varies daily during our sample periods. This variable is the weighted average of the daily growth rates of COVID-19 cases in counties in which the commercial property manager owns properties. The weights are the percentages of a CRE portfolio (based on book value) allocated to each county prior to the pandemic outbreak at the end of 2019Q4. Given that the testing capacity and, perhaps, the accuracy of COVID-19 tests varies considerably across locations over our sample period, our measure of geographically weighted COVID-19 case growth is likely measured with error. However, these growth rates were reported daily and widely discussed during the early stages of the pandemic and therefore are reasonable proxies for the information investors had available on a day-to-day basis about the spread of the pandemic.

To evaluate firm-level stock performance across property types, we calculate returns over 1-day, 2-day, and 3-day windows using a sample of 11,210 firm-day observations for 198 equity REITs from January 21 through April 15, 2020. These returns are risk-adjusted based on the S&P 500 Index and the FTSE-NAREIT All Equity REITs Index. In our univariate analyses, we find that REITs that focus their investments on data center, cell tower, self-storage, and warehouse properties produced positive risk-adjusted returns during the early stages of the pandemic. The worst performers were hospitality and retail REITs due to canceled travel, imposed closures, and shelter-in-place orders in most cities and states.

In our multivariate analysis, we regress 1-day, 2-day, and 3-day risk-adjusted returns on each CRE portfolio's *GeoCOVID* on day t-1. The first reported case in the U.S. occurred on January 21, 2020. However, to account for the fact that COVID-19 exposure begins at different times for different firms depending on the locations of their properties, we include the number of days since the first reported COVID-19 case in any county in which the commercial property manager owns properties. We also construct a geographically weighted population density variable based on each property held by a REIT. Two additional asset-specific controls are included in the pooled, cross-sectional regressions: the extent to which the CRE portfolio is concentrated by (county) location or by property type. Lastly, we include a large set of firm characteristics as controls.

Covid Economics 22, 26 May 2020: 205-260

Our baseline results suggest that a one-standard-deviation increase in *GeoCOVID* is associated with a 0.24 percentage points decrease in risk-adjusted returns on the next day. In terms of economic magnitude, this return reduction is equivalent to 40% of the sample mean (-0.6 percentage points) of risk-adjusted returns. Comparing across different property types, we find that the negative effect of a one-standard-deviation increase in *GeoCOVID* is equivalent to a reduction in returns that is equal to 64% and 138% of the sample mean return for the retail and residential sectors, respectively. In contrast, in the health care and technology sectors, a one-standard-deviation increase in *GeoCOVID* is associated with a 1-day return *increase* of 0.4 percentage points. This variation across property types is striking.

Next, we further investigate the importance of asset allocation. Our findings suggest that the strong negative association between our geographically weighted measure of the growth in COVID-10 cases and risk-adjusted returns is not simply driven by the national trend in reported cases. In addition, the risk-adjusted returns of firms with more assets allocated to population-dense areas are significantly more sensitive to *GeoCOVID*.

We also investigate the impact of various firm characteristics on the sensitivity of returns to *GeoCOVID*, including leverage, cash holdings, Tobin's Q, return momentum, institutional ownership, investment, and EBITDA. After conditioning on firms' property type and geographic concentrations, the number of days since the outbreak of the pandemic, and population density, only a firm's stock returns in the fourth quarter of 2019 are associated with stock market reaction to *GeoCOVID*.

How do investors react to announcements of important (expected) non-pharmaceutical interventions (NPIs), such as shelter-in-place orders (SIPOs), or school and business closures? Investors likely expected such policies to slow the spread of the virus, a long-term benefit, but at the expense of reduced economic activity, at least in the short run. Did expectations about the offsetting effects of these policies in slowing the spread of the virus and their impact on economic activity affect the abnormal returns of firms? We again use our property holdings data to determine for each CRE portfolio the announcement dates of state of emergency (SOE) declarations, shelter-in-place orders, and other interventions expected to damage economic activity.

Consistent with our earlier results, investors' responses to expected NPIs vary dramatically across the property sectors. For example, the returns of CRE portfolios focused on data centers, self-storage and industrial properties are less negatively affected by the announcements. Other firm characteristics do not explain cross-sectional variation in

Covid Economics 22, 26 May 2020: 205-260

announcement effects. We also find that 1-day risk-adjusted returns respond less negatively to *GeoCOVID* after SOE announcements, suggesting investors anticipated that the positive effect these policies would have on reducing the spread of the virus would mitigate their economic costs. These event study results are robust to different announcement types (e.g., SOE declaration, SIPOs), to the selection of event dates based on different locational characteristics of the CRE portfolio (e.g., announcements in the top-3 states in which a firm holds properties, announcements in the firm's headquarters state), as well as to different event windows.

Our analysis of the effects of the COVID-19 pandemic on trading activity reveals a positive relation between *GeoCOVID* and trading volume and share turnover. However, due to sharp stock price declines and high price volatility, increases in *GeoCOVID* are also associated with an increase in illiquidity as measured by Amihud (2002).

Lastly, we conduct robustness tests using just the hump-shaped period of rapid-and-then-decelerating growth in COVID-19 cases from February 27 to April 13, 2020, as well as an extended sample period that runs through April 30, 2020. Our results are not sensitive to the use of these alternative sample periods.

Taken together, our findings highlight the importance of the asset-level attributes of a firm's portfolio to stock price reactions to the pandemic. Specifically, the key drivers are the property type (business) focus of the CRE tenants, the geographic allocation of assets (proxied by *GeoCOVID* and *GeoDensity*), and the interaction between these two attributes.

Most of the existing studies on the COVID-19 shock focus either on the index-level or firm-level. Using index-level return data, Alfaro et al. (2020) find that large increases in predicted infection rates are associated with larger negative stock returns. Gormsen and Koijen (2020) examine the behavior of stock and bond indices to explore how different shocks are reflected in asset prices. Sinagl (2020) provides evidence that industries with higher cash-flow risk had lower excess returns, higher systematic risk, and lower risk-adjusted returns in the first quarter of 2020.

A number of studies have also examined the effects of COVID-19 at the firm level. Ramelli and Wagner (2020) focus on the exposure of firms' international supply chains to China. They find that the stock returns of companies with more China exposure have reacted more negatively. They also find that corporate debt and cash holdings are important determinants of stock price responses to COVID-19. Ding, Levine, Lin, and Xie (2020) provide global evidence on the relationship between various firm characteristics and stock price

Covid Economics 22, 26 May 2020: 205-260

reactions to COVID-19 confirmed cases. They conclude that stock prices react less negatively when firms are financially strong, have less exposure to global supply chains and consumers, and have better corporate social responsibility and corporate governance.

Hassan, van Lent, Hollander, and Tahoun (2020) develop measures of a firm's COVID-19 exposure from earnings-call transcripts for a global sample of more than 11,000 firms across 84 countries. They find that firms' primary concerns are a decline in product demand, increased uncertainty, and disruption in supply chains. Gerding, Martin, and Nagler (2020) examine firm-level stock returns across 100 countries and find that stocks reacted more negatively to the COVID-19 outbreak in countries with higher debt-to-GDP ratios, suggesting the importance of governments' perceived fiscal capacity to help mitigate the pandemic's effects.

We believe ours is the first paper to examine how the COVID-19 pandemic has affected stock returns through a firm's underlying assets. Given the extraordinary nature of this pandemic, researchers have found that existing models may no longer be adequate (Barro et al., 2020; Alfaro et al., 2020) and are therefore exploring new measures to better capture firm-level exposures to epidemic diseases (e.g., Hassan et al., 2020). By constructing a geographically weighted COVID-19 growth variable at the asset-level, our paper contributes to the rapidly growing literature that investigates the effect of the COVID-19 pandemic on financial markets.

To the best of our knowledge, we are the first to examine the outbreak of COVID-19 in real estate market.[6] Economic history literature might shed some light on the impact of the COVID-19 pandemic on real estate markets. Ambrus et al. (2020) study a cholera epidemic in one neighborhood of nineteenth-century London. They find that geographically concentrated income shocks have a long-run negative impact on rents and housing prices over the following 160 years. Francke and Korevaar (2020) study the plague in Amsterdam and cholera in Paris between the late 16th century and 1811. They document large reductions in rents and house prices within the affected areas during the first six months of an epidemic; however, these shocks were transitory. More recently, Wong (2008) examines how SARS affected the property market in Hong Kong and found a small average house price decline of

[6] Milcheva (2020) examines REIT returns across a few Asian countries and the U.S. during the COVID-19 pandemic and finds that the global COVID-19 shock propagates to real estate markets through financial channels. Van Dijk, Thompson and Geltner (2020) document substantial drops in transaction volumes in the private real estate markets.

Covid Economics 22, 26 May 2020: 205-260

CEPR PRESS

Covid Economics 22, 26 May 2020: 205-260

-1.5%. More broadly, our study is related to the large literature on the economic effects of pandemics, disease, and health shocks (e.g., Bleakley, 2007; Weil, 2007; Nunn and Qian, 2010; Correia et al., 2020; Ambrus et al., 2020; Francke and Korevaar, 2020). Outside of the pandemic literature, our study contributes to the growing literature of the geography of assets and the extent to which "local" information about the productivity of a firm's assets is capitalized into stock prices (e.g., Parsons, Sabbatucci, and Titman, 2020; Garcia and Norli, 2012; Bernile et al., 2015; Dougal et al., 2015; Jannati et al., 2019; Smajlbegovic, 2019; Ling, Wang, and Zhou, 2019, 2020a, 2020b; Wang and Zhou, 2020).

The remainder of the paper proceeds as follows. In section 2, we examine the impact of COVID-19 on stock returns using index-level return data. Section 3 contains a description of our firm-level data set, while summary statistics and our regression results are presented and discussed in section 4. Section 5 provides a brief summary and a discussion of the potential long run effects of the pandemic.

2. Index-Level Stock Market Performance During the Pandemic

Figure 1 plots daily indices for the S&P 500, Russell 2000, and the FTSE-NAREIT All Equity REITs Index from 2015 through April 23, 2020.[7] Each index is set equal to 100 at year-end 2014. Starting from the end of February 2020, the U.S. stock market reaction to the COVID-19 pandemic has been dramatic. Overall, the total return index on the S&P 500, equity REITs, and the Russell 2000 declined 16%, 23%, and 26%, respectively, during March. Before February 2020, the correlation of the FTSE-NAREIT index and the S&P 500 is just 0.581. However, the daily return correlation among these three indices was at least 0.94 during March.

Figure 2 plots daily returns for office, industrial, retail, residential, health care, and lodging/resort REITs from 2015 through April 23, 2020.[8] Even prior to the onset of the pandemic, returns varied substantially by the property type focus of the REIT. For example, from year-end 2014 through February 28, 2020, the corresponding returns on industrial,

[7] Equity REITs own income-producing real estate and obtain most of their revenues from rents. Mortgage REITs invest in mortgages or mortgage-backed securities. According to the FTSE-NAREIT Index, equity REITs had a total equity market capitalization of $1.2 trillion as of February 29, 2020.

[8] As of February 29, 2020, the FTSE-NAREIT All Equity REITs Index contained 18 office, 13 industrial, 33 retail, 21 residential, 17 health care, and 15 lodging/resort REITs. See *REIT Watch*, March 2020 (www.nareit.com). Retail REITs include firms that invest in shopping centers, regional malls, and free-standing properties. Residential REITs include listed companies that invest in apartments, manufactured housing, and single-family (rental) homes.

Covid Economics 22, 26 May 2020: 205-260

retail, residential, health care, and lodging/resort equity REITs were 22.3%, -1.6%, 14.8%, 5.9%, and 7.0%, respectively. This variation in returns across property types highlights a significant limitation associated with the use of industry-level return data for the entire sample of REITs.

Figure 1: Total Return Indices: S&P 500, Russell 2000, FTSE-NAREIT

This figure depicts daily indices for the S&P 500, Russell 2000, and the FTSE-NAREIT All Equity REITs (FNER) Index from 2015 through April 23, 2020. Each index is set equal to 100 at year-end 2014.

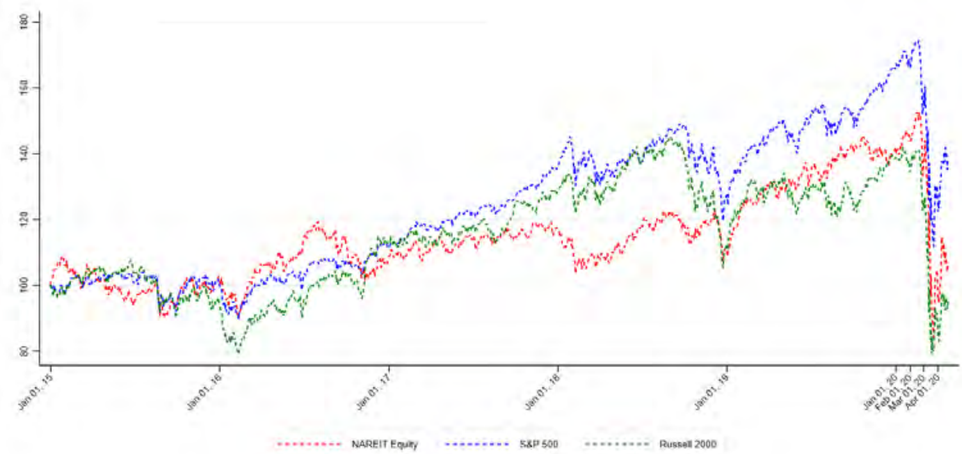


Figure 2: Total Return Indices: REIT Property Types

This figure depicts daily indices for the FTSE-NAREIT All Equity REITs indices for office, industrial, retail, residential, health care, and lodging/resort REITs from 2015 through April 23, 2020.

During March of 2020, the cumulative total return index for retail REITs declined by a staggering 49%. This March decline was closely followed by lodging/resort REITs (-44%) and health care REITs (-41%); again, with significant day-to-day variation. The lockdown on "non-essential" retail in most parts of the country has been, and continues to be, destructive. According to Green Street Advisors, about 50 percent of the 1,000 department stores in U.S. malls are vulnerable to permanent closure by the end of 2021. If struggling department store anchors go out of business as a result of the COVID-19 pandemic, other troubled tenants at those shopping centers likely will activate lease clauses to shutter their stores (Boswell 2020). Travel restrictions and social distancing guidelines have resulted in the travel and tourism industry coming to a standstill. Although healthcare real estate is not immune to the impact of coronavirus, the various types of health care real estate—including hospitals, medical offices, and senior housing—have all been affected and are faring differently (Bass 2020).[9]

The total return indices for office and residential REITs also declined sharply in March 2020: 25% and 26%, respectively. Although the longer-term nature of office leases may be providing some protection for office property owners, evidence is appearing that corporations of all sizes plan to use less real estate after the pandemic subsides.[10] The results for residential REITs are surprising because the share price declines have been larger than what can be explained by their market betas or by expected short-term reductions in rental income. However, the extent to which the payment situation will worsen as more Americans lose their jobs is creating significant uncertainty. Moreover, tenant groups and nonprofits in multiple cities are pushing for rent control and are encouraging rent strikes designed to persuade the government to halt rent and mortgage payments (Lang, 2020).

Of the six major types included in Figure 2, the best performing during this bear period was industrial (primarily warehouses), which suffered a decline in its total return index of just 10% and recovered a modest 3% during April of 2020 (through April 23). Short-term and long-term growth in e-commerce spurred by coronavirus-stimulated changes in

[9] For example, Health care Realty Trust, a health care REIT that specializes in medical offices, experienced a small average daily (3-day) risk-adjusted returns of -0.2% (-0.4%) during our sample period. On the other hand, one of its worst-performing peers, Capital Senior Living Corporation, was down by more than 1.7% per day (or -5.2% over three days), on average.

[10] Sixty-nine percent of corporate real estate professionals said their company will take up less real estate after observing the feasibility of employees working from home according to a CoreNet Global survey conducted between April 22 and April 27, 2020. A survey from the research firm Gartner released April 3 revealed that 74% of the 314 chief financial officers they surveyed said they planned to downsize the number of people that came into the office each day.

shopping behavior should further benefit industrial REITs. Although not displayed in Figure 2, infrastructure REITs and data center REITs were the best performing property types from March 1 to April 23. The total return index for infrastructure REITs and data center REITs *increased* 5% and 15%, respectively. As a result of widespread stay-at-home orders, e-commerce activity amid the clampdown on brick-and-mortar shopping and increased telecommuting and distance learning triggered more data traffic. Millions of Americans have also increasingly relied on their cellphones to stay connected during the coronavirus pandemic (Egan 2020).

Although the use of property type indices is a substantial improvement over the use of an aggregate, industry-level index, these property type indices still mask significant variation across firms in the exposure of their CRE portfolios to the COVID-19 pandemic. Because the number of reported COVID-19 cases varies substantially by regions, we next describe the dataset that allows us to measure the exposure of a firm's real estate portfolio to the growth in reported COVID-19 cases.

3. Data

To measure time-varying, firm-level exposure to the growth in confirmed COVID-19 cases in each county, we collect the following data from the S&P Global Real Estate Properties (formerly SNL Real Estate) database for each property held by a listed equity REIT at the end of 2019Q4: property owner (institution name), property type, geographic (county) location, book value, initial cost and historic cost. This produces a REIT-property-level data set containing 73,406 property observations for 201 unique equity REITs. We first calculate, for each REIT i, the percentage of its property portfolio, based on depreciated book values, invested in each county at the end of 2019.[11] We then match these portfolio allocations with the daily growth rates of county-level COVID-19 confirmed cases, which are obtained from the Coronavirus COVID-19 Global Cases database at Johns Hopkins University.[12] These county-level growth rates are then value-weighted by the percentage of the CRE portfolio invested in each county. This produces an estimated daily COVID-19 exposure of each CRE portfolio (*GeoCOVID*).

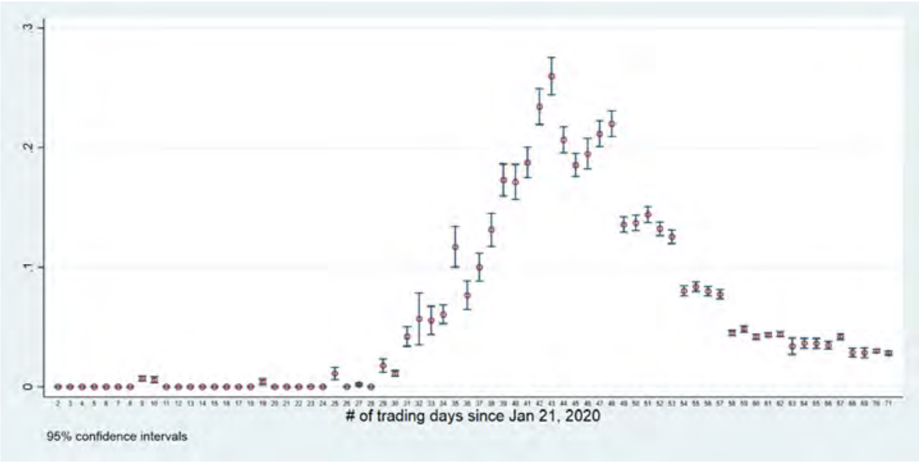
[11] The use of book values in place of unobservable true market values may understate (overstate) the value-weighted percentage of a CRE portfolio invested in regions that have recently experienced a relatively high (low) rate of price appreciation.
[12] https://github.com/CSSEGISandData/COVID-19

Covid Economics 22, 26 May 2020: 205-260

Figure 3 shows the trend of *GeoCOVID* since the first reported case in the U.S. on January 21, 2020. The horizontal axis marks the number of *trading* days since the first outbreak. The average daily increase in reported cases was approximately zero until day 27 (February 27, 2020), consistent with the nation-wide trend of reported cases.[13,14] Another important takeaway from Figure 3 is the hump-shaped pattern of *GeoCOVID* from day 27 to day 58 (February 27 to April 13, 2020). Given the reduced growth of COVID cases after April 13, 2020 and data availability when our analysis was conducted, our sample period runs from January 21 to April 15, 2020. In robustness tests, we show that our results are robust to the expansion of our sample period to April 30 or when we restrict our analysis to the hump-shaped period of *GeoCOVID* from February 27 to April 13, 2020.

Figure 3: Trends in Geographically weighted COVID-19 Growth

This figure shows the means and 95% confidence intervals of daily geographically weighted COVID-19 growth for the period from January 21, 2020, through April 30, 2020. Geographically weighted COVID-19 growth (*GeoCOVID*) is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4.



[13] For the nation-wide trend, see https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html (last access: May 12, 2020)

[14] As *GeoCOVID* is a weighted average of county-level growth rates based on the percentage of the CRE portfolio invested in each county, we also compare *GeoCOVID* with a simple average of growth rates in 2,572 counties in which REITs own properties. In untabulated results, we find that the simple average of daily COVID growth rates was also about zero from January 21 to February 27, 2020, except for few "spikes." This is because for each county the growth rates in the first few days since the first reported case are relatively high. For example, the growth rate from one case to two cases is higher than the growth from ten to twenty. In general REITs own properties in dense population counties; the virus was spread from counties with higher population densities to those with lower population densities. Therefore, the property weights smooth out the spikes by placing less weight on high growth rates in counties less population. Thus, *GeoCOVID* has, on average, a smaller mean and standard deviation than the simple average of county-level COVID growth.

Covid Economics 22, 26 May 2020: 205-260

We require non-missing values for the following items for each REIT at the end of each day from January 1, 2019, to April 15, 2020: firm identifier (SNL Institution Key), total return, stock price, property type, and stock market capitalization. The initial sample includes 224 unique equity REITs traded on NYSE, Amex, and Nasdaq in 2019Q4. According to S&P Global and NAREIT, CRE portfolios are classified into twelve major property types, including office, industrial, retail, residential, diversified, hospitality (lodging/resorts), health care, self-storage, specialty, timber, data center, and infrastructure. Due to a small number of firms, we include timber REITs in the specialty category and combine infrastructure and data center REITs into a "technology" category.[15] Appendix 2 summarizes property type descriptions. Quarterly accounting data and daily total returns on individual REITs and on our broad-based market indices are obtained from the S&P Global Companies database. The 30-day U.S. Treasury rate is downloaded from the Federal Reserve System website.[16] After merging with *GeoCOVID*, our sample includes 198 equity REITs and 12,338 firm-day observations.

We estimate daily risk-adjusted returns following Rehse et al. (2019). We obtain return sensitivities for each firm using a simple market model estimated from January 1, 2019 to January 20, 2020. We use two stock market indices: the S&P 500 Index and the FTSE-NAREIT All Equity REITs Index. Next, we use the estimated firm-level return sensitivities to compute daily risk-adjusted returns for the baseline period between January 21, 2020 and April 15, 2020. Daily risk-adjusted returns are calculated as the difference between REIT returns in excess of risk-free rate and the product of returns on the market index and the corresponding return sensitivity.[17]

We first use *GeoCOVID* reported on day t-1 to predict stock returns on day t. However, because the news contained in the number of new cases of COVID-19 reported on day t-1 may take more than the subsequent day to be fully incorporated into stock prices, we also use *GeoCOVID* reported on day t-1 to predict cumulative returns over the subsequent two days

[15] The FTSE-NAREIT All Equity REITs Index contained only four timber REITs, five infrastructure (primarily cell tower) REITs and five data center REITs as of February 29, 2020. See *REIT Watch*, March 2020 (www.nareit.com).
[16] See https://www.federalreserve.gov/releases/h15/
[17] Share price changes, and therefore total returns, are dependent on how much debt a company employs. Therefore, unlevered returns may provide a more accurate picture of how investors repriced the different property sectors, and individual REITs, during the early stages of the pandemic (Green Street Advisors, 2020). We plan to redo our analysis using unlevered returns as a robustness check.

(day t and day t+1). Finally, because investors may be able to partially predict reported *COVID-19 Growth* using epidemiological models, we use *GeoCOVID* reported on day t -1 to predict aggregate stock returns over a three-day window: day t -1, day t, and day t+1. These multiple-day return measures are constructed using non-overlapping windows (days) so that each observation of the dependent variable is independent of the prior and subsequent observation (Harri and Brorsen, 1998).

Wheaton and Thompson (2020) propose a power function that measures the cumulative number of confirmed COVID-19 cases across the major U.S. counties from January 21, 2020 to the end of March 2020. They calibrate the power parameters using a log-linear regression equation. Among the parameters, days since the onset of the pandemic in that county and the population density of the county predict the cumulative number of confirmed cases. Similar to Wheaton and Thompson (2020), we define *Days since outbreak* as the number of days since a COVID-19 case was reported in any county in which the REIT owns property. To account for the expected non-linearity in the growth rate of COVID-19 cases, we also include the quadratic term of *Days since outbreak*, or *Days since outbreak*^{2}, in our analysis.

Greater population density in a geographic area complicates social distancing and therefore increases the likelihood the virus will spread. To test this conjecture, we construct a measure of the average population density of the counties in which the REIT owns properties. *GeoDensity* is the average of county-level population densities per square mile in 2019, weighted by the percentage of the CRE portfolio invested in the corresponding county at the end of 2019Q4. County-level population densities are downloaded from the S&P Global Geographic Intelligence database.

Our final dataset for regression analysis consists of 11,210 firm-day (198 REITs) observations. Our control variables include determinants of the daily stock returns identified in the prior literature. These variables are all measured as of the end of 2019. *GeoHHI* and *PropHHI* are Herfindahl indices that capture the degree to which the firm concentrates its property portfolio across counties or by property type.[18] *Leverage* is the total book value of debt divided by the book value of total assets, *Cash* is the sum of cash and equivalents divided by lagged total assets, *Size* is the reported book value of total assets, and *Tobin's Q* is the

[18] For example, *GeoHHI* is the property-level Herfindahl Index (HHI) calculated as the sum of squared proportions of the total book value of a CRE portfolio located in county j.

market value of equity, plus the book value of debt, divided by the book value of total assets. *LAG3MRET* is defined as the firm's cumulative return during 2019Q4, *InstOwn* is a REIT's institutional ownership percentage, *Investment* is defined as the growth rate in non-cash assets over the fourth quarter of 2019, and *EBITDA/AT* is EBITDA divided by the book value of assets.[19] Appendix 1 summarizes variable definitions and data sources.

4. Results

4.1 Summary Statistics

Table 1 reports summary statistics for our 11,210 firm-day risk-adjusted return observations. During our sample period from January 21, 2020 to April 15, 2020, the average 1-day risk-adjusted return based on the S&P 500 (FTSE-NAREIT All Equity REITs Index) is -0.6% (-0.8%). The mean 2-day risk-adjusted return is -1.3% (-1.5%). The number of observations in our 2-day return sample is approximately half of the 1-day sample because of the non-overlapping estimation windows. The mean 3-day risk-adjusted return is -1.9% (-2.2%). The standard deviation of 1-day risk-adjusted returns for both the S&P 500 and the FTSE-NAREIT All Equity REITs benchmarks are about ten times their means, reflecting the extreme stock market volatility during the early stages of the pandemic. The 25th percentiles are approximately three times more negative than the mean, while the 75th percentiles are all positive and of large magnitudes relative to the corresponding means.

Firm-level, geographically weighted COVID-19 growth averaged 6.6% per day with a standard deviation of 9.4% during our sample period. Because we track firms' portfolio exposures since the first reported U.S. case on January 21, 2020, more than 25% of our stock-day observations are associated with no growth in reported cases, as shown by the 25th percentile. The geographically weighted growth rate in firms' exposure also varies substantially; for example, more than 25% of firms experienced daily growth in COVID-19 cases of more than 11.7%. The mean (and median) *Days since outbreak*, as of April 15, 2020, is 33 days.

Geographically weighted population density, *GeoDensity*, averages 4,887 persons per square mile. The 25th percentile was 1,180; the 75th percentile was 4,165. The summary statistics for other control variables (measured as of the end of 2019Q4) are comparable to prior studies. The average CRE portfolio in our sample has a property concentration

[19] EBITDA is earnings before interest, taxes, depreciation, and amortization expenses.

Covid Economics 22, 26 May 2020: 205-260

(Herfindahl Index) of 0.788, a geographic concentration of 0.119 (measured using county data), a leverage ratio of 49%, cash holding of 3.7%, a book value of assets equal to $6.6 billion, and a Tobin's Q of 1.5. The percentage of stock owned by institutional investors averages 81%. The percentage growth rate in non-cash assets during 2019Q4 (*Investment*) averaged 9.2% but varies substantially across firms. The ratio of EBITDA to the book value of total assets has a mean of 2.1%. Nineteen percent of REITs focus on retail properties, 14% on hospitality properties, and 11% on office assets and health care properties.[20] The means of the ten property type dummies are in line with the constituents by property type discussed in Appendix 2.

4.2 Stock Performance across Property Types

Figure 4 displays the means and 95% confidence intervals of risk-adjusted returns across property types from January 21, 2020, through April 15, 2020. We observe similar patterns for different return horizons (1-day, 2-day, and 3-day), and for the S&P 500 and equity REIT market models (Panel A and B, respectively). The best performing property types were technology, self-storage, and warehouses. Cell towers that transmit data communications and high-tech facilities that host Cloud servers are in high demand because many people are working remotely from home. The worst performers were hospitality and retail REITs due to canceled travel, imposed closures, and shelter-in-place orders in most cities and states. Diversified REITs also underperformed as a sector because many hold retail and multi-use properties. Owners of specialty REITs (e.g., casinos, golf courses, timber, and agriculture) were also negatively affected by reduced demand. Office and residential properties were less negatively affected over our sample period, perhaps because of longer-term leases and relatively inelastic demand. The results are little changed when the FTSE-NAREIT All Equity REITs Index is used as our market benchmark instead of the S&P 500.

Covid Economics 22, 26 May 2020: 205-260

[20] The disaggregation of CRE portfolios by major property type may mask some variation across sub-property types. For example, Green Street Advisors (2020) disaggregate "residential" properties into apartments, student housing, single-family rental, and manufactured home parks.

Covid Economics 22, 26 May 2020: 205-260

Figure 4: Risk-Adjusted Return by Property Types

This figure shows the means and 95% confidence intervals of risk-adjusted returns across property types for the period from January 21, 2020, through April 15, 2020. *1-day risk adj. returns* are calculated as $R_{i,d} - \beta_i M_d$. β_i is estimated from the market model for firm *i* from the beginning of 2019 to January 20, 2020. $R_{i,d}$ denotes stock returns for firm *i* on day *d*. M_d denotes daily returns on either the S&P 500 index (Panel A) or the FTSE-NAREIT All Equity REITs Index (Panel B). *2-day (3-day) risk adj. returns* are the non-overlapping cumulative risk-adjusted returns from day *d* (*d-1*) to day *d+1*. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types.

Panel A: Risk-Adjusted Returns based on S&P 500 Index

Panel B: Risk-Adjusted Returns based on NAREIT Equity Index

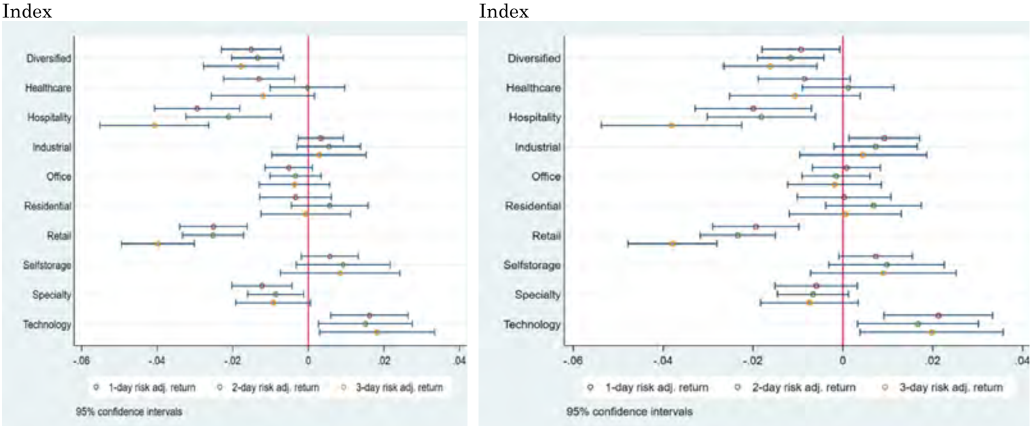


Figure 5, Panel A, shows a heat map of average daily COVID-19 growth at the county level during our sample period. In Panels B-D, we show the geographic distribution of CRE portfolios as of 2019Q4. These geographic patterns are shown in terms of percentiles. Although retail and health care REITs display a similar geographic pattern, these two sectors performed quite differently, as shown in Figure 1. This suggests that some property types might continue to perform better as the pandemic continues to unfold.

Although it seems that COVID-19 growth is highly correlated with overall CRE property holdings, there are substantial variations across firms, making geographic asset allocation an important factor in explaining stock returns. Consider two firms with similar characteristics in terms of property type focus and size. One firm's portfolio is heavily concentrated in areas severely affected by the COVID-19 pandemic, while the other firm's portfolio is mostly concentrated in less affected counties. How does the difference in asset location and geographic weights affect stock reactions during the pandemic?

The importance of geographic asset allocation can be illustrated with the following example. We plot the pre-pandemic asset allocations for two residential REITs, BRT

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Covid Economics 22, 26 May 2020: 205-260

Apartments Corp. (BRT) and Investors Real Estate Trust (IRET), in Panel E and F of Figure 5, respectively. For the two maps on the left-hand side of the panel, solid circles indicate that the growth rates of COVID-19 cases in the corresponding counties are above 9.2%, which is the median daily growth rates across all the U.S. counties over our sample period. Hollow circles indicate growth rates below the median. The size of the circles indicates the magnitude of growth rate deviation from the median. For the ease of comparison, we plot the heat map of COVID-19 growth rates for counties in which the firm holds properties (from Panel A) on the right-hand-side of the panel.

Compared with BRT, IRET's property portfolio has a much lower correlation with the geography pattern of growth in COVID-19 cases. The large hollow circles in Panel F suggest that a large percentage of IRET's portfolio is located in less affected areas. In terms of return differences, the median of 1-day, 2-day, and 3-day risk-adjusted returns ranges +0.03% to +0.6% for IRET, compared with a range of -0.05% to -1% for BRT. As a benchmark, the sample medians for all residential REITs are -0.4%, 0.9%, -1.4%, respectively. Clearly, firms holding more properties in less affected areas are more resilient to the pandemic. Although this example does not provide a definitive answer to our question, it reveals the potential importance of geographic asset allocations during the pandemic

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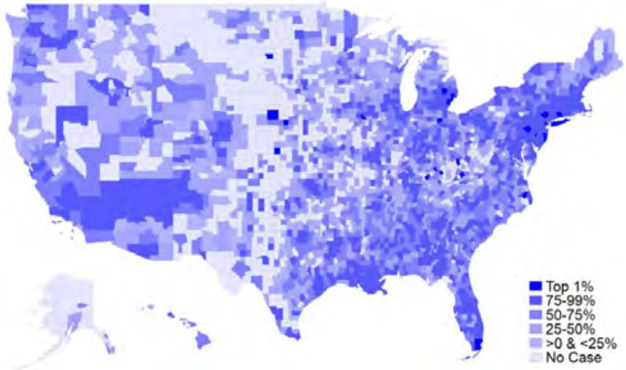
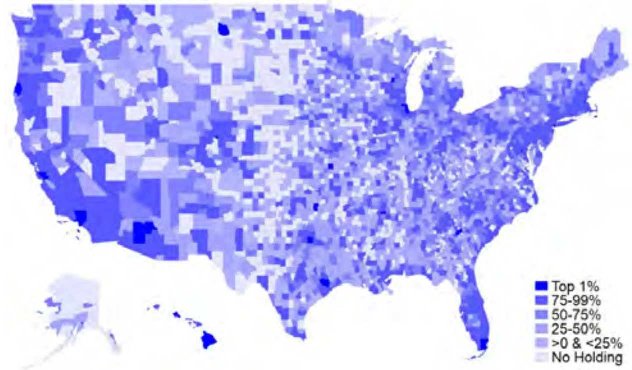
Figure 5: COVID-19 Growth and Property Holdings

Panel A shows geographic patterns of the average daily growth rates of COVID-19 confirmed cases in the U.S. counties for the period from January 21, 2020, through April 15, 2020. Panels B-D shows the geographic distribution of CRE portfolios as of 2019Q4. Geographic patterns are shown in terms of percentiles. Panel B is based on all property types. Panel C (D) is based on retail (health care). Panel E and F provide two examples of firm-level asset allocation on stock performance. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types.

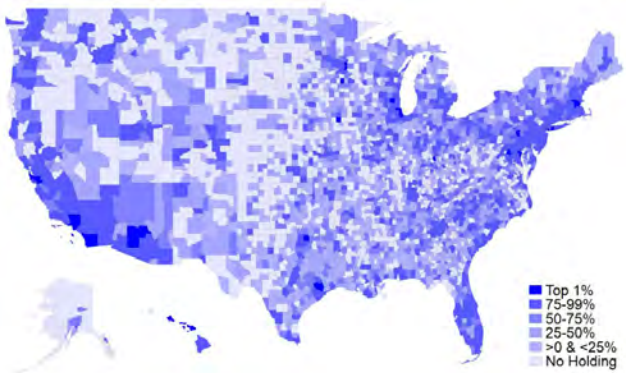
Panel A: COVID-19 Growth (County Level)



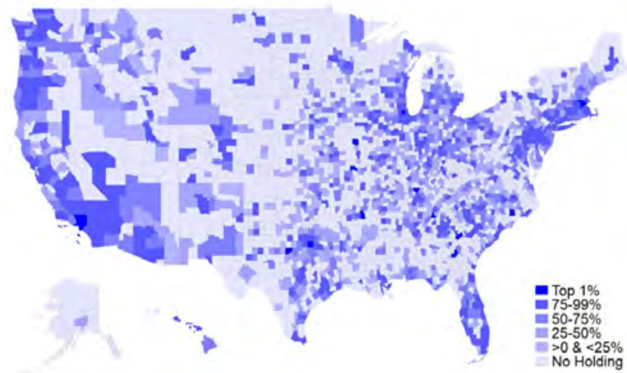
Panel B: Average Property Holdings (County Level)



Panel C: Average Property Holdings (County Level), Retail



Panel D: Average Property Holdings (County Level), Health Care



Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

Panel E: An illustrative example of firm-level Asset Allocation, using BRT Apartments Corp.

Panel F: An illustrative example of firm-level Asset Allocation, using Investor Real Estate Trust

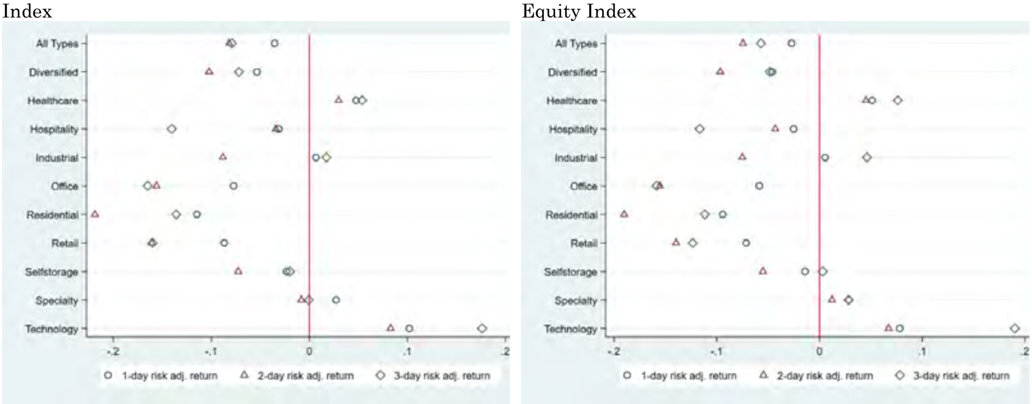
To gain further insight, we next plot correlations between risk-adjusted returns and geographically weighted COVID-19 growth by property types. As displayed in Figure 6, the correlations are mostly negative, suggesting a firm's exposure to COVID-19 is negatively correlated with its stock performance. The correlation pattern across property types is different from the return pattern displayed in Figure 1. For example, healthcare and technology REITs display a positive correlation even though risk-adjusted returns for these property types are mostly negative. Overall, these correlations suggest that both property location and property type focus affect the vulnerability of a CRE portfolio to the COVID-19 pandemic.

Figure 6: Correlations between Risk-Adjusted Returns and COVID-19 Growth by Property Type

This figure presents the correlations between risk-adjusted returns across property types and the growth rate of COVID-19 cases. Panel A depicts the correlations for risk-adjusted returns based on the S&P 500 Index. Panel B depicts the correlations for risk-adjusted returns based on the S&P 500 Index based on the NAREIT Equity Index. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types.

Panel A: Risk-Adjusted Returns based on S&P 500 Index

Panel B: Risk-Adjusted Returns based on NAREIT Equity Index



4.3 Baseline Results - Risk-adjusted returns and geographically weighted COVID-19 growth

We begin our multivariate analysis by estimating the relation between the daily growth rate in reported COVID-19 cases and risk-adjusted CRE returns, *Ret*. The one-day risk-adjusted return for firm *i* on day *t* is calculated by first regressing the firm's daily stock return in excess of the U.S. Treasury yield on the contemporaneous total return on the S&P

500 Index or the FTSE-NAREIT Equity Index.[21] This regression is estimated for each firm using daily data from January 1, 2019 through January 20, 2020. The results of this regression are then used to calculate *Ret* for each REIT over our sample period. These 1-day "market model" results are reported in columns (1) to (3) of Table 2, panel A. The results for the 2-day market model (estimated using day *t* and day *t*+1 returns) are reported in columns (4) to (6). Finally, the 3-day model (estimated using days *t-1*, *t*, and *t*+1 returns) are reported in columns (7) to (9). Our main test variable is geographically weighted COVID-19 growth (*GeoCOVID*) on day *t*-1.

As an initial baseline, we regress 1-day risk-adjusted returns on *GeoCOVID*. Property type fixed effects are included in this pooled, cross-sectional regression with 11,210 observations. Standard errors are clustered at the firm level. In Column (1), the estimated coefficient on *GeoCOVID* is negative and highly significant, indicating that an increase in a firm's portfolio exposure to COVID-19 cases on day *t*-1 is associated with significantly lower risk-adjusted returns on day *t*.

To our baseline specification, we next add *Days since outbreak* and *Days since outbreak*^{2}. To control for variation in the population density of counties in which the REIT owns properties, we also include *GeoDensity* in the specification. Finally, we include our set of firm-level control variables defined above. Property type fixed effects are retained to control for the firm's property type focus. The results from estimating this expanded regression are reported in column (2) of Table 2, panel A. The estimated coefficient on *GeoCOVID* remains negative and highly significant. Economically, a one-standard-deviation increase in *GeoCOVID* on day *t*-1 is associated with a 0.24 percentage points decrease [=-0.026*0.094 (the sample mean)] in risk-adjusted returns on day *t*. This economic magnitude is equivalent to more than 40% of the sample mean decrease in returns (-0.6 percentage points).

The estimated coefficient on *Days since outbreak* is negative and highly significant (t-stat=-7.01). This suggests that 1-day risk-adjusted returns are significantly related to the duration of the firms' exposure to COVID-19 cases. However, the estimated coefficient on *Days since outbreak*^{2} is positive and highly significant (t-stat-8.73). This estimated non-linear effect of *Days since outbreak* suggests that risk-adjusted returns decline as the

[21] Daily Fama-French factors were not available for our sample period. We will test the robustness of our results using Fama-French factors when they become available.

Covid Economics 22, 26 May 2020: 205-260

CEPR PRESS

Covid Economics 22, 26 May 2020: 205-260

pandemic worsens, but the rate of decline decreases over time, perhaps because investors understand the concept of "flattening the curve."[22] The estimated coefficient on *GeoDensity* is positive and highly significant, indicating that CRE portfolios in dense population areas perform better, controlling for COVID-19 growth rates and days since the outbreak.[23]

Among the firm-level control variables, the estimated coefficient on *Leverage* is negative and significant at the 1% level, suggesting investors expect firms that employ more financial leverage to underperform during the market downturn. Although a repeat of the credit crisis that occurred during the Global Financial Crisis is unlikely, the probability that more highly leveraged firms will experience financial distress surely increased during the early stages of the pandemic. The estimated coefficient on *LAG3MRET* is positive and highly significant (t-stat=20.05). This indicates that the firm's stock returns during the fourth quarter of 2019 are predictive of risk-adjusted returns in March and April of 2020. We also find weak evidence that *Ret* is negatively related to the extent to which a firm concentrates its portfolio by property type (*PropHHI*) and geography (*GeoHHI*).

We next estimate our 1-day risk-adjusted return regression using firm fixed effects in place of our set of firm-level explanatory variables. These results are reported in column (3) of Panel A. The estimated coefficients on *GeoCOVID* and *Days since outbreak* remain negative and highly significant and the coefficient on *Days since outbreak*^{2} remains positive and highly significant (t-stat=8.24). These results suggest that the large and significant coefficient estimates we observe for *GeoCOVID* are not being driven by an omitted (time-invariant) firm characteristic.

The results from the estimation of our 2-day market model are reported in columns (4) to (6). Although this two-day return window decreases the number of independent return observations from 11,210 to 5,510, the magnitude and significance of the estimated coefficients on *GeoCOVID* are larger in all three specifications than in the corresponding one-day regression model. Moreover, the estimated coefficient on *Days since outbreak* remains negative and highly significant. The coefficients on *GeoDensity*, *Leverage*, and *LAG3MRET* remain highly significant using two-day return windows, and we continue to find some weak evidence *Ret* is negatively related to property type and geographic concentrations. Finally,

[22] In epidemiology, the flattening of the curve refers to the expectation that the number of people infected over a period of time will increase at a decreasing rate.

[23] *GeoDensity* could be related to property type. For example, industrial and technology properties tend to be located in low population density areas. This multicollinearity should work against us finding a significant result for *GeoDensity*.

Covid Economics 22, 26 May 2020: 205-260

our 3-day market model results are reported in columns (7) to (9). Overall, this further widening of the risk-adjusted return window has little effect on our coefficient estimates or conclusions about the impact of *GeoCOVID* on the pricing of CRE portfolios.

To examine the performance of CRE portfolios relative to other portfolios during the COVID-19 outbreak, we redo the analysis reported in Table 2, panel A using the total returns on the FTSE-NAREIT All Equity REITs Index in place of the S&P 500. This requires, among other things, regressing each firm's excess stock returns on the contemporaneous total return on the equity REIT index using daily data from January 1, 2019 through January 20, 2020. This equation is then used to calculate daily risk-adjusted returns over the sample period. These results are reported in panel B of Table 2. Inspection of the panel reveals that using the FTSE-NAREIT All Equity REITs Index as our benchmark in place of the S&P 500 has little effect on the magnitude or statistical significance of the estimated coefficients on *GeoCOVID*, *Days since outbreak*, *Days since outbreak*^{2}, or *GeoDensity*. The lack of sensitivity of our results to the change in the market benchmark is at least partially attributable to the high correlation (0.94) of daily returns on the FTSE-NAREIT All Equity REITs Index and the S&P 500 Index during March and April of 2020.

4.4 Risk-adjusted Returns and Geographically Weighted COVID-19 Growth Across Property Types

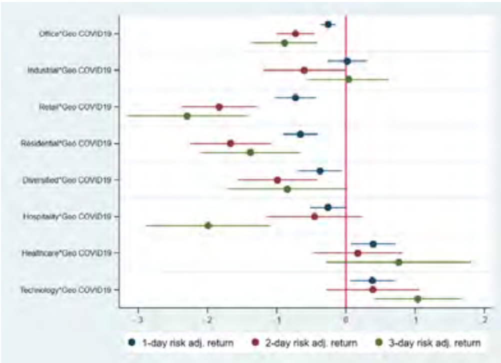
Given the strong negative relation between risk-adjusted returns and geographically weighted COVID-19 growth we uncover, we next investigate the extent to which this relation varies across property types. As discussed earlier, different property sectors face different COVID-19 exposures and show a striking variation in terms of risk-adjusted returns (Figure 4) and correlations between returns and COVID-19 growth (Figure 6). We therefore augment the regressions reported in Table 2 with interactions between *GeoCOVID* and our property type dummies. We suppress the intercept and saturate the model with all combinations of property type dummies and *GeoCOVID* interactions. The estimated coefficients on the interaction terms can therefore be interpreted as the property-type specific effects of *GeoCOVID*. As before, we include our full set of firm-level controls.

Covid Economics 22, 26 May 2020: 205-260

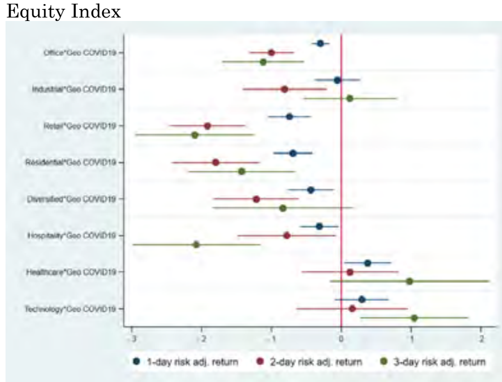
Figure 7: Coefficients on Property Type and *GeoCOVID* Interactions

This figure presents the coefficients on property type interactions with geographically weighted COVID-19 growth in Table 3. Panel A depicts the coefficients from models using risk-adjusted returns based on the S&P 500 Index as the dependent variable in Panel A of Table 3. Panel B depicts the coefficients from models using risk-adjusted returns based on the NAREIT Equity Index in Panel B of Table 3. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types.

Panel A: Risk-Adjusted Returns based on S&P 500 Index



Panel B: Risk-Adjusted Returns based on NAREIT Equity Index



The results of these tests are displayed in Table 3. The mean coefficient estimates on the interaction terms and the corresponding 95% confidence intervals are displayed in Figure 7. We continue to find a negative relation between *GeoCOVID* and risk-adjusted returns for most of the property types. In terms of economic magnitude, retail and residential REITs experienced the largest negative risk-adjusted returns, followed by office and hospitality REITs. For retail REITs, a one-standard-deviation increase in *GeoCOVID* is associated with a reduction in 1-day risk-adjusted returns of 0.69 percentage points (=-0.073 × 0.094), which represents 64% of the mean risk-adjusted return for retail REITs (=0.69% ÷ 1.08%). The cumulative 2-day and 3-day effects for retail properties are even larger, ranging from 1.72 to 2.15 percentage points.[24] For residential REITs, a one-standard-deviation increase in *GeoCOVID* corresponds to a return reduction of 0.62 to 1.57 percentage points, depending on the return window and risk adjustment methods. Given that the mean value of risk-adjusted return for residential is -0.45, the impact of a one-standard-deviation increase in *GeoCOVID*

[24] There might be multicollinearity between *GeoCOVID* and our property type dummies. For example, retail properties, especially neighborhood shopping centers, are generally located in most, if not all, communities in a way that high quality office properties are not. However, this multicollinearity should work against us finding significant results.

corresponds to 138% to 349% of the mean. Hospitality REITs also experienced a large impact: a one-standard-deviation increase in *GeoCOVID* corresponds to a return reduction of 0.24 to 1.88 percentage points, representing 22% to 171% of the mean (-1.09 percentage points). Overall, the magnitudes of these negative effects are striking in industries most impacted by the pandemic.

In contrast, the estimated *GeoCOVID* interactions for specialty REITs cannot be distinguished from zero in any of the six regression specifications, and the interaction term for industrial REITs is negative and significant in the 2-day return specifications, but otherwise indistinguishable from zero. However, CRE portfolios focused on health care and technology properties display positive (or zero) coefficients on the interaction terms. Using risk-adjusted returns based on the S&P 500, a one-standard-deviation increase in *GeoCOVID* is associated with a 0.4 percentage point increase in 1-day returns in both of these sectors.

4.5 The Importance of Asset Allocation

The results reported in Table 2 demonstrate that *GeoCOVID* predicts future risk-adjusted returns. Given that prior studies using a nation-wide growth rate of COVID-19 also find negative stock price responses (e.g., Ding et al., 2020; Alfaro et al., 2020), we investigate whether our geographically weighted COVID growth measure is simply picking up the national trend. In other words, if portfolio allocations are heavily tilted toward areas that suffered the most during the early stages of the pandemic (e.g., New York and New Jersey), our results could be influenced by the high correlation between the geography of CRE portfolioss and the geography of COVID-19 growth (see Figure 5). If so, our firm-level, geographically weighted measure of the growth in COVID-19 cases would not contribute additional explanatory power, after controlling for the national trend.

To investigate this issue, we re-run our baseline results using daily national COVID growth rates (*USCOVID*) in place of *GeoCOVID*. These results are reported in Columns (1)-(3), Table 4. Consistent with prior studies, this nationwide measure is negatively related to risk-adjusted returns. Next, we include both *GeoCOVID* and *USCOVID* in our pooled, cross-sectional regressions. These results are reported in Columns (4)-(6). We find that, after controlling for the national trend, investors still react negatively to increases in our geographically weighted measure of COVID-10 growth. Comparing the economic significance of these two variables, we find that the effect of a one-standard-deviation increase in

Covid Economics 22, 26 May 2020: 205-260

GeoCOVID on risk-adjusted return is comparable to that of *USCOVID* in the 2-day window and slightly higher than that of *USCOVID* in the 1-day and 3-day windows.[25]

The unreported variance inflation factor (VIF) diagnosis suggests multicollinearity exists when both *USCOVID* and *GeoCOVID* are included in the regression.[26] We therefore orthogonalize *GeoCOVID* with respect to *USCOVID* and include both *USCOVID* and orthogonalized *GeoCOVID* (*O.GeoCOVID*) in the return regressions. The negative effects of *O.GeoCOVID* on risk-adjusted returns are still significant, as shown in Columns (7)-(9), even though the orthogonalization against national COVID-19 growth strips out the explanatory power of *GeoCOVID* that is correlated with the geography of the pandemic growth.[27] Our results using risk-adjusted returns based on the FTSE-NAREIT index (unreported) are qualitatively similar. These findings support the importance of asset allocation in explaining stock market reactions to the pandemic. The results are robust to various model specifications and controls, as well as to different return windows and market model benchmarks.

Although our geographically weighted measure of COVID growth provides increased explanatory power, the relative ability of national rates of growth in COVID-19 cases to explain the cross-section of risk-adjusted returns is somewhat surprising. As discussed above, equity REITs must invest primarily in income-producing real estate; moreover, these real assets are relatively easier to locate. Our analysis clearly reveals that investors have been able to differentiate the future income generating ability of the various property types (for example, industrial versus retail). We would also expect that marginal investors in REIT stocks would be able to accurately identify CRE portfolios heavily weighted toward areas hit hard in the early days of the pandemic and punish those stocks relatively more than others with portfolios less tilted toward COVID-19 "hot spots." However, it is widely known that the panic selling associated with sudden and substantial stock market downturns causes return

[25] The standard deviations of *USCOVID* and *GeoCOVID* are 0.63 and 0.94, respectively. Therefore, a one-standard-deviation increase in *USCOVID* is associated with a reduction in risk-adjusted return of 0.12, 0.47, and 0.51 percentage points over the 1-day, 2-day, and 3-day window, respectively. Similarly, a one-standard-deviation increase in *GeoCOVID* is associated with a reduction in risk-adjusted return of 0.15, 0.41, and 0.53 percentage points over the 1-day, 2-day, and 3-day window, respectively.

[26] The correlation coefficient between *USCOVID* and *GeoCOVID* is about 0.4.

[27] The notion that the national rate of COVID-19 growth represents the geography of the pandemic growth can be explained by a comparison between Panel A and B of Figure 5. The national growth is driven by places with more population (therefore more cases). As the geography of COVID-19 growth (in Panel A of Figure 5) is highly correlated with the geography of property holdings (in Panel B), the orthogonalization strips out the former from the latter.

Covid Economics 22, 26 May 2020: 205-260

correlations of all stocks to increase. Our conjecture is that CRE portfolios less tilted toward COVID-19 hot spots will outperform during the eventual recovery of the broader stock market.

To further examine the importance of geographic asset allocation, we investigate how population densities, property type concentrations, and geographic concentrations of CRE portfolios affect the sensitivity of stock returns to *GeoCOVID*. Wheaton and Thompson (2020) study the determinants of how rapidly the virus grows once it has been seeded within an MSA or a county. They conclude that population density predicts the growth rate of COVID-19 cases. Also, prior literature (e.g., Hartzell et al., 2014; Ling et al., 2019) highlights the importance of property type concentrations and geographic concentrations in determining the performance and returns of CRE portfolios.

For each of the three asset allocation variables, we create a dummy variable for above-median values and interact it with *GeoCOVID*. We also include *GeoCOVID* in the estimation; thus, the interaction term measures whether, for example, population density augments or mutes the negative impact of *GeoCOVID* on returns. In all model specifications, we include our full set of control variables (except the variable of interest itself) and property type fixed effects. As shown in Table 5, above-average population density is associated with higher 1-day, 2-day, and 3-day risk-adjusted returns. However, the coefficient estimate on the interaction term is negative and significant at the 5% level or higher in all three return windows, suggesting the sensitivity to *GeoCOVID* increases and returns are more negatively affected if the firm allocates more assets to areas with high population density. The economic magnitude of this effect is large: asset allocation in areas with above-median population density intensifies the negative reaction to COVID-19 by 2.3 to 10 percentage points.

In contrast, high property type and geographic concentrations are not associated with risk-adjusted returns; moreover, they have no impact on the sensitivity of returns to *GeoCOVID*. If listed REITs tend to invest in population-dense metropolitan areas, we should expect population density and geographic concentration to have similar effects on return responses to *GeoCOVID*. However, our results suggest this is not the case. During the early stages of the pandemic, only population density is associated with greater sensitivity of stock returns to the degree to which firms have high COVID-19 exposure.

4.6 The Impact of Firm Characteristics

Next, we further examine the extent to which different firm characteristics affect the impact of *GeoCOVID* on risk-adjusted returns. Similar to our Table 5 results, we create

Covid Economics 22, 26 May 2020: 205-260

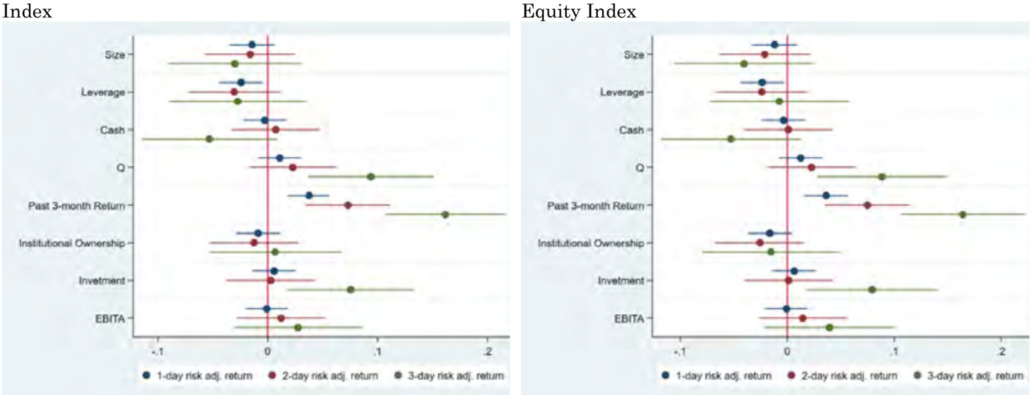
dummy variables for above-median values of *Size*, *Leverage*, *Cash*, *Tobin's Q*, *LAG3MRET*, *InstOwn*, *Investment*, and *EBITDA/AT*. We then interact these dummies with *GeoCOVID*. We include our full set of control variables (except the variable of interest itself) and property type fixed effects in all model specifications. The regression results are summarized in Table 6, and the coefficient estimates and 95% confidence intervals are displayed in Figure 8.

Figure 8: Coefficients on Firm Characteristics

This figure presents the coefficients on firm characteristics estimated in Table 5. Panel A depicts the coefficients from models using risk-adjusted returns based on the S&P 500 Index as the dependent variable in Panel A of Table 5. Panel B depicts the coefficients from models using risk-adjusted returns based on the NAREIT Equity Index as the dependent variable in Panel B of Table 5. See Appendix 1 for variable descriptions.

Panel A: Risk-Adjusted Returns based on S&P 500 Index

Panel B: Risk-Adjusted Returns based on NAREIT Equity Index



Return momentum has a significant effect on both risk-adjusted returns and the sensitivity of returns to *GeoCOVID*; that is, firms that previously experienced high return growth were more resilient during the early stages of the pandemic. More specifically, firms with strong returns in the fourth quarter of 2019 produced returns that are 3.8 percentage points less sensitive to COVID-19 growth rates (as shown in Panel A). There is evidence in the 3-day results that firms with high growth potential (*Tobin's Q*) also reacted less negatively to their exposure to *GeoCOVID*. Overall, we conclude that, after conditioning on the firm's property type focus, with the exception of return momentum, firm characteristics have a modest impact on stock price reactions to *GeoCOVID*.

4.7 The Impact of Non-pharmaceutical Interventions (NPI)

There has been an intensive debate on the appropriate policy responses to curb the spread of COVID-19. Obviously, there is a trade-off between slowing the spread of the virus and economic activity. For example, Correia, Luck, and Verner (2020) find that non-pharmaceutical interventions (NPIs) mitigated the negative effects of the 1918 Flu pandemic on economic growth. In contrast, Lilley, Lilley, and Rinaldi (2020) suggest that NPIs have no effect on economic growth. Given the data limitations and scope of our study, we are not able to disentangle the effects of NPIs from those of COVID-19. Nevertheless, an event study investigation of investors' responses to the announcements of these non-pharmaceutical interventions (NPIs) helps us understand how changes in expectations about the efficacy of these policies affect firms differently. Specifically, we expect that CRE portfolios focused on data centers, self-storage and industrial properties are affected less by the social distancing mandated by NPIs, such as lockdown and shelter-in-place orders.

NPIs have been passed at different administrative levels (e.g., city, county, and state levels). We therefore start with open source data collected by Jataware, a machine learning company that automates the collection of news articles and detects whether an article mentions a COVID-19 NPI using natural language processing (NLP) classifiers (Bidirectional Encoder Representations from Transformers (BERT)).[28]

As pointed out by Cui, Heal, and Kunreuther (2020), a policy enacted by one jurisdiction might influence other jurisdictions to adopt a similar policy. Therefore, for each state we identify the NPI event date as the earliest date the NPI was enacted at either the city, county, or state level. This allows us to manually compare our event dates with those used in Dave, Friedson, Matsuzawa, and Sabia (2020) and Mervosh, Lu, and Swales (2020). We also verify our NPI event dates using google searches (e.g., google trends).[29]

We construct two sets of event dates from this search: announcements of states of emergency (SOE) and announcements of shelter-in-place orders (SIPOs), stay-at-home orders, or school and business closures. A SOE empowers a government entity to perform actions or impose policies that it would normally not be permitted to undertake. SIPOs and stay-at-home orders require residents to remain home for all but essential activities (e.g., purchasing

[28] The NPI Data is available at https://github.com/jataware/covid-19-data.
[29] See, for example, Mervosh et al. (2020): https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html. (Last Access: May 12, 2020)

Covid Economics 22, 26 May 2020: 205-260

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food or medicine, caring for others).[30] In most states, SOE announcements preceded SIPOs; the average gap between a SOE announcement and the announcement of a SIPO at the state level is about 10 days. Thus, investors should have anticipated SIPOs when SOEs were announced, as evidence suggests declines in local commuting begin after SOE announcements (Couture et al., 2020). We therefore use the SOE announcements as our preferred event date for (expected) NPIs with SIPOs used as a robustness check.

Similar to our construction of *GeoCOVID*, we measure each firm's property holdings at the end of 2019Q4. We then find the earliest SOE, or SIPO, announcement date using three methods: (1) the earliest announcement date in any state in which a firm owns property; (2) the earliest date in one of the three states that contain the largest property holdings of the firm (based on the book value of the firm's property holdings); and (3) the date of the announcement in the firm's headquarters state. This produces six (expected) NPI announcement dates for each firm. For brevity, we discuss our event study results using the announcements of (1) SOEs in the firm's top-3 states, (2) SIPOs in the firm's top-3 states, and (3) SOEs in the firm's HQ state.[31]

We first estimate abnormal returns (AR) for each firm using daily excess returns and a market model. The estimation window includes 250 days of stock returns and ends 50 days before the event window. The event window is from day -30 to day +30 relative to the NPI announcement. Next, we average across the abnormal returns for all firms that focus on a particular property type to find average abnormal returns (AARs) on day *t*. Finally, we chain-link the AARs over *T* days in the event window to obtain the buy-and-hold cumulative average abnormal return (CAAR). Figure 9 depicts the cumulative average abnormal returns (CAARs) across property types around the announcement of SOEs (Panel A) and SIPOs (Panel B) based on the firm's top-3 states.

Inspection of Figure 9 reveals that, on average, returns were negatively affected by SOE announcements. In addition, the pattern of CAARs by property type is consistent with our previous finding that technology, self-storage and industrial REITs have been the least affected by the pandemic. In contrast, retail and hospitality have experienced the hardest hit. Health care REITs, especially those specialized in senior housing, also have large negative CAARs, although across the entire sample period their risk-adjusted returns are close to zero

[30] Many states announced stay-at-home orders that have similar effects on business activity as SIPOs. We therefore do not differentiate between stay-at-home orders and SIPOs.
[31] Results based on the other three announcement dates are similar and available upon request.

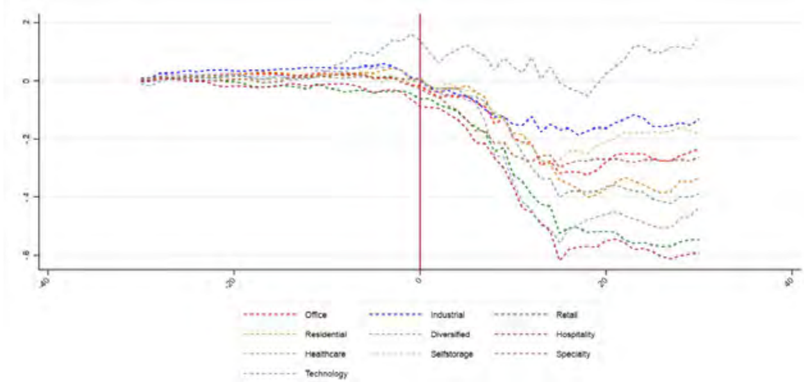
Covid Economics 22, 26 May 2020: 205-260

(Figure 4) and their return correlation with *GeoCOVID* is positive (Figures 6 and 7). A comparison of Panel A and Panel B suggests that CAARs started to decline before SIPO announcements. This confirms our conjecture that, after the announcements of SOEs, SIPOs were anticipated by investors. At the firm level, we chain-link abnormal returns over *T* days (e.g., 3, 5, 11, and 21 days) to obtain the buy-and-hold cumulative abnormal returns (CARs). We summarize the results based on CARs over 3- and 11-day windows in Appendix 3. Our findings suggest that REIT returns plummeted in response to NPI announcements. For example, using announcements of SOEs in the firm's top-3 states, we find that the average 11-day CAR is -10% for all REITs and -15% (-11%) for hospitality (retail) REITs. The only exception is technology REITs, which seem immune to NPIs in our event study windows.

Figure 9: Market Reactions to Non-Pharmaceutical Interventions

This figure depicts the cumulative average abnormal returns (CAARs) across property types around the announcement of state-level non-pharmaceutical interventions (vertical line at day 0). The announcement date for a firm is defined as the earliest date of state-of-emergency declaration in any jurisdiction (city or county) in the top-3 states ranked by the size of its property holdings (headquarters state) in Panel A (Panel B). See Appendix 2 for descriptions of property types.

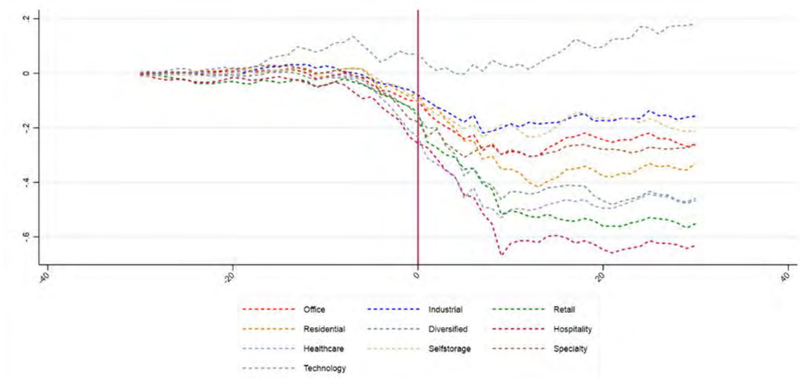
Panel A: State-of-Emergency Declaration



Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

Panel B: Shelter-in-Place Orders



How do changes in expectations about public policy affect firms with different characteristics? In untabulated results, we find no consistent evidence that CARs are correlated with leverage, cash holdings, Tobin's Q, return momentum, institutional ownership, investment, and EBITDA. This is consistent with our earlier finding (Table 6) that firm characteristics have little effect on the negative stock price impact of the pandemic.

Given our earlier finding that risk-adjusted returns are negatively associated with *GeoCOVID*, we next investigate whether the sensitivity of returns to *GeoCOVID* is reduced after policy responses to the crisis. We construct an indicator variable for post-SOE-announcement period for each firm and interact it with *GeoCOVID*. These two variables are added to the baseline risk-adjusted return specifications reported in Table 2 that include our full set of control variables and property type fixed effects. Results reported in Table 7 suggest that 1-day risk adjusted returns respond less negatively to *GeoCOVID* after SOE announcements. This result is robust to using both the firm's headquarters state and the top-3 states in which the portfolio manager invests to identify the date of announcement. However, the post-announcement sensitivity of returns to *GeoCOVID* remains unchanged when using 3-day returns or when using 2-day returns and the date of the SOE in the firm's top 3 states. In addition, the coefficients on the post-SOE dummy and *GeoCOVID* are consistently negative and highly significant in all model specifications.

In sum, investors' responses to expected NPIs vary dramatically across property types. However, other firm characteristics do not explain cross-sectional variation in the abnormal returns. Moreover, there is some evidence that investors respond less negatively to COVID growth rates when anticipated public policies are announced to reduce the spread of the virus.

4.8 Liquidity and geographically weighted COVID-19 growth

How does the COVID-19 pandemic affect trading activities? To address this question, we examine the impact of *GeoCOVID* on daily trading activity using our previously constructed sample of CRE portfolios. We first estimate the relation between the daily growth rate in reported COVID-19 cases on day *t*-1 and the log of trading volume, *ln Volume*, on day *t*. Our specification also includes *Days since outbreak*, *Days since outbreak*^{2}, and *GeoDensity*. Our full set of firm-level control variables are also included although these coefficients estimates are suppressed to conserve space. Property type fixed effects are included in this pooled, cross-sectional regression with 11,210 observations. Standard errors are clustered at the firm level. The results are displayed in column (1) of Table 8.

The estimated coefficient on *GeoCOVID* is positive and highly significant, indicating that an increase in a firm's property portfolio exposure to COVID-19 cases on day *t*-1 is associated with significantly higher transaction volume on day *t*. The estimated coefficient on *Days since outbreak* is also positive and highly significant at the 1% level. This suggests that trading volume is significantly related to the duration of the firms' exposure to COVID-19 cases. However, the estimated coefficient on *Days since outbreak*^{2} is negative and significant. The estimated coefficient on *GeoDensity* is negative and weakly significant.

In the second stage of our trading activity analysis, we replace *ln Volume* with the log of the daily turnover of outstanding shares, *ln Turnover*. These results are reported in column (2) of Table 8. The estimated coefficient on *GeoCOVID* is positive and highly significant(t-stat=9.41) and the estimated coefficient on *Days since outbreak* is also positive and highly significant (t-stat=5.28). However, the estimated coefficient on *Days since outbreak*^{2} cannot be distinguished from zero. The estimated coefficient on *GeoDensity* remains negative and increases in statistical significance.

Although trading volume and share turnover are widely used proxies for share liquidity, they are highly correlated with volatility, which can impede market liquidity. Therefore, these measures might be less reliable during turbulent market conditions. For instance, until February 17, the historical level of the CBOE Volatility Index (VIX) is below \$20. However, when governments in the European Union announced responses to the outbreak of COVID-19 with partial lockdowns on March 5, the level of VIX surged to \$39.62.

Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

It further jumped to an unprecedented level of $82.69 on March 16, when world stock markets dropped by as much as 11%. To address this mismatch between trading volume and market liquidity, Amihud (2002) proposes a measure of share liquidity that captures the responsiveness of daily share prices to daily trading volume. In particular, the more responsive a firm's share price is to trading volume, the more *illiquid* is the stock. We define *lnAmihud* as the logarithm of Amihud's (2002) illiquidity measure. In column (3) of Table 8, we present the results from estimating our pooled-cross-sectional regression using *lnAmihud* as the dependent variable. The estimated coefficient on *GeoCOVID* is positive and weakly significant(t-stat=1.67). This indicates that increases in *GeoCOVID* are associated with an increase in illiquidity. Recall that Amihud's (2002) illiquidity measure is defined as the daily volume price impact. Thus, although increases in *GeoCOVID* on day t-1 are associated with increased trading activity on day t (columns (1) and (2)), share prices actually become more sensitive to trading volumes (column (3)) due to increased volatility.

To further investigate the effects of the COVID-19 pandemic on trading activity and illiquidity in the listed CRE market, we first replace the volume of stock transaction on day t-1 with the change in the number of transaction from day t-2 to day t-1. We define this daily change variable as Δ*lnVol*. Similarly, Δ*lnTurn* and Δ*lnAmihud* are defined as the change in share turnover and the change in Amihud illiquidity, respectively, from day t-2 to day t-1. These regression results are reported in columns (4) through (6) of Table 8. As with our level regressions, *GeoCOVID* is associated with an increase in both transaction volumes and share turnover, but also with increased illiquidity, as defined by Amihud (2002).

4.9 Robustness Tests using Alternative Sample Periods

In Table 9, we report our baseline results estimated using the hump-shaped period of *GeoCOVID* from February 27 to April 13, 2020 (as shown in Figure 3 and discussed in Section 2), as well as an extended period from January 21 to April 30, 2020. The coefficient estimates on *GeoCOVID* are negative and statistically significant in all model specifications. We conclude that our results are highly robust to alternative sample (sub)periods.

5. Conclusion and Discussion

How does the shock of COVID-19 transmit to the equity markets from a firm's underlying assets? To answer this question, we employ asset-level data from the commercial real estate (CRE) market and construct a novel measure of geographically weighted exposure to COVID-19 growth (*GeoCOVID*) using a sample of equity REITs during the early stages of the pandemic from January 21, 2020, to April 15, 2020.

We first document a large variation in performance across REITs' property type focus. Different property sectors face different exposures to the pandemic, and REIT returns reflect these differences. Technology, self-storage, and industrial warehouse REITs produced positive risk-adjusted returns while hospitality and retail REITs performed the worst. Examining the correlation between returns and *GeoCOVID* across property types, we find the returns for REITs specialized in retail, office, and residential (health care and technology) are negatively (positively) correlated with *GeoCOVID*.

Using different benchmarks for risk adjustment, different return windows, and different model specifications, we find a consistent negative relationship between risk-adjusted returns and *GeoCOVID*. Specifically, firms in retail and residential react more negatively among all sectors. In contrast, the performance of the health care and technology sectors correlate positively with *GeoCOVID*.

It is important to note that *GeoCOVID* explains risk-adjusted returns even after controlling for the national growth rate of COVID cases and after we orthogonalize *GeoCOVID* with respect to the nation-wide measure. Furthermore, we find that firms with more assets allocated to areas with higher population density react more negatively to the pandemic. An investigation of a variety of firm characteristics reveals that only a firm's stock returns in the fourth quarter of 2019 are associated with the stock market reaction to *GeoCOVID*, after conditioning on firms' property type and geographic concentrations, days since the outbreak, and population density.

Our event study results using announcements of state of emergency declarations and non-pharmaceutical interventions (NPIs) confirms that the variation in abnormal return is mainly driven by property type focus, not other firm characteristics. Despite negative short-term market reactions, there is some evidence of changes in expectations about the efficacy of these NPI policies as the sensitivity of risk-adjusted returns to *GeoCOVID* is reduced after these announcements. These results suggest that investors expected the effectiveness of these policies in slowing down the spread of the virus to outweigh their expected economic cost. Finally, we find both trading activity and illiquidity increases with *GeoCOVID*. Our results are robust to alternative sample periods, including the hump-shaped period of rapid and then decelerating growth in COVID-19 cases, as well as extending the sample period through April 30, 2020.

Covid Economics 22, 26 May 2020: 205-260

Taken together, our results highlight the importance of asset-level attributes in explaining investors' reactions to the pandemic. Although our sample period is relatively short, movements in stock returns contain forward-looking information and stock prices are based on prospective future earnings. Whether the shock of COVID-19 on CRE prices remains large in the long run depends crucially on the resilience of the overall economy and, perhaps more importantly, how perceptions of risk changes after the pandemic. For example, a few firms (e.g., Morgan Stanley, JPMorgan Chase, and Nielsen) currently occupying large amounts of office space in Manhattan have indicated that they expect to occupy considerably less space once the pandemic passes.[32] However, it remains to be seen if stock prices during the early stages of the pandemic overreacted or underreacted to this anticipated change in office occupancy. As Warrant Buffett stated: "a lot of people have learned that they can work at home." Dingel and Neiman (2020) find that 37 percent of jobs in the US can be done entirely at home. Many top occupations (e.g., computer, legal, management, sales) and top industries (e.g., finance and insurance, information) are those currently occupying large amounts of CRE space. Permanent changes in work and lifestyle should differentially affect the rent generating ability and perceived risk of different types of business activities, as suggested by our finding of substantial variation across property types. These differential effects are certain to be observed across industry sectors outside of the CRE space.

Finally, the economic effects of social distancing are most severe among businesses that reply heavily on face-to-face communication or close physical proximity. As pointed out by Koren and Peto (2020), the agglomeration premium might fall when firms find it less attractive to locate in high density areas in a post-pandemic spatial equilibrium. This would suggest a reduced rent premium in highly desirable (pre-pandemic) urban areas, as suggested by our finding of negative return responses to increases in the growth of COVID-19 cases and to increases in population density in locations in which firms own assets.

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Table 1: Summary Statistics

This table shows summary statistics (number of observations, mean, standard deviation (SD), and 25th, 50th, and 75th percentiles) for a sample of 11,210 firm-day observations from the period January 21, 2020, through April 15, 2020.

Variable	N	Mean	SD	p25	p50	p75
Risk Adj. Returns (*based on S&P500*)						
1-day risk adj. return	11,210	-0.006	0.061	-0.022	-0.001	0.013
2-day risk adj. return	5,510	-0.013	0.079	-0.039	-0.003	0.016
3-day risk adj. return	3,800	-0.019	0.102	-0.054	-0.005	0.019
Market Liquidity Measures						
Volume	11,210	55925	111902	5489	21964	62027
Turnover	11,210	0.011	0.013	0.005	0.008	0.014
Amihud	11,210	0.263	6.528	0.000	0.001	0.005
ΔVolume	11,210	19.063	4.610	17.220	19.974	22.057
ΔTurnover	11,210	0.023	0.023	0.010	0.017	0.028
ΔAmihud	11,210	0.081	0.461	0.001	0.002	0.010
Risk Adj. Returns (*based on NAREIT*)						
1-day risk adj. return	11,210	-0.008	0.070	-0.026	-0.001	0.016
2-day risk adj. return	5,510	-0.015	0.087	-0.046	-0.004	0.017
3-day risk adj. return	3,800	-0.022	0.112	-0.061	-0.006	0.020
COVID-19 Exposure Variables						
GeoCOVID	11,210	0.066	0.094	0	0.005	0.117
Days since outbreak	11,210	33	29	11	33	56
Control Variables						
GeoDensity	11,210	4887	9373	1180	1793	4165
PropHHI	11,210	0.788	0.280	0.583	0.949	0.999
GeoHHI	11,210	0.119	0.175	0.020	0.049	0.126
Leverage	11,210	0.490	0.159	0.403	0.474	0.575
Cash	11,210	0.037	0.083	0.005	0.013	0.036
Size	11,210	6641	10129	1664	3925	8297
Tobin's Q	11,210	1.498	0.584	1.147	1.372	1.690
LAG3MRET	11,210	0.034	0.061	0.001	0.040	0.066
InstOwn	11,210	0.811	0.237	0.688	0.880	0.979
Investment	11,210	0.092	0.331	-0.032	0.028	0.171
EBITDA/AT	11,210	0.021	0.012	0.015	0.020	0.025
Office	11,210	0.111	0.314	0	0	0
Industrial	11,210	0.068	0.252	0	0	0
Retail	11,210	0.189	0.392	0	0	0
Residential	11,210	0.074	0.261	0	0	0
Diversified	11,210	0.147	0.354	0	0	0
Hospitality	11,210	0.142	0.349	0	0	0
Health Care	11,210	0.105	0.307	0	0	0
Self-storage	11,210	0.037	0.188	0	0	0
Specialty	11,210	0.095	0.293	0	0	0
Technology	11,210	0.032	0.175	0	0	0

Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

Table 2: Baseline Results – Risk-Adjusted Returns and Geographically Weighted COVID-19 Growth

This table shows regression results on the relationship between risk-adjusted returns and the growth rate of geographically weighted COVID-19 cases. The dependent variable, *Ret,* is the daily risk adj. returns in Columns (1)-(3), the 2-day risk adj. returns in Columns (4)-(6), and the 3-day risk adj. returns in Columns (7)-(9). *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Panel A (B) shows the results using risk-adjusted returns based on the S&P 500 Index (NAREIT Equity Index) as the dependent variable. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Risk-Adjusted Returns based on S&P 500

	(1) *Ret (1-day)*	(2) *Ret (1-day)*	(3) *Ret (1-day)*	(4) *Ret (2-day)*	(5) *Ret (2-day)*	(6) *Ret (2-day)*	(7) *Ret (3-day)*	(8) *Ret (3-day)*	(9) *Ret (3-day)*
GeoCOVID	-0.024***	-0.026***	-0.022***	-0.070***	-0.086***	-0.080***	-0.089***	-0.099***	-0.088***
	(-4.70)	(-3.82)	(-3.01)	(-6.72)	(-5.98)	(-5.13)	(-5.91)	(-4.72)	(-3.89)
Days since outbreak		-0.000***	-0.000***		-0.000***	-0.000***		-0.001***	-0.001***
		(-7.01)	(-6.72)		(-6.39)	(-5.89)		(-6.53)	(-6.23)
Days since outbreak^2		0.000***	0.000***		0.000***	0.000***		0.000***	0.000***
		(8.73)	(8.24)		(9.00)	(8.42)		(8.51)	(8.06)
ln(GeoDensity)		0.001***			0.001***			0.002***	
		(5.17)			(6.08)			(5.73)	
PropHHI		-0.001*			-0.003**			-0.005**	
		(-1.97)			(-2.16)			(-2.22)	
GeoHHI		-0.002*			-0.003			-0.006*	
		(-1.97)			(-1.28)			(-1.86)	
Leverage		-0.003***			-0.006***			-0.009***	
		(-2.82)			(-2.99)			(-2.93)	
Cash		-0.003*			-0.006			-0.011*	
		(-1.66)			(-1.38)			(-1.74)	
ln(Size)		0.000			0.000			0.000	
		(1.42)			(1.41)			(0.92)	
Tobin's Q		0.001*			0.001**			0.002**	
		(1.79)			(1.98)			(2.18)	
LAG3MRET		0.000***			0.000***			0.001***	
		(20.05)			(20.76)			(19.42)	
InstOwn		0.001			0.001			0.003	
		(0.65)			(0.57)			(1.10)	
Investment		0.000			0.000			0.000	
		(0.19)			(0.02)			(0.32)	
EBITDA/AT		0.005			0.011			0.013	
		(0.33)			(0.42)			(0.33)	
Constant	-0.005***	-0.001	-0.004***	-0.008***	-0.003	-0.008***	-0.013***	-0.002	-0.011***
	(-12.18)	(-0.70)	(-8.99)	(-10.00)	(-0.73)	(-8.46)	(-10.86)	(-0.43)	(-8.97)
FE	Prop type	Prop type	Firm	Prop type	Prop type	Firm	Prop type	Prop type	Firm
R Squared	0.005	0.012	0.013	0.016	0.034	0.037	0.018	0.041	0.044
Observations	11210.000	11210.000	11210.000	5510.000	5510.000	5510.000	3800.000	3800.000	3800.000

Panel B: Risk-Adjusted Returns based on NAREIT

	(1) *Ret (1-day)*	(2) *Ret (1-day)*	(3) *Ret (1-day)*	(4) *Ret (2-day)*	(5) *Ret (2-day)*	(6) *Ret (2-day)*	(7) *Ret (3-day)*	(8) *Ret (3-day)*	(9) *Ret (3-day)*
GeoCOVID	-0.021***	-0.031***	-0.028***	-0.069***	-0.108***	-0.105***	-0.070***	-0.103***	-0.094***
	(-3.92)	(-4.32)	(-3.61)	(-6.44)	(-7.15)	(-6.53)	(-4.42)	(-4.53)	(-3.80)
Days since outbreak		-0.000***	-0.000***		-0.000***	-0.001***		-0.001***	-0.001***
		(-6.99)	(-6.30)		(-6.24)	(-5.34)		(-6.66)	(-5.98)
Days since outbreak²		0.000***	0.000***		0.000***	0.000***		0.000***	0.000***
		(10.55)	(9.57)		(10.79)	(9.79)		(10.24)	(9.37)
ln(GeoDensity)		0.001***			0.002***			0.002***	
		(6.58)			(7.35)			(6.80)	
PropHHI		-0.002**			-0.003**			-0.005**	
		(-2.31)			(-2.50)			(-2.52)	
GeoHHI		-0.003**			-0.003			-0.008**	
		(-2.15)			(-1.12)			(-2.09)	
Leverage		-0.003***			-0.007***			-0.010***	
		(-3.48)			(-3.75)			(-3.62)	
Cash		-0.004**			-0.008*			-0.014**	
		(-2.41)			(-1.88)			(-2.54)	
ln(Size)		0.000			-0.000			-0.000	
		(0.16)			(-0.06)			(-0.34)	
Tobin's Q		0.001***			0.001***			0.002***	
		(2.61)			(3.22)			(3.04)	
LAG3MRET		0.000***			0.000***			0.001***	
		(22.85)			(24.27)			(22.43)	
InstOwn		0.001			0.001			0.004	
		(1.14)			(1.03)			(1.62)	
Investment		-0.000			-0.001			-0.001	
		(-0.92)			(-1.33)			(-0.85)	
EBITDA/AT		-0.001			0.004			-0.004	
		(-0.07)			(0.18)			(-0.12)	
Constant	-0.006***	-0.002	-0.006***	-0.011***	-0.004	-0.013***	-0.018***	-0.005	-0.018***
	(-14.70)	(-1.05)	(-10.98)	(-12.04)	(-0.99)	(-11.04)	(-13.66)	(-0.80)	(-11.60)
FE	Prop type	Prop type	Firm	Prop type	Prop type	Firm	Prop type	Prop type	Firm
R Squared	0.004	0.013	0.014	0.014	0.041	0.043	0.014	0.045	0.048
Observations	11210.000	11210.000	11210.000	5510.000	5510.000	5510.000	3800.000	3800.000	3800.000

Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

Table 3: Risk Adjusted Returns and Geographically weighted COVID-19 Growth by Property Type

This table shows regression results on the relationship between daily risk-adjusted returns and the growth rate of geographically weighted COVID-19 cases interacted with property type dummies. Columns (1)-(3) ((4)-(6)) present the results using risk-adjusted returns based on the S&P 500 Index (NAREIT Equity Index) as the dependent variable. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Control variables are the same as Columns (2) in Table 2 and suppressed. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk Adj. using S&P500			*Risk Adj. using NAREIT*		
	Ret (1-day)	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*
Office × GeoCOVID	-0.026***	-0.073***	-0.089***	-0.030***	-0.100***	-0.112***
	(-4.67)	(-5.24)	(-3.69)	(-4.59)	(-6.13)	(-3.75)
Industrial × GeoCOVID	0.002	-0.060**	0.004	-0.006	-0.081***	0.012
	(0.13)	(-2.02)	(0.13)	(-0.34)	(-2.67)	(0.36)
Retail × GeoCOVID	-0.073***	-0.183***	-0.229***	-0.074***	-0.192***	-0.210***
	(-4.80)	(-6.62)	(-5.23)	(-4.79)	(-6.95)	(-4.89)
Residential × GeoCOVID	-0.066***	-0.167***	-0.138***	-0.069***	-0.180***	-0.143***
	(-5.15)	(-5.67)	(-3.78)	(-4.88)	(-5.66)	(-3.68)
Diversified × GeoCOVID	-0.037**	-0.099***	-0.085*	-0.044**	-0.122***	-0.084
	(-2.34)	(-3.38)	(-1.92)	(-2.58)	(-3.93)	(-1.64)
Hospitality × GeoCOVID	-0.026**	-0.045	-0.199***	-0.031**	-0.078**	-0.208***
	(-2.00)	(-1.30)	(-4.38)	(-2.25)	(-2.19)	(-4.47)
Health Care × GeoCOVID	0.039**	0.017	0.076	0.038**	0.013	0.098*
	(2.41)	(0.52)	(1.43)	(2.20)	(0.35)	(1.69)
Self-storage × GeoCOVID	-0.016**	-0.073***	-0.039	-0.021***	-0.089***	-0.041
	(-2.20)	(-2.93)	(-0.70)	(-2.77)	(-3.69)	(-0.78)
Specialty × GeoCOVID	0.016	-0.020	-0.013	0.011	-0.026	-0.003
	(0.92)	(-0.62)	(-0.17)	(0.66)	(-0.71)	(-0.04)
Technology × GeoCOVID	0.038**	0.039	0.104***	0.030	0.016	0.105***
	(2.33)	(1.14)	(3.27)	(1.50)	(0.39)	(2.66)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R Squared	0.023	0.058	0.071	0.022	0.061	0.071
Observations	11210	5510	3800	11210	5510	3800

Table 4: Asset Allocation and COVID-19 Growth

This table shows regression results on the relationship between risk-adjusted returns and alternative measures of COVID-19 exposure. The dependent variable, *Ret,* is the 1-day, 2-day, or 3-day risk-adjusted returns based on S&P500. *USCOVID* is the U.S. daily growth rate of COVID-19 cases. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. *O.GeoCOVID* is the *GeoCOVID* orthogonalized by *USCOVID*. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ret (1-day)	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*
USCOVID	-0.023***	-0.086***	-0.089***	-0.020***	-0.076***	-0.080***	-0.024***	-0.089***	-0.097***
	(-8.86)	(-14.39)	(-14.84)	(-7.06)	(-12.00)	(-12.87)	(-8.75)	(-14.09)	(-13.40)
GeoCOVID				-0.016**	-0.044***	-0.056***			
				(-2.15)	(-2.91)	(-2.73)			
O.GeoCOVID							-0.001**	-0.003***	-0.004***
							(-2.15)	(-2.91)	(-2.73)
Days since outbreak	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.85)	(-5.85)	(-6.86)	(-6.22)	(-4.87)	(-5.80)	(-6.22)	(-4.87)	(-5.80)
Days since outbreak^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(7.55)	(6.70)	(6.90)	(7.83)	(7.15)	(7.21)	(7.83)	(7.15)	(7.21)
ln(GeoDensity)	0.000***	0.000**	0.001***	0.000***	0.001***	0.001***	0.000***	0.001***	0.001***
	(3.19)	(2.58)	(3.62)	(3.77)	(3.41)	(4.33)	(3.77)	(3.41)	(4.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R Squared	0.013	0.045	0.050	0.014	0.046	0.052	0.014	0.046	0.052
Observations	11,210	5,510	3,800	11,210	5,510	3,800	11,210	5,510	3,800

Covid Economics 22, 26 May 2020: 205-260

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Table 5: Risk-Adjusted Returns and Geographically Weighted COVID-19 Growth by Asset Allocation

This table shows regression results on the relation between risk-adjusted returns and the geographically weighted growth rate of confirmed COVID-19 cases, interacted with geographically weighted population density (*GeoDensity*), property type concentration (*PropHHI*), and geographic concentration (*GeoHHI*). The dependent variable, *Ret,* is the 1-day risk adj. return in Columns (1) to (3), the 2-day risk adj. return in Columns (4) to-(6), and the 3-day risk adj. return in Columns (7) to (9). *Dummy (above median)* indicates that the asset allocation variable of a firm is above the sample median. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Panel A (B) shows the results using risk-adjusted returns based on the S&P 500 Index (FTSE-NAREIT All Equity REITs Index) as the dependent variable. The control variables included are the same as those used in our baseline regressions (see Table 2). The control variable results are suppressed. See Appendix 1 for variable descriptions. Property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Ret (1-day)* *Density*	(2) *Ret (1-day)* *PropHHI*	(3) *Ret (1-day)* *GeoHHI*	(4) *Ret (2-day)* *Density*	(5) *Ret (2-day)* *PropHHI*	(6) *Ret (2-day)* *GeoHHI*	(7) *Ret (3-day)* *Density*	(8) *Ret (3-day)* *PropHHI*	(9) *Ret (3-day)* *GeoHHI*
Panel A: Risk Adj. Return (Using S&P500)									
Dummy (above median) ×	-0.023**	-0.000	-0.004	-0.056**	-0.002	-0.003	-0.108***	-0.041	-0.063**
GeoCOVID	(-2.20)	(-0.03)	(-0.41)	(-2.59)	(-0.12)	(-0.15)	(-3.58)	(-1.36)	(-2.02)
Dummy (above median)	0.002***	-0.000	0.000	0.005***	-0.000	0.001	0.009***	0.002	0.005**
	(2.63)	(-0.01)	(0.67)	(3.32)	(-0.05)	(0.80)	(4.14)	(1.07)	(2.33)
GeoCOVID	-0.011	-0.024***	-0.022**	-0.048**	-0.081***	-0.080***	-0.029	-0.077***	-0.051*
	(-1.06)	(-3.04)	(-2.32)	(-2.30)	(-4.73)	(-4.65)	(-1.00)	(-3.29)	(-1.73)
R Squared	0.010	0.009	0.009	0.028	0.027	0.027	0.034	0.032	0.033
Panel B: Risk Adj. Return (Using NAREIT)									
Dummy (above median) ×	-0.024**	0.001	-0.001	-0.065***	-0.004	-0.006	-0.141***	-0.032	-0.081**
GeoCOVID	(-2.16)	(0.12)	(-0.12)	(-2.96)	(-0.18)	(-0.30)	(-4.43)	(-1.00)	(-2.52)
Dummy (above median)	0.002**	-0.000	0.001	0.005***	-0.000	0.002	0.011***	0.001	0.007***
	(2.55)	(-0.39)	(0.79)	(3.71)	(-0.26)	(1.56)	(4.96)	(0.55)	(3.12)
GeoCOVID	-0.015	-0.030***	-0.028***	-0.062***	-0.101***	-0.098***	-0.012	-0.083***	-0.040
	(-1.42)	(-3.49)	(-2.98)	(-2.86)	(-5.46)	(-5.64)	(-0.37)	(-3.20)	(-1.34)
R Squared	0.008	0.008	0.008	0.028	0.026	0.026	0.031	0.028	0.029
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
Observations	11210	11210	11210	5510	5510	5510	3800	3800	3800

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Table 6: Risk-Adjusted Returns and Geographically Weighted COVID-19 Growth by Firm Characteristics

This table shows regression results on the relationship between daily risk-adjusted returns and geographically weighted growth rate of COVID-19 confirmed cases interacted with firm financial characteristics. The dependent variable, *Ret,* is the daily risk adj. returns in Panel A, the 2-day risk adj. returns in Panel B, and the 3-day risk adj. returns in Panel C. *Dummy (above median)* indicates that the firm characteristic variable of a firm is above sample median. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Property type fixed effects are included in the regression. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Firm Characteristics	*Ln(Size)*	*Leverage*	*Cash*	*Tobin's Q*	*LAG3MRET*	*InstOwn*	*Investment*	*EBITA/AT*
Panel A. Dependent variable: 1-day risk adj. return (using S&P500)								
Dummy (> Median)	0.001*	0.001	0.000	-0.000	0.003***	0.001	-0.000	0.000
	(1.70)	(1.34)	(0.34)	(-0.58)	(3.49)	(1.13)	(-0.31)	(0.69)
GeoCOVID	-0.022**	-0.018***	-0.027***	-0.035***	-0.047***	-0.020**	-0.032***	-0.029***
	(-2.06)	(-2.70)	(-2.90)	(-3.69)	(-4.70)	(-2.00)	(-3.67)	(-3.03)
Dummy (> Median) ×	-0.014	-0.024**	-0.003	0.011	0.038***	-0.009	0.006	-0.001
GeoCOVID	(-1.38)	(-2.42)	(-0.27)	(1.10)	(3.87)	(-0.86)	(0.58)	(-0.10)
R Squared	0.009	0.010	0.009	0.009	0.008	0.009	0.009	0.009
Observations	11210	11210	11210	11210	11210	11210	11210	11210
Panel B. Dependent variable: 2-day risk adj. return (using S&P500)								
Dummy (> Median)	0.002	0.001	-0.000	-0.001	0.007***	0.001	0.000	0.000
	(1.22)	(0.38)	(-0.25)	(-0.47)	(3.38)	(0.91)	(0.12)	(0.02)
GeoCOVID	-0.091***	-0.091***	-0.103***	-0.113***	-0.137***	-0.088***	-0.103***	-0.109***
	(-4.33)	(-6.81)	(-5.52)	(-6.03)	(-6.32)	(-4.30)	(-5.23)	(-5.69)
Dummy (> Median) ×	-0.016	-0.031	0.007	0.023	0.073***	-0.012	0.003	0.012
GeoCOVID	(-0.77)	(-1.44)	(0.36)	(1.12)	(3.71)	(-0.60)	(0.14)	(0.60)
R Squared	0.027	0.027	0.027	0.027	0.024	0.027	0.027	0.027
Observations	5510	5510	5510	5510	5510	5510	5510	5510
Panel C. Dependent variable: 3-day risk adj. return (using S&P500)								
Dummy (> Median)	0.003	-0.001	0.004*	-0.005**	0.007**	0.001	-0.004**	-0.001
	(1.26)	(-0.24)	(1.68)	(-2.35)	(2.28)	(0.31)	(-2.17)	(-0.33)
GeoCOVID	-0.073**	-0.092***	-0.065**	-0.141***	-0.179***	-0.087***	-0.138***	-0.114***
	(-2.25)	(-4.27)	(-2.02)	(-4.94)	(-5.82)	(-2.80)	(-4.89)	(-3.92)
Dummy (> Median) ×	-0.030	-0.027	-0.053*	0.094***	0.162***	0.007	0.075**	0.027
GeoCOVID	(-0.97)	(-0.86)	(-1.70)	(3.26)	(5.83)	(0.22)	(2.60)	(0.93)
R Squared	0.032	0.032	0.032	0.034	0.032	0.032	0.033	0.032
Observations	3800	3800	3800	3800	3800	3800	3800	3800
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type

Covid Economics 22, 26 May 2020: 205-260

Table 7: Risk Adjusted Returns and Non-Pharmaceutical Interventions

This table shows regression results on the relationship between daily risk-adjusted returns and the growth rate of geographically weighted COVID-19 cases interacted with dummies proxied for any expected non-pharmaceutical interventions (NPIs). Columns (1)-(2), (3)-(4), and (5)-(6) present the results using 1-day, 2-day, and 3-day risk-adjusted returns as the dependent variable. *Post SOE(HQ)* and *Post SOE(Top-3)* indicate that a state-of-emergency declaration has been made in any jurisdiction (either city or county) within the headquarters state of a firm and the top-3 states ranked by the size of its property holdings, respectively. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Control variables are the same as Columns (2) in Table 2 and suppressed. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Risk Adj. (using S&P500)	*Ret (1-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (2-day)*	*Ret (3-day)*	*Ret (3-day)*
Post SOE(HQ)	-0.016***		-0.018***		-0.018***	
	(-7.62)		(-4.57)		(-3.09)	
Post SOE(HQ) × GeoCOVID	0.069***		0.063***		0.042	
	(5.10)		(2.78)		(0.78)	
Post SOE (Top-3 States)		-0.015***		-0.019***		-0.030***
		(-10.29)		(-6.59)		(-7.41)
Post SOE (Top-3 States) ×		0.030**		0.016		-0.057
GeoCOVID		(2.58)		(0.70)		(-0.94)
GeoCOVID	-0.086***	-0.056***	-0.169***	-0.128***	-0.223***	-0.118**
	(-7.89)	(-5.39)	(-9.33)	(-6.65)	(-4.61)	(-2.03)
Days since outbreak	0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.22)	(1.47)	(-0.28)	(0.48)	(-0.55)	(1.49)
Days since outbreak²	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(7.20)	(7.84)	(7.15)	(7.74)	(6.52)	(7.44)
ln(GeoDensity)	-0.000	-0.000	0.001	0.001*	0.000	0.001
	(-0.67)	(-0.40)	(1.48)	(1.85)	(0.56)	(0.89)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R Squared	0.022	0.023	0.061	0.063	0.091	0.096
Observations	11210	11210	5510	5510	3800	3800

Covid Economics 22, 26 May 2020: 205-260

Table 8: Market Liquidity and Geographically weighted COVID-19 Growth

This table shows regression results on the relationship between daily market liquidity measures and the growth rate of geographically weighted COVID-19 cases. Columns (1)-(3) ((4)-(6)) present the results using the log of level (change) of the logarithms of dollar volume, turnover, and Amihud's illiquidity as the dependent variable. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Control variables are the same as Columns (2) in Table 2 and suppressed. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Level			*Change*	
	lnVolume	*lnTurnover*	*lnAmihud*	*ΔVolume*	*ΔTurnover*	*ΔAmihud*
GeoCOVID	0.692***	0.022***	0.080*	1.540***	0.045***	0.222**
	(3.54)	(9.41)	(1.67)	(3.98)	(9.53)	(2.15)
Days since outbreak	0.006***	0.000***	0.002**	0.012**	0.000***	0.003**
	(2.70)	(5.28)	(2.47)	(2.60)	(5.13)	(2.49)
Days since outbreak^2	-0.000***	-0.000	-0.000**	-0.000***	-0.000	-0.000***
	(-3.13)	(-1.57)	(-2.58)	(-2.93)	(-1.16)	(-2.60)
ln(GeoDensity)	-0.111*	-0.001***	0.020	-0.222*	-0.002***	0.026
	(-1.72)	(-3.37)	(1.45)	(-1.72)	(-3.35)	(1.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R Squared	0.850	0.211	0.224	0.861	0.255	0.233
Observations	11210	11210	11210	11210	11210	11210

Covid Economics 22, 26 May 2020: 205-260

Table 9: Risk Adjusted Returns and Geographically weighted COVID-19 Growth During Different Periods

This table shows regression results on the relationship between daily risk-adjusted returns and the growth rate of geographically weighted COVID-19 cases during different sample periods. Columns (1)-(3) present the results based on 1-day, 2-day, and 3-day risk-adjusted returns during the humped period (from trading day 27 to 58 (February 27 to April 13, 2020) depicted in Figure 3. Columns (4)-(6) present the results using the extended sample period from January 21 to April 30, 2020. *GeoCOVID* is the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Control variables are the same as Columns (2) in Table 2 and suppressed. See Appendix 1 for variable descriptions and Appendix 2 for descriptions of property types. The numbers in parentheses are *t*-statistics. Standard errors are clustered at firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hump-shaped Period (February 27 to April 13, 2020)			*Extended Period (January 21 to April 30, 2020)*		
Risk Adj. using S&P500	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*	*Ret (1-day)*	*Ret (2-day)*	*Ret (3-day)*
GeoCOVID	-0.020**	-0.057***	-0.073***	-0.029***	-0.092***	-0.104***
	(-2.21)	(-3.01)	(-2.66)	(-4.82)	(-7.39)	(-5.69)
Days since outbreak	-0.001***	-0.001***	-0.003***	-0.000***	-0.000***	-0.001***
	(-5.24)	(-4.23)	(-5.17)	(-6.07)	(-5.46)	(-5.83)
Days since outbreak^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(8.66)	(7.70)	(8.56)	(9.77)	(10.16)	(9.72)
ln(GeoDensity)	-0.000	-0.001	-0.001	0.000	0.001***	0.001**
	(-1.03)	(-1.09)	(-0.96)	(0.80)	(2.85)	(2.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Prop type	Prop type	Prop type	Prop type	Prop type	Prop type
R Squared	0.035	0.064	0.117	0.014	0.042	0.045
Observations	5890	3040	1900	13161	6392	4326

Covid Economics 22, 26 May 2020: 205-260

Covid Economics 22, 26 May 2020: 205-260

Appendix 1: Variable Definitions

Variable	Source	Definition
Daily Risk Adj. Returns		
1-day risk adj. return	S&P Global, NAREIT	The daily risk-adjusted returns are calculated as $R_{i,t} - \beta_i M_t$. β_i is estimated from the market model for firm *i* from the beginning of 2019 to January 20, 2020. $R_{i,t}$ denotes stock returns for firm *i* on day *t*. M_d denotes daily returns on either the S&P 500 index or the NAREIT All Equity Index.
2-day risk adj. return	S&P Global, NAREIT	The non-overlapping cumulative risk-adjusted returns from day *t* to *t+1*.
3-day risk adj. return	S&P Global, NAREIT	The non-overlapping cumulative risk-adjusted returns from day *t-1* to *t+1*.
Market Liquidity Measures		
Volume	S&P Global	The daily dollar trading volume (in $1,000).
Turnover	S&P Global	The daily dollar trading volume divided by the daily market capitalization.
Amihud	S&P Global	The absolute daily stock return divided by the daily dollar trading volume.
COVID-19 Exposure Variables		
GeoCOVID	JHU COVID-19 Global Cases, S&P Global	The COVID-19 geographic exposure of a firm, calculated as the average of county-level daily growth rates of COVID-19 cases, weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. County-level daily growth rate of confirmed COVID-19 cases in county *l* on day *t* is calculated as $ln(1 + \#CASES_{l,t}) - ln(1 + \#CASES_{l,t-1})$.
HighGeoCOVID	JHU COVID-19 Global Cases, S&P Global	An indicator variable that equals one if *GeoCOVID* for firm *i* on day *t* is in the upper quartile of the growth rates across all counties in which the firm owns any property on day *t*
USCOVID	JHU COVID-19 Global Cases, S&P Global	The daily growth rates of COVID-19 confirmed cases across the U.S..
Days since outbreak	JHU COVID-19 Global Cases, S&P Global	The number of days since the outbreak of the COVID-19 pandemic in counties where a firm owns any property at the end of 2019Q4.
Days since outbreak^2	JHU COVID-19 Global Cases, S&P Global	The quadratic term of *Days since outbreak*.
Control Variables		
GeoDensity	S&P Global	The average of county-level population density weighted by the percentage of the CRE portfolio allocated to each county at the end of 2019Q4. Population density is defined as the number of people per square miles.
GeoHHI	S&P Global	The Herfindahl Indexes of each firm's property weights across the U.S. counties at the end of 2019Q4.
PropHHI	S&P Global	The Herfindahl Indexes of each firm's property weights in each of the ten property categories, including office, industrial, retail, residential, diversified, hospitality, health care, self-storage, specialty, and technology at the end of 2019Q4.
Leverage	S&P Global	Sum of total long-term debt and debt in current liabilities divided by book value of assets at the end of 2019Q4.

Variable	Source	Definition
Appendix 1. continued		
Cash	S&P Global	The ratio of cash and cash equivalents to book value of assets at the end of 2019Q4.
Size	S&P Global	The book value of assets at the end of 2019Q4.
Tobin's Q	S&P Global	The ratio of the market value of equity plus the book value of debt to the book value of assets/
LAG3MRET	S&P Global	Cumulative stock returns over 2019Q4 (in percentage).
InstOwn	S&P Global	The ratio of the number of shares held by institutional investors to the total number of shares outstanding at the end of 2019Q4.
Investment	S&P Global	The percentage growth rate in non-cash assets during 2019Q4.
EBITDA/AT	S&P Global	The ratio of EBITDA to book value of total assets at the end of 2019Q4.

Covid Economics 22, 26 May 2020: 205-260

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Covid Economics 22, 26 May 2020: 205-260

Appendix 2: Property Type Descriptions

This Appendix summarizes REITs by property types. The classification is based on S&P Global and NAREIT.

Property Type	# Stocks	Description
Office	22	Office REITs own and manage office real estate and rent space in those properties to tenants. Those properties can range from skyscrapers to office parks. Some office REITs focus on specific types of markets, such as central business districts or suburban areas. Some emphasize specific classes of tenants, such as government agencies or biotech firms.
Industrial	14	Industrial REITs own and manage industrial facilities and rent space in those properties to tenants. Some industrial REITs focus on specific types of properties, such as warehouses and distribution centers. Industrial REITs play an important part in e-commerce and are helping to meet the rapid delivery demand.
Retail	37	Retail REITs own and manage retail real estate and rent space in those properties to tenants. Retail REITs include REITs that focus on large regional malls, outlet centers, grocery-anchored shopping centers and power centers that feature big box retailers. Net lease REITs own freestanding properties and structure their leases so that tenants pay both rent and the majority of operating expenses for a property.
Residential	15	Residential REITs own and manage various forms of residences and rent space in those properties to tenants. Residential REITs include REITs that specialize in apartment buildings, student housing, manufactured homes and single-family homes. Within those market segments, some residential REITs also focus on specific geographical markets or classes of properties.
Diversified	32	Diversified REITs own and manage a mix of property types and collect rent from tenants. For example, diversified REITs might own portfolios made up of both office and industrial properties.
Hospitality	27	Hospitality REITs own and manage hotels and resorts and rent space in those properties to guests. Hospitality REITs own different classes of hotels based on features such as the hotels' level of service and amenities. Hospitality REITs' properties service a wide spectrum of customers, from business travelers to vacationers.
Health Care	20	Health care REITs own and manage a variety of health care-related real estate and collect rent from tenants. Health care REITs' property types include senior living facilities, hospitals, medical office buildings and skilled nursing facilities.
Self-storage	7	Self-storage REITs own and manage storage facilities and collect rent from customers. Self-storage REITs rent space to both individuals and businesses.
Specialty	18	Specialty REITs own and manage a unique mix of property types and collect rent from tenants. Specialty REITs own properties that do not fit within the other REIT types. Examples of properties owned by specialty REITs include movie theaters, casinos, farmland and outdoor advertising sites. This category also includes four Timber REITs which specialize in harvesting and selling timber.
Technology	6	This category includes Data Center and Infrastructure REITs. Data center REITs own and manage facilities that customers use to safely store data. Data center REITs offer a range of products and services to help keep servers and data safe, including providing uninterruptable power supplies, air-cooled chillers and physical security. Infrastructure REITs' property types include fiber cables, wireless infrastructure, telecommunications towers and energy pipelines.
Total	198	

Appendix 3: Market Reactions to Non-Pharmaceutical Interventions

This table presents summary statistics on cumulative abnormal returns (CARs). In columns (1)-(2) ((3)-(4)), the announcement date for a firm is defined as the earliest date of state-of-emergency declaration (shelter-in-place orders) in any jurisdiction (city or county) in the top-3 states ranked by the size of its property holdings. In columns (5)-(6), the announcement date is defined as the earliest date of state-of-emergency declaration in any jurisdiction in the headquarters state. CARs are constructed based on two event windows, including (-1,1) and (-5,5), which represent, respectively, 3-day and 11-day windows. Patell (1976) *t*-statistics with Kolari and Pynnonen (2010) adjustments are reported within parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 3 SOE		*Top 3 SIPO*		*HQ SOE*	
Property Type	CAR(-1,1)	CAR(-5,5)	CAR(-1,1)	CAR(-5,5)	CAR(-1,1)	CAR(-5,5)
Overall	-0.04***	-0.10***	-0.12***	-0.36***	-0.09***	-0.26***
	(-8.11)	(-9.65)	(-16.88)	(-35.23)	(-28.09)	(-45.99)
Office	-0.05***	-0.07***	-0.07***	-0.25***	-0.09***	-0.20***
	(-6.46)	(-6.25)	(-6.14)	(-18.26)	(-15.39)	(-21.51)
Industrial	-0.06***	-0.10***	-0.05***	-0.19***	-0.09***	-0.16***
	(-6.45)	(-5.25)	(-4.17)	(-11.59)	(-12.28)	(-13.48)
Retail	-0.03***	-0.11***	-0.17***	-0.38***	-0.07***	-0.28***
	(-3.81)	(-7.04)	(-15.81)	(-27.39)	(-12.35)	(-29.17)
Residential	-0.06***	-0.04**	-0.07***	-0.29***	-0.03***	-0.20***
	(-6.37)	(-2.15)	(-4.01)	(-16.52)	(-7.33)	(-13.78)
Diversified	-0.03***	-0.07***	-0.11***	-0.42***	-0.06***	-0.15***
	(-4.21)	(-6.93)	(-15.14)	(-37.30)	(-11.49)	(-20.47)
Hospitality	-0.06***	-0.15***	-0.13***	-0.48***	-0.14***	-0.44***
	(-8.19)	(-10.62)	(-10.56)	(-20.04)	(-27.20)	(-45.52)
Health Care	-0.07***	-0.11***	-0.19***	-0.57***	-0.22***	-0.48***
	(-5.59)	(-4.39)	(-17.92)	(-33.60)	(-30.50)	(-36.10)
Self-storage	-0.02	-0.06***	-0.08***	-0.24***	-0.05***	-0.19***
	(-1.42)	(-4.77)	(-7.57)	(-17.47)	(-6.25)	(-10.86)
Specialty	-0.04***	-0.16***	-0.13***	-0.34***	-0.05***	-0.18***
	(-7.41)	(-16.05)	(-21.77)	(-33.85)	(-7.11)	(-18.68)
Technology	-0.03	0.03	-0.04	-0.10***	-0.01*	-0.09**
	(-1.19)	(1.03)	(-1.64)	(-3.42)	(-1.77)	(-2.50)

Covid Economics 22, 26 May 2020: 205-260