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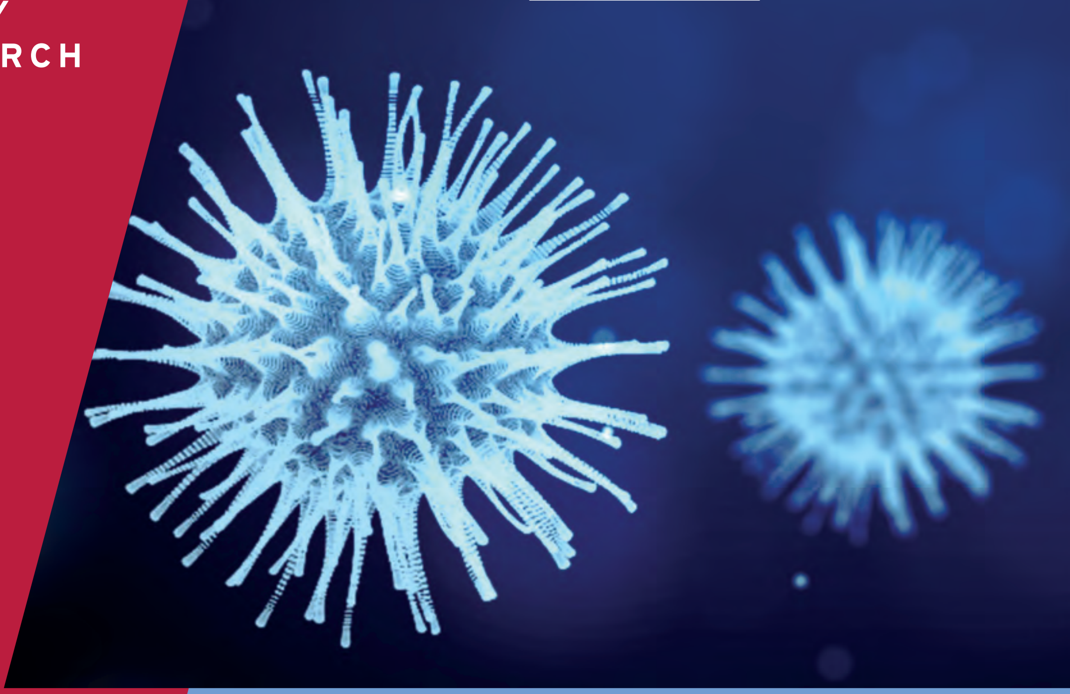

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

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Covid Economics
Vetted and Real-Time Papers

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Covid Economics
Vetted and Real-Time Papers

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Covid Economics **Issue 7, 20 April 2020**

Does social distancing matter?[1]

Michael Greenstone[2] and Vishan Nigam[3]

Date submitted: 14 April 2020; **Date accepted:** 15 April 2020

This paper develops and implements a method to monetize the impact of moderate social distancing on deaths from Covid-19. Using the Ferguson et al. (2020) simulation model of Covid-19's spread and mortality impacts in the United States, we project that three to four months of moderate distancing beginning in late March 2020 would save 1.7 million lives by October 1. Of the lives saved, 630,000 are due to avoided overwhelming of hospital intensive care units. Using the projected age-specific reductions in death and age-varying estimates of the United States Government's value of a statistical life, we find that the mortality benefits of social distancing are about $8 trillion or $60,000 per US household. Roughly nine-tenths of the monetized benefits are projected to accrue to people age 50 or older. Overall, the analysis suggests that social distancing initiatives and policies in response to the Covid-19 epidemic have substantial economic benefits.

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1 Both authors contributed equally to this work and declare no competing interests. We thank Claire Fan, Ian Pitman, Catherine Che, and especially Alice Schmitz for excellent research assistance; and Orley Ashenfelter, Magne Mogstad, Ishan Nath, Jonathan Cohen, Chinmay Lohani and Atakan Baltaci for several valuable conversations. All errors are our own. Preprint: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561244 Code and data: https://www.michaelgreenstone.com/paperscategories#vsl.

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Introduction

The novel coronavirus (COVID-19) pandemic is considered the greatest public health threat since the 1918 Influenza Pandemic that infected one-third of the world's population and killed at least 50 million people. COVID-19 cases and fatalities are growing exponentially and globally there is much uncertainty about the ultimate impacts. Perhaps as unsettling as the projected health impacts are the uncertainties around them that are wracking societies with fear.

In the absence of vaccines, countries around the world are implementing various forms of "social distancing" as a policy to slow the virus' spread. This social distancing takes many forms but, at its core, its aim is to keep people apart from each other by confining them to their homes in order to reduce contact rates. The health impacts of social distancing are evident in the limited number of deaths in China, especially when compared with countries such as Italy which implemented social distancing policies more slowly and sporadically. At the same time, the economics costs are clear in both Chinese and Italian data, and in the US Goldman Sachs is projecting quarter on quarter annualized growth rates of -6 per cent in Q1 and -24 per cent in Q2 (Hatzius et al. 2020). Further, historically unprecedented US unemployment claims have begun to arrive and the near term outlook for the job market is grim (Hatzius et al. 2020). The demonstrated benefits in China (as well as South Korea and Singapore) and the sharp and large economic costs naturally raise critical questions about whether social distancing is worth it from an economic point of view (Hilsenrath and Armour 2020; Bender and Ballhaus 2020; Thunstrom et al. 2020).

This paper develops and implements a method to estimate the economic benefits of social distancing. Our baseline finding is that a moderate form of social distancing is projected to reduce fatalities by 1.76 million in the next 6 months and that would

produce economic benefits worth $7.9 trillion. These benefits are over one-third of US GDP and larger than the entire annual federal budget. Distributed among US households, they are roughly equal to current median household income of $60,000.

Further, these economic benefits are likely a lower bound. This is because they do not account for social distancing's potential effects on morbidity rates, quality of medical care for non-COVID-19 medical problems, or uncertainty surrounding the mortality impacts. It is also worth underscoring that the estimates depend on assumptions about the value of a statistical life (VSL) and estimated benefits remain substantial when other plausible assumptions are made. Finally, we find that the benefits from social distancing also remain substantial in less aggressive COVID-19 scenarios; for example, the economic benefits of social distancing are $3.6 trillion even in a scenario where the peak of daily death rates is 60 per cent lower than in the Imperial College model (Ferguson et al. 2020) of COVID-19 spread that we rely on in this paper.

The method has two main steps. First, we compare two scenarios from the prominent Ferguson et al. (2020) COVID-19 study: a mitigation scenario, which they define as "combining home isolation of suspect cases, home quarantine of those living in the same household as suspect cases, and social distancing of the elderly and others at most risk of severe disease" that lasts for three to four months, and a "no policy" scenario. The mitigation scenario is projected to reduce the number of COVID-19 caused fatalities by a total of 1.76 million over a 6-month period, relative to the no policy scenario. This reduction in fatalities is composed of 1.13 million fewer deaths of COVID-19 patients treated in hospitals, particularly in intensive care units (ICUs); and 0.63 million fewer deaths of COVID-19 patients that are unable to receive ICU care because of pandemic-related overcrowding.

Second, the reduction in fatalities from the mitigation scenario is divided into 9 age categories and then monetized using the United States Government's VSL, which we adjust for age (Thaler and Rosen 1976; Ashenfelter and Greenstone 2004; Murphy and

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Topel 2006; OMB 2003; US EPA 2015). In total, the benefits from the mitigation scenario equal $7.9 trillion. Deaths avoided and monetized benefits are unequal: cohorts under age 50 comprise 11 per cent of monetary benefits (3 per cent of total deaths avoided); ages 50-69 comprise 52 per cent of monetary benefits (28 per cent of avoided deaths), and those 70 and older comprise 37 per cent of monetary benefits (69 per cent of avoided deaths). The differences in monetary benefits across age groups reflect that COVID-19 mortality rates are increasing in age while the VSL is generally decreasing in age.

Finally, we note that the particular benefits estimates are only as reliable as Ferguson et al.'s projections on COVID-19's spread and health risks. The method can be used with any set of projections, so as more information arrives and research advances, this approach can be applied to other projections and to infer the benefits of alternative policy responses.

The remainder of the paper is organized as follows. Section I describes our methods to project the direct and "overflow" COVID-19 caused deaths, based on Ferguson et al. (2020). Section II describes our approach to monetizing the avoided deaths in order to develop an estimate of the benefits of the mitigation social distancing scenario. Finally, Section III interprets the results, discusses some caveats, and concludes.

Mortality impacts of social distancing

This section develops estimates of the projected mortality impacts of COVID-19, exclusively relying on Ferguson et al.'s (2020) "individual-based simulation model" that was developed to support pandemic influenza planning. The paper, which has been highly influential in the policy arena, combines data on early outbreaks of COVID-19 with demographic and hospital availability data from the United States to project

COVID-19 infection rates, hospitalization rates, demand for critical care (intensive care units), and mortality rates. It attempts to discipline these projections with data on COVID-19 experiences in China, Italy, Great Britain, and the United States (Ferguson et al. 2020).

Our emphasis is on Ferguson et al.'s "no policy" and mitigation social distancing scenarios. In the no policy scenario, there is uncontrolled growth of the coronavirus pandemic that leads to an 81 per cent infection rate in the United States by 1 October and 2.2 million deaths. As a basis of comparison, in late February the CDC projected a 48-65 per cent infection rate and deaths of 0.16 million (with a 0.25 per cent infection fatality rate) to 1.7 million (1 per cent fatality rate) over a year starting March 2020 (Fink 2020). Importantly, other empirical studies point to a case fatality rate close to 1 per cent (Verity et al. 2020, Mizumoto and Chowell 2020), and other expert estimates suggest a 30-70 per cent US-wide infection rate without any distancing (Axelrod 2020, Ramsey 2020). The Ferguson et al. estimates, while slightly more pessimistic, are thus broadly consistent with other projections of COVID-19 transmission.

The mitigation scenario emphasized by Ferguson et al. is a moderate form of social distancing that consists of 7-day isolation for anyone showing coronavirus symptoms, a 14-day voluntary quarantine for their entire household, and dramatically reduced social contact for those over 70 years of age.[2] All measures begin in late March. The isolation and household quarantine measures are assumed to be in place for three months and reduced contact for people over 70 lasts four months. Ferguson et al. project that the mitigation scenario will reduce peak hospital demand by two-thirds and total deaths to 1.1 million.

[2] Ferguson et al. also model other subsets of mitigation, such as school and university closures, but these have limited impact and the mortality impacts are not emphasized.

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We focus on the mitigation scenario because it approximates what the United States is implementing, albeit unevenly across the country. With perhaps the exception of urban California, Washington and New York, as of the time of writing most US states have not pushed China-style shutdowns of the level necessary to suppress COVID transmission (Glanz et al. 2020). In other words, the US may "flatten the curve" of infection but not stop it entirely. Ferguson et al. also make projections about a "suppression" scenario that includes dramatically reduced contact for the entire population, and involves either a rebound epidemic (that strongly resembles our mitigation scenario) or repeated imposition of social distancing for two years. We view the latter as far from anything being implemented in the United States. One thing to note is that both the no policy and mitigation scenarios only extend through 1 October, so it is reasonable to assume that a vaccine will not be developed in this timeframe.

A novel feature of our analysis is that we improve upon Ferguson et al.'s estimated mortality projections by accounting for the potential shortages in the supply of hospital intensive care services, for example ICU beds, respirators, and trained staff. Specifically, Ferguson et al.'s headline death projections assume that all COVID-19 patients receive the appropriate medical care, so their projections do not account for potential shortages in ICU beds or respirators. Indeed, it is precisely the possibility of these shortages that account for the policy push to "flatten the curve" and avoid their repercussions. Our approach is to label the Ferguson et al. projections of deaths as "direct deaths" and separately develop projections of "overflow deaths," which are those that result from hospital ICUs reaching capacity and being unable to serve some COVID-19 patients. As we detail, we project that social distancing would reduce overflow deaths by an additional 630,000 fatalities.

In summary, we project that social distancing reduces COVID-19 caused deaths by 1.76 million deaths. This is composed of reductions of 1.13 million direct deaths and 630,000 overflow deaths. The remainder of this section describes how we develop these

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projections of the reductions in direct and overflow deaths due to social distancing and their distribution across 9 age categories.

Direct deaths

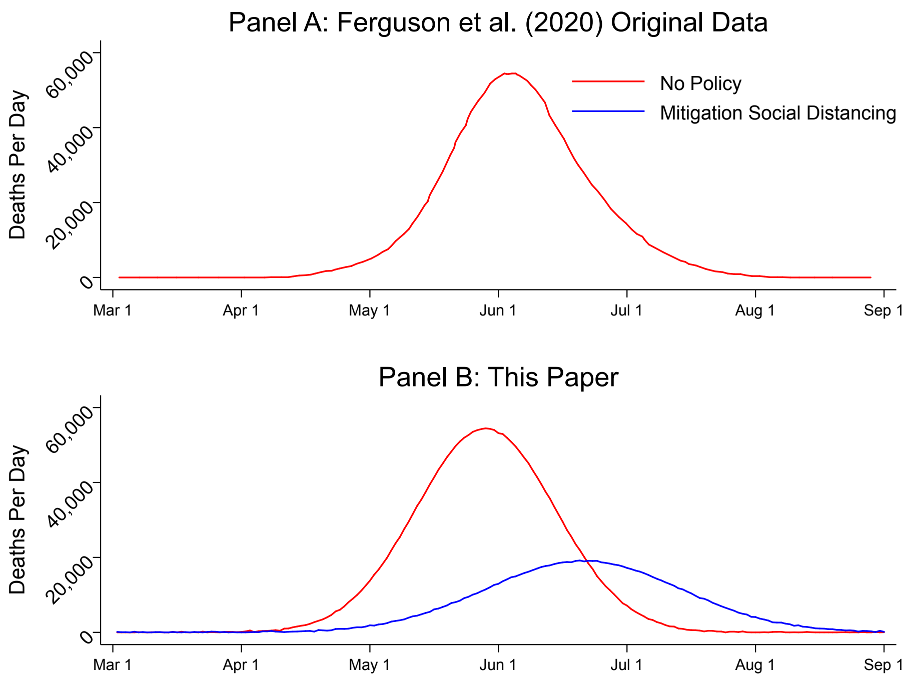
We begin by reproducing the Ferguson et al. estimates of direct deaths in the US: 2.2 million with no policy and 1.1 million with “mitigation” social distancing. To do so, we develop a method that, under simple assumptions about the progression of coronavirus, allows us to construct the full daily distribution of deaths. This step is necessary because it was infeasible to acquire the full dataset underlying the Ferguson et al. analysis, undoubtedly due to the great demands placed on the authors as they model the progression of COVID-19 and replay updated findings to policymakers.

Our approach assumes that daily COVID-19 cases, deaths, and ICU bed demand follow a normal distribution. Normal distributions roughly approximate epidemic growth curves, which are slightly right-skewed since they grow exponentially until reaching herd immunity. Normality is also convenient because given the center (date of peak), height at peak, and width (distance from start to peak), it is possible to recover the full distribution (i.e., daily fatality counts).

For an example of our strategy, consider Figure 1. Panel A reproduces Ferguson et al.’s distribution of daily deaths, which we extracted from their paper.[3] The center of the distribution is around 1 June and the standard deviation visually appears to be about 16 days, so we can plot a normal distribution. Lastly, about 55,000 deaths per day happen at the peak. We then scale the entire distribution to peak at that value and sum deaths across all days to obtain total deaths from 1 March to 1 October 2020. So although we don’t have the underlying data, we are able to reproduce this distribution with the red

[3] Panel A corresponds to the US curve in Figure 1a of Ferguson et al. (2020), which is expressed in deaths per 100,000 people; we multiply through by the US population to obtain total US deaths.

Fig 1. Modeling of Direct Deaths from COVID-19



Notes: Figure shows how we construct daily direct deaths under various social distancing policies. The original distribution of US deaths with no policy from Ferguson et al. (2020) is given in Panel A. Panel B shows our normal approximation of this distribution, and a similar policy under mitigation social distancing. Total direct deaths (areas under the curves) are 2.2 million with no policy and 1.1 million with mitigation social distancing, exactly matching reported deaths in Ferguson et al.

line in Panel B; our reconstructed version adds up to the same 2.2 million direct deaths that Ferguson et al. project for their no policy scenario by construction.[4] The blue distribution in Panel B for daily deaths under the mitigation scenario is recovered with the same approach and, again by construction, produces exactly the 1.1 million deaths that Ferguson et al. project.[5]

[4] For some distributions, we have even less information. The only Ferguson et al. (2020) plot showing curves with and without moderate distancing is for critical care cases in Great Britain, not deaths in the USA. However, that plot still lets us infer that the epidemic peak is one-third as high and takes 40 per cent more time to occur relative to 1 April, and has a 40 per cent larger standard deviation, compared to no policy. These points are sufficient to construct direct deaths with mitigation in the United States.

[5] We add a mean zero error to our reconstructed normal distributions, such as in Panel B.

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The bottom line from this analysis is that social distancing is projected to reduce the number of COVID-19 deaths by 1.1 million between 1 March and 1 October. This is simply the difference in the number of direct deaths in the no policy and mitigation scenarios.

Overflow deaths

We next estimate ICU overflow deaths under the no policy and mitigation scenarios, as well as their difference which is the number of fatalities averted through COVID-related social distancing. We believe that these are the first projections of overflow deaths or, put more plainly, the mortality costs of failing to “flatten the curve”. Previous work (e.g., Ferguson et al. 2020, Jha et al. 2020) project hospital bed and ventilator needs in excess of capacity, but do not project the impact of these shortages on total fatalities.[6]

A little background on ICU services is helpful to understand this calculation. Patients in the ICU receive specialized beds, ventilators, and care from doctors and nurses with specialized training. The United States has 85,000 beds in intensive care units (Tsai et al. 2020). Of those, 32,000 (37 per cent) are unoccupied and immediately available to treat COVID-19 patients. The total number of beds that COVID-19 patients could fill, known as “surge” capacity, lies between the two. In times of emergency, some space can be made by canceling elective surgeries, but cancer patients and others with ongoing treatment must stay put. We follow Ferguson et al. in assuming ICU “surge” capacity of 45,000 beds (=32,000 unoccupied ICU beds plus 13,000 ICU beds made available by canceling

[6] The challenge in estimating overflow deaths is that the death rate changes as a function of the number of patients, so a standard SIR model that takes COVID-19 death rates at an input will not directly capture this phenomenon. In contrast, empirical comparisons between overwhelmed and calmer hospital systems (ex: Wuhan vs. rest of China) are challenging because distancing policies are most severely implemented in overwhelmed areas, confounding comparisons.

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elective surgeries).[7] Increasing ICU capacity any further requires new physical beds and equipment, as well as proportional increases in the number of ICU doctors and nurses. The first step in projecting overflow deaths is then to project the number of ICU beds available each day for COVID-19 patients and the daily number of new patients in need of ICU care. We follow Ferguson et al. and assume that each ICU patient occupies a bed for exactly 10 days. Given the surge capacity of 45,000 ICU beds[8], this means that a total of 4,500 ICU beds become available each day for COVID-19 patients. Ferguson et al. projects the number of new COVID-19 patients that need ICU services each day for both scenarios.[9]

Figure 2 reports the results from this exercise. The dashed black line is the number of ICU beds that become available each day for COVID-19 patients in need of ICU-level care. The red and blue distributions are the number of new COVID-19 patients that require ICU services each day under the no policy and mitigation social distancing scenarios, respectively. The patients underneath the dashed black line receive ICU services, while those above it are projected to be denied them.

Under social distancing, 1.57 million fewer COVID-19 patients that merit ICU services are denied them. Specifically, the no policy number of COVID-19 patients in need of ICU services that are denied them is equal to the sum of the left (1.92 million) and center (0.60 million) shaded regions. In the mitigation social distancing scenario, this is equal to sum of the center (0.60 million) and right (0.35 million) regions. Therefore, the benefit of social distancing (i.e., the difference in these two numbers) is the difference between these two numbers or 1.57 million.

[7] The authors assume the US has 14 ICU beds per 100,000 people, which is 45,000 overall. This is slightly lower than the Tsai et al. (2020) estimate of 58,000 potentially available ICU beds.
[8] Ferguson et al. (2020) report that US ICU surge capacity is 14 beds per 100,000 people; we multiply by US population and divide by 10 days/ICU patient to obtain the ICU surge capacity shown in Figure 2.
[9] Plots in Ferguson et al. (2020) are of projected ICU beds occupied by day, which we divide by 10 days per ICU patient to obtain the number of *new* patients per day, as shown in Figure 2.

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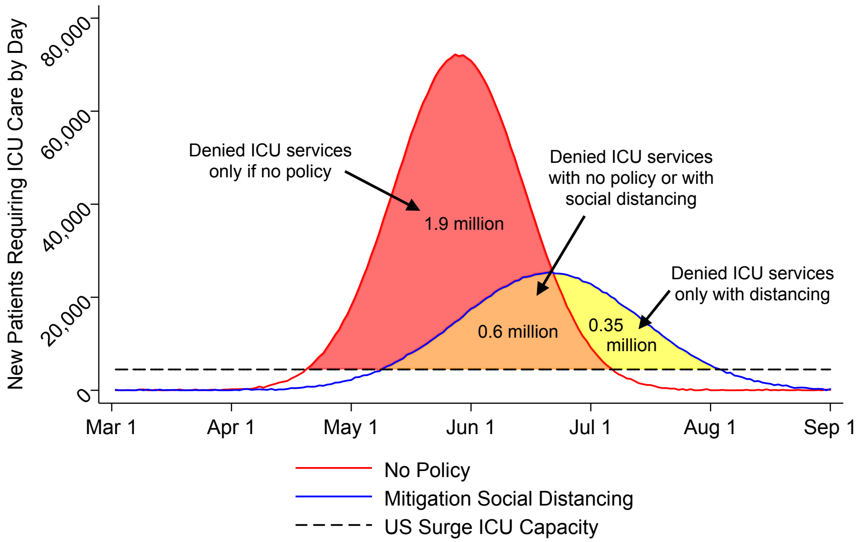
Fig 2. Predicted ICU Patient Flows



Notes: Figure illustrates our computation of *overflow* deaths from patients unable to receive ICU care. Daily flows of patients requiring ICU care are constructed from Ferguson et al. (2020) projections of bed demand. Patients above US surge capacity (black line) are denied ICU treatment: the leftmost (red) and middle (orange) areas with no policy and the middle (orange) and rightmost (yellow) areas with "mitigation" social distancing. The difference of 1.6 million represents COVID-19 patients denied ICU treatment, each of which has a 50 per cent chance of survival with ICU treatment (Ferguson et al. 2020) and a 10 per cent chance of survival if denied care.

The prospects for these 1.57 million ICU indicated, but denied, patients are poor and we project that an additional 630,000 of them would die. This calculation requires an estimate of the difference in mortality rates for ICU-indicated COVID-19 patients who can and cannot get ICU services. We rely on Ferguson et al.'s assumption that the survival rate for ICU-level COVID-19 patients in ICUs is 50 per cent and our read of the literature that suggests that the survival rate falls to 10 per cent or below if they are denied ICU services (Emanuel et al. 2020, Long et al. 2015). In summary, 1.57 million coronavirus ICU patients face a 40 per cent higher death rate in the no policy scenario, relative to the mitigation social distancing scenario. Put another way, social distancing reduces the projected number of overflow deaths by 630,000 in the United States between 1 March and 1 October 2020, providing a quantitative rationale for efforts to "flatten the curve".

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Age distribution of COVID-19 deaths

The next step in the analysis is to assign projected COVID-19 caused deaths – which we have computed for the entire US population – to age groups. Ferguson et al. (2020) report the distribution of total deaths from the no policy scenario across nine age groups (i.e., 0-9, 10-19, … , 70-79, and 80+).[10] We apply this same distribution of total deaths to the mitigation scenario. This is not an innocuous assumption, because the marginal deaths in this scenario may have a different age distribution, but alternative information is unavailable.[11]

The monetary value of social distancing

This section describes our approach to monetizing reductions in fatalities and then uses it to develop an estimate of the economic benefits of the mitigation social distancing scenario, relative to the no policy scenario.

The value of a statistical life and the monetary benefits of changes in mortality rates

It is natural to consider social distancing like any of hundreds of policies that aim to reduce the risks that people face. As just one example of such policies, governments pay for guardrails on the side of roads, because they increase survival rates in car accidents. A policy like social distancing similarly increases survival rates.

To convert the main benefit of social distancing – reducing the mortality impact of COVID-19 – into dollar terms, we turn to the value of a statistical life (VSL). The VSL is a

[10] Ferguson et al. report the infection fatality rate and probability of requiring ICU care by age group. We multiply each by 2017 age-group population from the US Census to obtain the age-wise distribution of direct and overflow deaths, respectively.

[11] In an extreme case, suppose distancing purely inhibits coronavirus from reaching nursing homes; if so, our approach will project deaths to elderly populations when in reality none have died.

tool from economic theory which is now a standard ingredient in the cost-benefit analyses that undergird decision-making by the United States Government, and scores of foreign, state, and local governments (OMB 2003). In principle, the VSL measures how much the average US citizen is willing to pay for a reduction in the probability of death.[12] It is one statistical life, which is a reduction in mortality rates equivalent to saving one life on average. For instance, suppose the average American is willing to pay $10,000 to avoid a 0.1 per cent chance of death, then the VSL is equal to $10,000/0.001 lives saved or $10 million per statistical life saved. So, a policy that is expected to save 1 life has $10 million in social benefits.

There are two reasons, one theoretical and one practical, to use the VSL to capture the benefits of social distancing policies. First, the VSL captures the *full* benefits an individual expects to derive from her own life, including from leisure, time with friends and family, and consumption of goods and services. The legal system often relies on individual's remaining lifetime earnings, but such a measure fails to capture many features of what people value about their life, including their consumption of non-market goods like leisure time spent with family members (Murphy and Topel 2006).

Second, our approach is a standard one: US federal agencies such as the EPA and Department of Transportation have used the VSL for many decades to evaluate a long list of policies in a variety of domains (transportation and environment are two common areas). These policies, like social distancing, have benefits measured in lower mortality but costs measured in dollars; the VSL allows the US government to compare the two, rather than neglecting that which cannot be valued.

[12] It is important to underscore that the VSL is not the amount of money that a person would be willing to trade for certain loss of life (presumably all of their wealth) but rather for a small change in the probability of death.

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In practice, we compute the social benefits of reducing COVID-19 mortality rates as:

$$Benefits = VSL_j * \sum_j (R_j^{direct} * Pop_j + R_j^{overflow} * Pop_j)$$

where *j* is the age group. R_j^{direct} is the *reduction* in the direct death rate from implementation of the moderate social distancing scenario, relative to the no policy scenario, that was outlined in the previous section. $R_j^{overflow}$ is the analog for ICU overflow deaths rate, again as described above. Finally, Pop_j is the 2017 US population for the *j* age group and VSL_j is the value of a statistical life that is allowed to vary with age. The VSL is allowed to vary with age following Murphy and Topel (2006), but we require the average for people 18 and over to equal \$11.5 million[13] which matches the EPA's VSL for adults (US EPA 2015).

Empirical estimates of the monetary benefits of social distancing

Table 1 summarizes the paper's key results. The rows report on each of the 10 age categories and the US total. Column (1) reports the total US population. Columns (2d) details the projected reduction in direct deaths due to social distancing, with columns (2a) – (2c) reporting the ingredients in this calculation. Columns (3a) – (3d) repeat this exercise for overflow deaths. The total reduction in deaths due to social distancing (i.e., the sum of (2d) and (3d)) is reported in (4a). (4b) lists the age-specific VSL, which reflects the fact that income and remaining life expectancy vary across ages and many influence willingness-to-pay for reductions in mortality risk. To obtain column (4b) we obtain estimates of the VSL-age distribution from the authors of Murphy and Topel (2006) and rescale so that the population-weighted average for US adults (18+) equals the US EPA VSL of \$11.5 million. Finally, column (4c) reports the monetized value of the projected reduction in fatalities due to social distancing.

[13] The US EPA employs a 2020 VSL of \$9.9 million in 2011 dollars as part of the Clean Power Plan Final Rule Regulatory Impact Analysis. This estimate accounts for income growth to 2020; adjusting for inflation, the VSL is \$11.5 million in 2020 dollars.

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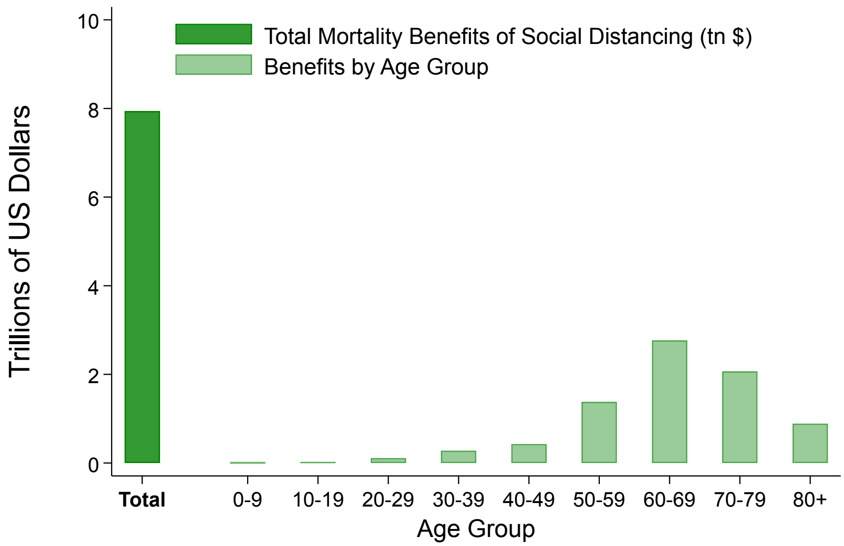
Table 1. Social Distancing's Projected Mortality Benefits and their Valuation in the United States

	Population	Direct Deaths				Overflow Deaths				All		
		No Policy	Mitigation Distancing	Difference		No Policy	Mitigation Distancing	Difference				
Age group	(1) US pop in millions	(2a) Pct of pop	(2b) Pct of pop	(2c) Pct of pop	(2d) Death count	(3a) Pct of pop	(3b) Pct of pop	(3c) Pct of pop	(3d) Death count	(4a) Death count	(4b) VSL in million USD	(4c) Benefits in trillion USD
0-9	39.8	0.001	0.001	0.001	265	0.001	0.000	0.000	177	442	14.7	0.01
10-19	41.4	0.004	0.002	0.002	827	0.002	0.001	0.001	554	1,381	15.3	0.02
20-29	45.0	0.020	0.010	0.010	4,487	0.009	0.003	0.005	2,405	6,892	16.1	0.11
30-39	42.7	0.052	0.026	0.027	11,364	0.023	0.009	0.014	6,091	17,455	15.8	0.28
40-49	40.2	0.098	0.048	0.050	20,032	0.045	0.017	0.028	11,048	31,080	13.8	0.43
50-59	42.9	0.391	0.192	0.200	85,635	0.179	0.069	0.111	47,598	133,234	10.3	1.38
60-69	36.4	1.435	0.704	0.732	266,364	0.656	0.250	0.405	147,585	413,949	6.7	2.76
70-79	21.3	3.327	1.631	1.696	362,001	1.514	0.578	0.936	199,692	561,694	3.7	2.06
80+	12.4	6.067	2.974	3.093	382,484	2.791	1.066	1.725	213,339	595,824	1.5	0.89
US Total					**1,133,460**				**628,491**	**1,761,951**		**7.94**

Notes: Table explains how projected deaths averted through social distancing are converted to their value to Americans. Mitigation-type social distancing reduces the average person's chance of dying directly from COVID-19 by the rate in column (2c) (e.g., 3.1 percent for people 80+), and additionally reduces the probability of death from hospital overcrowding by (3c). We scale by total population to compute *statistical* lives saved (2d) and (3d). Lastly, we sum lives saved and multiply by the VSL to compute total benefits; VSLs are lower for older populations because of lower incomes and life expectancies. The benefits in (4c) therefore represent the total value to all Americans of the reductions in mortality risk in (2c) and (2d), *not* the value of saving any particular life with certainty.

Fig 3. Monetary Benefits of Projected Mortality Reductions from Social Distancing



Notes: Figure shows total benefits (willingness-to-pay) for reduced COVID-19 mortality through social distancing. Total benefits of 7.94 trillion dollars equal the sum across age groups, where each age group's benefits are the change in expected mortality times the age-specific value of a statistical life. Despite facing lower mortality risk than above-70 cohorts, 50-59 and 60-69 year olds see large benefits because they have more years left to live and therefore higher VSLs.

The topline result is that social distancing is projected to reduce COVID-19 caused fatalities by 1.76 million by October 1 and that this is worth $7.9 trillion. This projected reduction in fatalities is composed of 1.13 million fewer deaths of COVID-19 patients receiving appropriate treatment (i.e., direct deaths) and 0.63 million fewer deaths of COVID-19 patients that are unable to receive ICU care because of pandemic related overcrowding (i.e., overflow deaths).

Figure 3 illustrates that the impacts are strikingly heterogeneous across age categories. People under the age of 50 have $0.85 trillion (11 per cent) of total benefits, reflecting their low chance of death from COVID-19. People aged 50-69 have $4.14 trillion (52 per cent) of total benefits, almost double their share of deaths avoided through social distancing; in contrast, people 70 and older get $2.95 trillion (37 per cent) of benefits despite comprising over two-thirds of deaths avoided. Cohorts aged 50-69 have larger

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total benefits than the 70+ group because the former have a higher VSL, reflecting the greater remaining life expectancies and expected future incomes of younger cohorts. More generally, it is apparent that COVID-19's risks and the benefits of social distancing are disproportionately concentrated among the older age groups.

Robustness to alternative assumptions

The credibility of the estimated $8 trillion in benefits relies directly on parameters in the Imperial College model. This subsection examines how the monetized benefits of the mitigation social distancing scenario change under alternative assumptions about the virulence of the no policy scenario and surge ICU capacity, as well as the choice of an alternative VSL.

Table 2 reports on this exercise. Row (1) repeats the findings from this paper's baseline analysis. We consider what happens if the peak daily mortality rate is reduced, through any of a variety of mechanisms including lower infection rates and lower mortality rates conditional on infection. A reduction in the peak daily mortality rate by 30 per cent reduces the benefits of social distancing to $6.5 trillion (row (2a)), while a 60 per cent reduction decreases it to $3.6 trillion (row (2b)). Row (3) reveals that although doubling ICU capacity would meaningfully reduce the costs of COVID-19 it would have little impact on the benefits of social distancing. This may seem surprising, but it is because the benefits of additional ICU capacity are roughly equal in both the no policy and mitigation social distancing scenarios.

Lastly rows (4a) – (4c), report the social benefits when alternative assumptions about the VSL are implemented. Row (4a) applies an age-invariant version of the US Government's VSL of $11.5 million, rather than allowing it to vary with age as is done throughout the rest of the paper (US EPA 2015). In this case, the total social benefits are about $20 trillion, more than 2.5 times larger than the baseline estimates. This

Table 2. Monetary Benefits of Projected Mortality Reductions from Social Distancing with Alternative Assumptions

	Deaths Avoided Through Distancing			Monetized Benefits
Assumption	Direct Deaths (millions)	Overflow Deaths (millions)	Total (millions)	Benefits (trillion USD)
(1) *Main*	1.13	0.63	1.76	**7.94**
Lower Spread				
(2a) Reduce peak of epidemic by 30%	0.94	0.50	1.43	**6.47**
(2b) Reduce peak of epidemic by 60%	0.57	0.22	0.79	**3.56**
More ICU Beds				
(3) Increase Surge ICU Capacity by 100%	1.13	0.63	1.77	**7.97**
Alternative VSL Assumptions				
(4a) Age-invariant VSL of $11.5mn (US EPA) for all deaths averted	1.13	0.63	1.76	**20.26**
(4b) Age-varying VSL with $3.5mn pop avg (Ashenfelter & Greenstone 2004)	1.13	0.63	1.76	**2.42**
(4c) Age-invariant VSL of $3.5mn (Ashenfelter & Greenstone 2004)	1.13	0.63	1.76	**6.20**

Notes: Table shows that that the total benefits of mortality reductions due to social distancing are similar under a series of alternative assumptions. (1) is the main estimate. In (2), we assume the peak of the epidemic, in terms of cases and deaths per day, was some fraction lower than in Ferguson et al. (2020). In (3) we double US surge ICU bed capacity and find a similar estimate of benefits, since ICU capacity increases lead to fewer deaths both with and without distancing. In (4a) we apply the US EPA 2020 VSL of $11.5 million to all deaths averted, without accounting for patient age, and show that under US regulatory practice the estimated benefits would be over $20 trillion. (4a) is analogous to (1) except that it uses a VSL of $3.5 million, obtained from Ashenfelter and Greenstone (2004) and adjusted for inflation and income growth to 2020. (4c) is analogous to (4a) but uses the updated Ashenfelter and Greenstone (2004) VSL.

finding is not surprising in light of the high proportion of saved lives that occur among people older than 60, who have relatively low VSLs in Table 1 because of their lower remaining life expectancy. While the age-invariant VSL has a legal basis in that it is US Government policy, it is challenging to justify from economic first principles of individual behavior.

Rows (4b) and (4c) use an updated version of Ashenfelter and Greenstone's (2004) estimate of the VSL, which equals $3.5 million when we adjust upwards[14] for income growth to 2020 and convert into current dollars. This lower VSL naturally produces

[14] Consistent with existing literature (e.g., Carleton et al. 2019), we use an elasticity of the VSL with respect to income of unity to adjust the Ashenfelter and Greenstone (2020) VSL to the present.

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smaller estimates of the benefits of distancing. With age adjustment, the total social benefits are $2.4 trillion, and without age adjustment they are $6.2 trillion. It is evident that assumptions about the VSL play an important role in our exercise, but even at the lower end social distancing still produces benefits of several trillion dollars.

Interpretation and conclusions

In this paper, we monetize one benefit of social distancing policies: a lower chance of dying from COVID-19. Building on Ferguson et al., we show that a moderate social distancing scenario, implemented nationwide, is projected to save 1.76 million lives in the United States, including 0.63 million purely from shortages of hospital ICU beds. Applying estimates of the VSL based on economic theory and pegged to the US government VSL, the paper finds that Americans would be willing to pay approximately $8 trillion for this reduction in mortality risk. Put another way, the estimated economic benefits of this mitigation social distancing scenario are roughly $8 trillion.

It is worth taking a moment to contextualize this finding. $8 trillion is over one-third of US GDP and larger than the entire annual federal budget. Put another way, the benefits of social distancing are roughly equal to current median household income of $60,000. Whether in regular times or during a pandemic, it is difficult to think of any intervention with such large potential benefits to American citizens. Importantly, while we measure benefits of distancing in dollars, they reflect the high value Americans place on small reductions in their chance of death – including consumption, leisure, time with family, and other aspects of life not easily monetized.

It is likely that the $8 trillion figure is an underestimate of social distancing's benefits because it misses several other channels. For example, the analysis does not account for the reduction in uncertainty around the mortality impacts of COVID-19, and valuing it in ways that reflect measured risk aversion would certainly increase the benefits. There is

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also the potential for social distancing to reduce the rates of non-fatal sickness experienced by the population, although this ultimately depends on the impacts on long run infection rates (Yang et al. 2020). Almond (2006) is an important data point, because it documents substantial long-run damages from *in utero* exposure to the 1918 influenza pandemic. Further, it seems reasonable to presume that social distancing will increase the quality of care for non-COVID-19 medical problems by reducing the strain on medical providers, facilities, and supplies. Finally, it seems plausible that the changes in mortality rates being considered here are "non-marginal"; the available evidence suggests that the VSL is increasing for non-marginal changes in fatality risk, meaning that the analysis should use a larger VSL (Greenberg et al. 2020).

While it is tempting to undertake a full cost-benefit analysis of social distancing, this would require reliable estimates of its substantial costs. We are unaware of comprehensive estimates of these costs and their development is beyond the scope of our analysis, so the paper cannot go further than developing an estimate of the gross economic benefits of social distancing.

Finally, we are undoubtedly in the early days of learning about COVID-19 and the potential policy and societal responses. This paper's broadest finding is that it has developed a method to estimate the monetary benefits of social distancing and other policy responses to COVID-19 as they emerge.

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Covid-19 helicopter money: Economics and politics[1]

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In a pandemic recession an extraordinary monetary policy – helicopter money – can be considered. If we define helicopter money as a monetization of irredeemable fiscal transfers to citizens that produces losses in the central bank balance sheet, and an independent central bank acts as a long-sighted policymaker, an optimal helicopter monetary policy can be identified. Yet, if the government in charge is made up of career-concerned politicians and citizens are heterogenous, the policy mix will produce distributional effects, and conflicts between politicians and central bankers will be likely. Political pressures will arise and the optimal helicopter money option will be less likely. The framework is applied in a discussion of the economics and politics of issuing COVID-19 perpetual bonds with the European Central Bank as the buyer.

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1. Introduction

Let us suppose now that one day a helicopter flies over this community and drops an additional $1,000 in bills from the sky, which is, of course, hastily collected by members of the community. Let us suppose further that everyone is convinced that this is a unique event which will never be repeated. (Milton Friedman, 1968)

The spread of the new coronavirus (COVID-19) in early 2020 led to some of the most significant declines in stock prices (Baker et al. 2020, Cahn and March 2020, Ramelli and Wagner 2020), contractions of real economic activities (Leiva-Leon et al. 2020) and deteriorations in expectations (Gormsen and Koijen 2020) seen in recent human experience (Barro et al. 2020, Breitenfellner and Ramskogler 2020, Danielsson et al. 2020), without mentioning the long-run macroeconomic effects of global pandemics (Jorda et at. 2020, Alfani 2020).

In economic thinking, the COVID-19 pandemic forces swept away many of the conventional taboos, such as the radical idea of a helicopter drop – that is, printing money and handing it out to people with no strings attached (Financial Times 2020, Yashiv 2020). The term uses the fanciful imagery that was originally invented by Milton Friedman (1968). Also the head of the French central bank Francois Villeroy de Galhau has floated the idea of printing money and giving it directly to companies (Financial Times 2020b).

Moreover over the past months media attention has zoomed on a new approach to macroeconomics, dubbed Modern Monetary Theory, whose proponents claim that governments can always print money without intertemporal budget constraints (Mankiw 2019), which implies that helicopter money is always a viable option. However, what we today call “unprecedented monetary policies” have historical precedents (Ugolini 2020).

The debate about helicopter money involves two separate policy issues. The first is how to create a financial backstop for households and firms through monetary cash transfers. The second is whether and how to involve the central bank in financing this backstop through direct monetization.

Direct cash handouts have already happened in two instances. In February 2020, the government of Hong Kong transferred HKD 10,000 (USD 1,270) to all residents financially affected by the virus as part of its overall policy response (Quah 2020). Similarly, the

government of Singapore provided small cash payments to all adult Singaporeans (Financial Times 2020). Other direct cash handouts have also been announced. Moreover, in 2009, the Australian government implemented a similar policy when it sent cheques to most taxpayers (Grenville 2013). However, fiscal cash handouts are not automatically helicopter money, and the same is true for any general mix of monetary and fiscal policies under which expansionary fiscal measures are financed by creating a monetary base (Carter and Mendes 2020). As such, we need a definition to avoid ambiguities (Blanchard and Pisani-Ferry 2020).

Given that the state and the central bank have separate balance sheets, we assume that helicopter money is in action when there is an outright money-financed fiscal transfer that produces losses in the central bank's balance sheet (Gali 2020). Our definition implies that a direct central bank money transfer is neither a necessary nor a sufficient condition for a helicopter money action, while some proposals suggested that a direct channel is more likely to be effective due to both higher consumer spending and higher inflation expectations (Muellbauer 2014). This is true even though some analyses cast doubt on whether it makes any difference that transfers come from the central bank or the government (Van Rooij and De Haan 2016). Needless to say that any central bank role as public debt manager does not imply any helicopter money, provided that – as in the case of the Bundesbank (Deutshe Bundesbank 2018) – the central bank does not grant any loan nor does it takes any state security into its own portfolio acting as public debt agent.

Moreover, we can have helicopter money without a permanent increase in non-interest-bearing central bank liabilities (Reichlin et al. 2013, Buiter 2014a, Borio et al. 2016, Bernanke 2016, Agarwal and Chakraborty 2019). Finally, this form of helicopter money differs from conventional and unconventional central bank asset purchases financed by issuing central bank reserves, as it represents an intended loss on the central bank's balance sheet. In this case, the corresponding public liabilities are irredeemable.

In other words, they are viewed as a permanent asset by the holder and as a capital liability by the issuer, but without any permanent change in the overall money base. Iintended central bank losses are more likely to be interpreted as a credible one-shoot monetary action than a change in the money base growth.

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However, the economics of a helicopter money option do not address crucial political issues that such an option involves. Extant research (Turner 2015, Bernanke 2016) emphasizes that, in general, political concerns are perhaps the most important reason for viewing helicopter money as a last-resort policy – it represents a source of risk to the central bank's independence.

Before the 2008 financial crisis, the independence of central banks had become the benchmark for evaluating the effectiveness of monetary institutions around the world. This institutional design was supported by a broad consensus (Cecchetti 2013, Bayoumi et al. 2014, Goodhart and Lastra 2017, Issing 2018). When the financial crisis emerged, the boundaries between monetary, banking and fiscal policies became blurred, triggering a debate on the shape of central bank regimes (Nier 2009, Cecchetti et al. 2011), especially with regard to central bank independence (Alesina and Stella 2010, Cukierman 2008 and 2013, Cecchetti 2013, Stiglitz 2013, Taylor 2013, Buiter 2014b, Balls et al. 2016, Sims 2016, Blinder et al. 2017, De Haan and Eijffinger 2017, Issing 2018, Rogoff 2019).

The mixing of a fiscal backstop and helicopter monetization is a case of policy blurring that can affect the relationship between politicians and central bankers. Therefore, we analyse the possible effects of a helicopter money option on central bank independence using the concept of political pressure (Binder 2018). We use this concept as a proxy for potential demand for reforming the current institutional setting. In general, we share the perspective that political cost-benefit analyses eventually shape central bank governance. Such drivers create dynamic institutional cycles with ups and downs (Masciandaro and Romelli 2015) during which the central bank's independence can exhibit different degrees of resilience in terms of how difficult is to change constitutions and laws (Alesina and Grilli 1992, Blinder 2010).

The remainder of this article is organised as follows. Section two presents the theoretical framework with its interactions among the relevant macro players - citizens, the government and an independent central bank - after which the optimal helicopter monetary policy is defined. Section three examines the importance of heterogeneity among citizens when politicians are in charge. Monetary policy can produce inequalities that trigger political pressures on the central bank. In both sections, the framework is applied in a discussion of European perpetual bonds with the European Central Bank acting as the buyer. The conclusions are presented in section four.

2. Pandemic Recession, Fiscal Backstop and Central Bank Independence: The Optimal Helicopter Money

In a given country, the economy consists of a population of citizens, a government and a central bank. The citizens are risk neutral, and they draw utility from consumption and disutility from labour. They use their net labour income and their assets to buy consumption goods. We focus on the special case of the policy mix between a fiscal backdrop and a helicopter monetization in a general economic setting where heterogeneity in the composition of citizen assets is coupled with homogeneity in labour income (Masciandaro and Passarelli 2019). These assumptions enable us to zoom in on the macroeconomic consequences of implementing an extraordinary fiscal policy using cash monetary transfers.

Starting with labour income, let individual utility from labour be:

$$l(1-\tau)-U(l). \tag{1}$$

Labour productivity is normalized to one. Then $l(1-\tau)$ is the after-tax (net) labour income. $U(l)$ is an increasing and convex effort function. After knowing τ, each citizen chooses how much to work in order to maximize his or her welfare. The optimality condition yields each individual's labour-supply function:

$$L(\tau)=U_l^{-1}(1-\tau). \tag{2}$$

Labour supply $L(\tau)$ is decreasing in the tax rate, $L_T<0$, which is the same for all citizens. Given the above-mentioned productivity and a population size of one, the labour supply represents the total income: $y=L(\tau)$. Therefore, in normal times, output growth in equilibrium depends on the tax policy. Moreover, each citizen can have assets with a market value of π. The citizens can used those assets as collateral in building up loans using competitive financial and banking markets. Let $\lambda\pi$ be the total amount of financial liabilities, where λ is the liability to asset ratio that parameterizes the citizen's financial leverage. The financial leverage is a proxy for the citizens' creditworthiness, which influences their welfare.

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If a pandemic occurs, policymakers have to react by implementing both fiscal and monetary policies. Those policies will affect the citizens, the labour markets, and the markets for goods and services. The sequence of events is as follows (see Figure 1).

Figure 1: Pandemic, Fiscal Deficit and Helicopter Money

0 *Pandemic and containment policy*	1 *Fiscal backstop and helicopter money*	2 *Macroeconomic outcomes*
PANDEMIC OUTBREAK	ECONOMIC POLICY	NEW NORMAL

At $t=0$, a pandemic breaks out and, consequently, the government designs and implements a containment policy. The starting point is the special nature of the pandemic-related recession. As a result of the pandemic, each national government faces an unpleasant dilemma between two public goals (Baldwin and Weder di Mauro 2020).

First, there is a need to protect public health by implementing a containment policy or social-distancing measures with the aim of minimizing the expected loss of life (Atkeson 2020). However, given the interactions between economic decisions and epidemics (Eichenbaum et al. 2020), any containment policy has economic costs that simultaneously affect the three fundamental pillars of a modern market economy: aggregate supply (Baldwin 2020a and 2020c, Del Rio-Chanona et al. 2020, Goodhart and Pradan 2020, Koren and Peto 2020), aggregate demand (Andersen et al. 2020, Del Rio-Chanona et al. 2020, Fornaro and Wolf 2020), and the banking (Acharya and Steffen 2020) and financial sector (Alfaro et al. 2020, Baker et al. 2020, Schoenfeld 2020), including the shadow-banking system (Perotti 2020).

Citizens suffer economic and financial losses that dampen their balance sheets. The losses that negatively affect both the asset value and the ability of households and firms (De Vito and Gomez 2020) to remain safe and sound borrowers. We assume that the government can absorb financial losses by implementing a fiscal backstop using cash transfers with the aim

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of keeping liquidity running (Baldwin 2020b). Temporary nationalisations can be implemented where needed (Becker et al. 2020). Financial markets and banks become a vehicle for public policy (Draghi 2020), as the historical experience tell us (Horn et al. 2020), where the government interventions are completely different from those used to rescue financial institutions during the 2008-2009 financial crisis (Igan et al. 2019). In most European countries, governments are facing or will face high expenditures to smooth out the negative recessive effects on households and firms. A high volume of public finance is needed to bridge corporate liquidity shortages and/or financial needs, and to compensate for temporary and/or permanent wage losses (Gnan 2020).

The possible outcomes in terms of losses can take the form of two opposite scenarios. At one extreme, no cash monetary transfers are implemented. In this no-transfer scenario, citizens completely lose their assets and their creditworthiness. At the other extreme, the fiscal backstop expansion that covers the bailout is complete. Therefore, when the pandemic occurs, a fiscal bailout policy can be designed that involves injecting fresh money equal to a proportion, β, of the citizen's value, $\pi(1+\lambda)$. Thus, β is the policy variable that parameterizes the fiscal bailout policy, where $\beta \in [0,1]$, with $\beta\pi$ representing the citizen's asset value after the bailout and $(1-\beta)\pi$ representing the losses due to the pandemic-related recession.

How can the cash transfers be financed? The government can raise taxation or issue debt, where the latter can be purchased by either citizens or the central bank. The government finances its policy by making a simultaneous decision regarding taxation and the issuance of new debt, knowing at the same time the central bank choices. The new debt, in turn, becomes an asset in the portfolios of citizens and the central bank.

The government defines the optimal fiscal bailout policy, β^*, recalling that $\beta \in [0,1]$. If the bailout policy, $\beta\pi(1+\lambda)$, is implemented, then the government supports the citizens' balance sheets. It finances this policy by issuing new debt at time 1. At the same time, it charges a linear income tax, τ, for servicing the debt at time 2. The overall government budget constraint is:

$$\beta(1+\lambda)\pi(1+i(1-\delta)) = \tau y, \tag{3}$$

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where τ is the tax rate, *y* is the income of the citizens before taxes, i is the interest paid on the government bond and δ is the share of the debt purchased by the central bank, where $\delta \in [0,1]$ (i.e. the helicopter monetization).

The interest rate on public bonds is determined according to a no-arbitrage condition with respect to a perfect, long-term, risk-free interest rate, which we normalize to zero for simplicity. For any unit of debt issued in time 1, the government repays $1+i(1-\delta)$ in time 2. The cost of debt, $i(1-\delta)$, is negatively associated with the degree of helicopter monetization. When a central bank is more accommodative (i.e. high δ), a lower portion of debt will be sold to citizens. Given the monetization δ, the government can determine its bailout policy, β, as well as the tax policy, τ. The overall policy design is $\tau = T(\beta,\delta)$.

The design of the economy policy action will influence the citizens' welfare. When the fiscal policy, β, is implemented at time 1, the *average* value of a citizen's portfolio will be affected. Its shape at time 2 will be the following:

$$\beta\lambda(1+\pi)+\beta(1+\lambda)(1-\delta)\pi(1+i)+\left[w-\beta(1+\lambda)(1-\delta)\pi\right]. \tag{6}$$

The first term is the value of the fiscal backstop, the second term is the value of the government bonds inclusive of interest payments, and the third term represents the difference between the initial wealth, *w*, and the value of the purchased bonds. Notably, the fiscal backstop influences welfare through two channels: the direct value of the monetary cash transfers and the indirect effect due to the interest payments on public bonds.

Disposable income and assets finance consumption. Such assumption can be particularly relevant during a pandemic: lockdowns produce material deprivation and households can draw on both income and wealth to address the unexpected shock. Combining income and wealth in a single index of deprivation it is possible to measure across countries how large and similar are the shares of the population that are likely to suffer from the containtment measures (Gambacorta et al. 2020) becoming potential recipients of a fiscal backstop.

Disposable income and assets finance consumption. Citizens draw utility from consumption, *c,* at time 2. The budget constraint of a citizen who owns an average portfolio is then:

$$c = l^*(1 - T(\beta,\delta)) + w + \beta(1+\lambda)\pi(1 + i(1-\delta) \equiv C(\beta,\delta), \tag{7}$$

where *l** is the optimal labour supply, which depends on the selected tax policy, such that $l^* \equiv L(\tau)$.

Finally, we need to consider welfare losses that may be caused by financial or monetary externalities. On the one side, the containment dampens the citizens' assets, thereby triggering further financial externalities. In the real world, the less the government is involved in supporting the economy, the more private balance sheets are likely to deteriorate. Consequently, failures in the banking and financial sector become more likely, creating a vicious spiral. Let the externality function be:

$$\frac{\varepsilon}{2}\left[(1-\beta)(1+\lambda)\pi\right]^2 \equiv E(\beta). \tag{8}$$

The externalities are increasing and convex in the amount of assets that evaporate, and they depend on the cash transfers, β, that the government implements. We assume that the costs of financial externalities are homogenous among citizens in order to show that it is sufficient to just have heterogeneity in asset composition among citizens to have a multiple equilibria setting.

However, the helicopter money is not a free lunch. In other words, it may create monetary externalities. We assume that the backstop monetization is associated with increasing monetary stability risks, such that that the monetary expansion associated with the central bank's losses can threaten the monetary stability goal when the pandemic-related recession ends. For the sake of simplicity, we assume that the costs of monetary instability, $I = I(\beta,\delta)$, are quadratic in the degree of accommodation δ:

$$\frac{\phi}{2}\delta^2\beta(1+\lambda)\pi \equiv I(\beta,\delta). \tag{9}$$

The monetary externalities are homogenous among citizens. This assumption help us to differentiate our helicopter money option from a permanent change in the monetary base. A permanent change implies a higher risk of inflation, which usually acts as a regressive tax.

Therefore, the indirect utility function, $V(\beta,\delta)$, of the average citizen at time 2 is:

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$$V(\beta,\delta) = C(\beta,\delta) - U(l^*) - E(\beta) - I(\beta,\delta). \tag{10}$$

As the population size is one, $V(\beta,\delta)$ also represents the social-welfare function.

The last step is the identification of the optimal helicopter monetary policy. We assume that as the central bank is independent from politics, it acts as a long-sighted social planner. As such, its actions should be consistent with the normative benchmark.

The motivation behind our assumption is well known. The role of central bank design emerged through the application of a game-theoretical approach following the discovery of the general time-inconsistency problems that characterize economic policy (Kydland and Prescott 1977, Calvo 1978). The key feature was the identification of the relationship between the political cost-benefit analysis of any incumbent government and the likelihood of a sub-optimal macroeconomic equilibrium. In this context, possible solutions to the problem of monetary policy effectiveness include an independent central bank (Sargent and Wallace 1981, Barro and Gordon 1983) or a conservative central banker (Rogoff 1985). At the same time, both concepts highlighted the importance of monetary stability in policy makers' goal functions. In this vein, the delegation of monetary policy to non-elected central bankers can be motivated by showing that bureaucrats are preferable to politicians for determining technical policy, while elected politicians retain decisions regarding purely redistributive policies under their direct control in order to please their voters (Alesina and Tabellini 2007).

Therefore, the central bank takes the relationship between the tax policy, τ, and the labour supply into account. It simultaneously sets the policy strategy regarding the fiscal backstop, β^*, and the monetary policy, δ^*, at time 1 in order to maximize the social-welfare function, $V(\beta,\delta)$.

Given the public budget constraint (3) and the labour supply (5), the budget constraint becomes:

$$\beta(1+\lambda)\pi(1+i(1-\delta)) = \tau L(\tau). \tag{11}$$

This gives the relationships among the three economic policies. By differentiating (11) and introducing the labour-supply elasticity, $\eta(\tau) \equiv -\tau L_T / L$, to highlight the tax-distortion effect, we obtain:

$$T_\beta = \frac{(1+\lambda)\pi(1+i(1-\delta)}{l^*(1-\eta(\tau))} > 0 \text{ and} \tag{12}$$

$$T_\delta = \frac{\beta(1+\lambda)\pi i}{l^*(1-\eta(\tau))} < 0, \tag{13}$$

where the tax policy and the helicopter money are inversely associated given that monetization lowers the debt-servicing costs and, consequently, the tax distortions. Then, using the overall social-welfare function (10), the two optimality conditions are:

$$V_\beta = C_\beta(\beta,\delta) - E_\beta(\beta) - I_\beta(\beta,\delta) \le 0 \text{ and} \tag{14}$$

$$V_\delta = C_\delta(\beta,\delta) - I_\delta(\beta,\delta) \le 0, \tag{15}$$

where strict inequality implies the corner solution (i.e. $\beta^* = 0$ or $\delta^* = 0$). In other words, if the social planner only considers "yes/no" decisions, the decisions are simple – the fiscal backstop must be implemented if the social benefits are greater than the social costs. The same is true for helicopter money. The optimal economy policy design addresses the trade-off between two public goals: externality smoothing and tax-distortion minimization. By solving the FOC system (14-15) and using (7-9), we obtain the socially optimal choices:

$$\beta^* = 1 - \frac{1}{\varepsilon(1+\lambda)\pi}\left[\tfrac{\eta}{1-\eta}(1+i(1-\delta^*)) + \frac{\phi}{2}\delta^{*2}\right] \text{ and} \tag{16}$$

$$\delta^* = \frac{\eta}{1-\eta}\frac{i}{\phi}. \tag{17}$$

If we focus on the central bank's decisions, the optimal level, δ^*, of helicopter money has well-defined properties. It increases: a) if the labour supply is relatively elastic, given that the corresponding tax-distortion risk is high; b) if the cost of debt servicing is high and c) if the monetary instability risks are low.

Moreover we can distinguish in a simple way the soft from the hard helicopter money option, if we assume that with the former the monetary stability risks are lower. In other words if δ_{HH} is the deficit monetization consistent with a permanent increase in central bank liabilities, it will follow that:

$$\delta^* > \delta_{HH}$$

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In the European Union setting, one example could be a special application of the Common European Debt option (Bruegel 2020). In light of the COVID19 pandemic, a European Transfer Plan could be designed in which all national needs related to the pandemic recession are aggregated (Bènassy-Quèrè et al. 2020a, Biancotti et al. 2020). Such a fiscal backstop could be financed through European Union assets (Garicano 2020) by issuing COVID Perpetual Bonds (Giavazzi and Tabellini 2020) via a specific vehicle (Amato et al. 2020) or, alternatively, the ESM (Bènassy-Quère et al. 2020b), with the European Central Bank (ECB) acting as buyer of these bonds. The ECB could credit the governments' accounts with a reduction in its capital (Gali 2020).

In order to apply our analysis, the ECB's action must be motivated by an independent evaluation of its Board that a decision to hold or permanently keep such Perpetual Bonds on its balance sheet (and the corresponding losses) will not harm its capacity to pursue its monetary-stability goal in the medium term. It must also believe that this will be an effective European economic tool. In so doing, the ECB will consider the constraints in increasing the tax revenues as well as the costs of debt issuance for the different European Union members with its likely domino effects. In this respect, it would be prudent to avoid triggering the fifth wave of rapid global debt accumulation and the consequent Euro redenomination risk, as the four previous waves ended with widespread financial crisis (Kose and al. 2020). In parallel, the COVID-19 pandemic represents an unprecedented shock for the labour market (Boeri et al. 2020, Fujita et al. 2020), which will deter any policymaker from financing a fiscal backstop through income taxes and/or value-added taxes; either a wealth-tax option (Landais et al. 2020) or a levy on financial assets (Gros 2020) cannot be excluded a priori, notwithstanding their consistency with a fiscal backstop cannot be taken for granted.

This could be a case of a European helicopter money, but would this European policy mix be politically feasible? In this regard, the cost/benefit analyses of the national governments are crucial.

3. Heterogenous Citizens and Their Politicians: One Type of Helicopter Money Doesn't Fit All

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In general, what is the fiscal backstop that a government can design? All else equal, including the uncertainty that stems from the policy hesitation in addressing the epidemic (Muller 2020) as well as the failure to prepare in advance to address rare events (Mackowiak and Wiederholt 2018), two situations can arise. Theoretically, if the government is a standard benevolent policymaker, its choices will be consistent with the social-planner decisions described in the previous section that aim to maximize economic efficiency. In other words, fiscal backstop and helicopter monetary policies will be both coordinated and optimal levers. The same is true if politicians are in charge but the citizens are completely homogeneous. However, even if the Economic and Monetary Union has efficient policymakers, the coordination outcome is not a given, as the Union does not yet have a device to achieve it (Reichlin and Shoenmaker 2020).

If politicians are in charge and citizens are heterogenous, different economic policies have relevant redistributive effects. In fact, the net transfers implied by efficient policies can be positive for some and negative for others. Cash money transfers and bond remuneration can influence the welfare of individual citizens differently when they are heterogeneous. However, as we noted before, if a policy task has distributional effects, the politicians would like to control those effects (Alesina and Tabellini 2007).

The distributional effects enter the picture because the mix of a fiscal backstop and helicopter money produces the “three D” (distributional, directional, duration) effects (Goodhart and Lastra 2017). The distributional effects result from changes in interest rates. The directional effect captures the impact of public policy on a certain sector and/or constituency of the economy (Brunnermeir and Sannikov 2013). The duration effect measures the monetary policy’s effect on overall public-sector liabilities, including the central bank’s balance sheet. The duration effect is associated with the dimensions and risk profile of the central bank’s balance sheet with its increasing relevance in the perimeter of monetary policy (Curdia and Woodford 2011, Reis 2013).

Helicopter monetization is associated with changes in the central bank’s balance sheet. At the same time, a fiscal backstop produces directional effects depending on how the concrete cash monetary policy is designed, while the distributional effect is associated with the

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corresponding debt policy. All in all, the overall economic policy strategy has redistributive consequences for citizens as well as political spillovers.

The redistributive effects are relevant as long as the policies are chosen through the political process (i.e. when the citizens are voters). In this regard, we consider majority voting with voter preferences that are associated with the economic consequences of a fiscal backstop financed via a helicopter monetary policy.

Given a voter *j*, let $\pi + \pi^j$ be the amount of assets in *j*'s portfolio at time 0. Specifically, depending on $\pi^j > 0$ or < 0, voter *j* will be a *leveraged citizen* relative to the average. Let $F(\pi^j)$ be the distribution of the leverage across the population. The leverage of the median voter will represent the extent to which the bank's ownership is concentrated.

Given a voter *j, l*et $\lambda + \lambda^j$ be the amount of his or her leverage at time 0. Depending on $\lambda\pi^j > 0$ or < 0, voter *j* will be a subsidized citizen relative to the average. Let $L(\lambda^j)$be the distribution of the subsidized citizens across the population. The leverage of the median voter will tell us whether the subsidized citizens represent the majority or a minority of the population.

However, voters can be heterogeneous as financial (bond) holders. Let $(\beta + b^j)(1+\lambda)(1-\delta)\pi$ be the amount of bonds in *j*'s portfolio at time 0. Depending on $b^j > 0$ or < 0, voter *j* will be a *wealthy citizen* relative to the average. Let $G(b^j)$ be the distribution of wealthy citizens in the population. The average of $G(b^j)$ is zero. The financial wealth of the median voter signals whether the wealthy voters represent the majority or a minority of the population.

Given the general individual utility function (10) and the above definitions of π^j, λ^j, b^j, the voter *j*'s utility $V^j(\beta,\delta)$is:

$$V^j(\beta,\delta) = V(\beta,\delta) + \beta\pi^j(1+\lambda) + b^j(1+\lambda)\pi i(1-\delta), \tag{18}$$

where the last two terms on the right-hand side account for the two forms of heterogeneity of voter *j* relative to the average. Each voter's preferences can differ from those of the social planner because of these two terms. Now we assume that the economic preferences reflect the

voters' policy preferences and are expressed using majority rule through sequential voting on the policy mix.

Zooming on the monetary policy preferences, given $V^j(\beta,\delta)$, the corresponding FOC and the social optimality condition V_δ, the optimal helicopter monetization for the voter *j* is:

$$V_\delta^j = V_\delta - b^j(1+\lambda)\pi i \le 0. \tag{19}$$

Assuming equation (19) holds as an equality, solving it yields:

$$\delta^j = (\frac{\eta}{1-\eta} - \frac{b^j}{\beta})\frac{i}{\phi}. \tag{20}$$

By comparing equation (20) with the socially optimal monetary policy (17), it is immediately evident that given a fiscal backstop $\beta \neq 0$, wealthy citizens dislike the helicopter monetization. By solving the voting game (Masciandaro and Passarelli 2019) and calling $m\delta$ the median voter, where $b^{m\delta}$ is the median of $G(b^j)$, the helicopter monetization level $\hat{\delta}$ chosen by the majority of voters would be:

$$\hat{\delta} = \delta * - \frac{b^{m\delta}}{\beta}\frac{i}{\varphi}. \tag{21}$$

The political distortion (i.e. $\left|\hat{\delta} - \delta *\right|$) will reflect four features of the economy. More specifically, given the fiscal backstop, the number of citizens against the helicopter money will be higher if: a) the majority of voters are wealthy, b) the interest rate is higher, c) the monetary stability risks are higher.

A perception of an unfair monetary policy can contribute to various forms of resentment and lead to hostility against the central bank. Moreover, the more the politicians in charge accommodate the demand for a level of helicopter monetization that differs from the central bank's optimal level, the greater the likelihood of political pressure. Notably, the political pressure can be considered as a proxy for the contingent demand for central bank reform. This interpretation can be confirmed by observing that the political pressure seems to be uncorrelated with legal – or *de jure* – central bank independence thus far (Binder 2018).

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The motivation is straightforward. Political pressures on the central bank may be relevant in shaping the actual monetary policy decisions, if the government in charge can threaten in some way the central banker role. For example if the institutional setting is such that any incumbent government in extraordinary times can retain the option to override the central banker's decision, the central banker can have the temptation to accommodate the political wishes in order to avoid being overridden (Lohman 1992). Political pressures can trigger monetary policy uncertainty. Such event could be captured in the simplest way assuming that the actual monetary policy decision δ_A is such that:

$$\delta_A = \lambda \left| \hat{\delta} - \delta^* \right| \tag{22}$$

where $0 < \lambda < 1$ represents the credibility of the political threat.

In the case of the European Union, the hostile sentiments against the ECB's monetary policies can be a factor to consider when explaining the various forms of nationalism, populism and Euroscepticism (Morelli 2020). Some researchers argue that the rise of populism may harm the consensus in favour of central bank independence (De Haan and Eijffinger 2017, Goodhart and Lastra 2017, Rajan 2017, Rodrik 2018). From an empirical point of view, the relationship between one aspect commonly attributed to populism – namely nationalism – and central bank independence has been empirically examined (Agur, 2018), while the relationships between both right-hand and left-hand populism and central bank independence have been discussed from a theoretical perspective (Masciandaro and Passarelli 2019).). Moreover if we assume that a correlation holds between the opinions on the so called "Corona Bond" issuing and the hostility against any kind of ECB monetization, the current debate - for example in Germany (Waltenberger 2020) - can offer interesting insights.

All in all, the more the citizens are heterogeneous and the more the elected representatives are career-concerned politicians, the more it will be true that the helicopter money that the independent central bank would like to implement will not fit the political preferences. In such situations, political pressures on the central bank are more likely and a helicopter monetary policy becomes less likely.

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4. Conclusions

This article discussed the design of relationships between a fiscal backstop implemented using cash transfers and a helicopter monetary policy that produces losses in the central bank's balance sheet without a permanent change in the money base. The analysis led to two results. If an independent central bank acts as a long-sighted policymaker, an optimal helicopter monetary policy can be identified. The features of such a policy can be defined by taking monetary-instability risks, the costs of issuing public debt and overall macroeconomic features into account. However, if the government in charge is made up of career-concerned politicians and citizens are heterogenous, then the policy mix will produce distributional effects. Conflicts between politicians and central bankers will be more likely and these, in turn, may trigger political pressures on the central bank. As such, helicopter money strategies are unlikely in such situations. The framework was applied in a discussion of the economics and politics of perpetual bonds with the European Central Bank as the buyer.

The discussion can be further enriched in many fruitful directions.

a) Monetary stability risks and citizen heterogeneity: In this regard, monetary instability is widely assumed to be a negligible social cost that is borne equally by all individuals as an outcome of temporary monetary base growth. If we were to associate monetary instability with specific idiosyncratic risks, we would assume that citizens can be also heterogeneous in their ability to address such risks through hedging, with some individuals bearing – or feeling that they bear – higher costs due to monetary instability (i.e. *inflation-adverse* citizens). Allowing for this kind of heterogeneity would lead to a straightforward prediction: the smaller the mass of risk-adverse citizens, the stronger the political pressure to engage in helicopter monetization.

b) Income and citizen heterogeneity: In this regard, labour income is assumed to be the same for all individuals. In the presence of income heterogeneity, the distributional effects are likely to increase. For example, given the decisions regarding monetary cash transfers, richer citizens are likely to have higher tax burden. Thus, all else equal, richer people would prefer smaller fiscal backstops. Similarly, in countries in which the less wealthy citizens are the majority, large monetary cash transfers will be more likely because the minority (i.e. the rich)

will bear most of the costs. Moreover, income heterogeneity can be correlated with other forms of asset heterogeneity. This can lead to interesting trade-offs.

c) Public debt, tax pressure and interest rates: In the focal context, government debt is only issued to address the pandemic-related recession, taxes are only raised to service that debt and the interest-rate level is consistent with the long-term risk-free interest rate. These are three simplifying assumptions. The insertion of initial taxation and initial debt into the framework would increase its complexity but probably not have any substantial consequences for the overall rationale. In contrast, interest rate endogeneity depending on the stock of debt is likely to exacerbate the policy trade-offs and, consequently, the relevance of the political distortions.

d) Central bank: The central bank's behaviour is assumed to be perfectly consistent with socially optimal planning. However, at least two factors can cast doubt on this assumption. First, modern monetary policy is often conducted by committees. In fact, the majority of central banks use committees (i.e. boards; Lybek and Morris 2004). This feature of central bank governance can deeply affect monetary policy decisions through at least three channels (Favaretto and Masciandaro 2016), which explore how: i) monetary policy committees work; ii) the composition of committees can shape monetary policy outcomes; and iii) psychology (i.e. the impact of cognitive biases). Central bank governance can influence monetary policy strategies in directions that are not automatically consistent with the social planner's choices. On the other hand, it is natural to wonder whether cases of political capture and/or bureaucratic capture could trigger deviations of the concrete monetary policy action from the (supposed) long-sighted perspective, such as those documented in the historical case of political pressure for partisan monetary policies (Abrams 2006).

e) Finally, from a methodological point of view, cognitive biases are not assumed to affect the relevant players: the voters are rational, i.e. they vote consistently with the re-distributional consequences of every policy strategy, and the policymakers are rational as well. However, behavioural biases can influence the preferences of both citizens and political actors. In general, behavioural insights can be used to explain how non-standard agents' choices can shape macroeconomic performance with reference to, for instance, long-standing debates on consumption, intertemporal substitution, the role of prices and wage stickiness. More specifically, behavioural

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economics can be used to explain the monetary policy mechanism (Molnar and Santoro 2014) by applying insights from prospect theory. Through the use of adaptive learning, reference-dependent preferences can be linked to loss aversion, such that losses in consumption utility resonate more than gains. At the same time, as we already noted below, motivational assumptions can be used to explain individual behaviour in policymaking, which is what behavioural political economics (Schnellenbach and Schubert 2015) is all about. This issue deserves further exploration in future research.

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Scenario analysis of non-pharmaceutical interventions on global Covid-19 transmissions[1]

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This paper introduces a dynamic panel SIR (DP-SIR) model to investigate the impact of non-pharmaceutical interventions (NPIs) on the COVID-19 transmission dynamics with panel data from 9 countries across the globe. By constructing scenarios with different combinations of NPIs, our empirical findings suggest that countries may avoid the lockdown policy with imposing school closure, mask wearing and centralized quarantine to reach similar outcomes on controlling the COVID-19 infection. Our results also suggest that, as of April 4th, 2020, certain countries such as the U.S. and Singapore may require additional measures of NPIs in order to control disease transmissions more effectively, while other countries may cautiously consider to gradually lift some NPIs to mitigate the costs to the overall economy.

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1. Introduction

Since December 2019, a coronavirus disease (COVID-19) has been spreading in China and now emerging as a global pandemic. In response to the COVID-19 crisis, many countries have ordered unprecedented non-pharmaceutical interventions (NPIs), including travel restriction, mask wearing, lockdown, social distancing, school closure, and centralized quarantine (such as cabin hospitals), all aiming to reduce the population contact rates and thus mitigate the virus transmission. On the other hand, prolonged NPIs have a large downside impact on the overall economic and social well-being, which may cause major concerns including increased unemployment rates and bankruptcy of firms. Therefore, it is of the utmost importance to investigate which interventions and to what extend have substantial impact on controlling the epidemiological dynamics, and how to choose the appropriate measures to fit country-specific socioeconomic circumstance. Understanding the impact of various NPIs on a global scale can provide insights for each country to choose the most cost-effective NPIs in a timely manner to contain and mitigate the virus spread.

A number of recent works studied the government intervention effects. [44] applied the Bass Susceptible-Infected-Recovered (Bass-SIR) model to study the lockdown and social distancing effects for province-specific epidemiological parameters in China. [42] used only the observed death data and proposed a (non-SIR based) Bayesian model to study several intervention effects on 11 European countries. [41] modified an individual-based simulation model to study the consequence of NPIs to reduce the COVID-19 mortality and healthcare demand in the UK and the U.S. [48] developed a Susceptible-Exposed-Infectious-Removed (SEIR) model to evaluated the impact of NPIs on the epidemic in Wuhan, China. [45] built a travel network-based SEIR model to study the impact of different NPIs in China. [40] proposed a time-dependent SIR model to account the impact of the Wuhan city lockdown and predicted the future trend of the COVID-19 transmission.

During the COVID-19 transmission process across the globe, several countries experienced an epidemic outbreak in 2020 at different timelines. The first COVID-19 epidemic outbreak started in Wuhan, China in late January. In early to mid-February, Singapore was near the top list of total confirmed cases outside China, and South Korea began to see rising numbers of total cases. A few days after the outbreak in South Korea in mid-February, outbreaks in Iran and Italy began in late February. In early March, the number of cases in many European countries sharply increased, shifting the epicenter from Asia to Europe. As of April 4th, European countries with the most confirmed cases include Italy, Spain, France, Germany, and the UK. While China and South Korea managed to control the virus spread and European countries are experiencing the outbreak, the U.S. quickly emerged as the biggest epicenter in the world, with the total cases surpassed China and Italy in late March, becoming the country with the most confirmed cases currently.

While countries experienced different timelines of the COVID-19 epidemic outbreaks, the non-pharmaceutical interventions each government imposed also varied accordingly. China implemented very strict NPIs right after the outbreak occurred in Wuhan, including travel restriction [20], lockdown [33], school closure [21], social distancing [22], wearing masks [23], and later on centralized quarantine [19]. South Korea imposed travel restriction [28], school closure [32], social distancing [35], wearing masks [1], and centralized quarantine [7], however it did not call a national lockdown. Singapore implemented travel restriction [30], social distancing [26], and centralized quarantine [27], without emphasis on mask wearing, school closure and a national lockdown. European countries have very similar government policies (at different time points) including travel restrictions, social distancing, school closure, and

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lockdown [24, 9, 36, 6, 17, 13, 3, 16, 10, 11, 14, 8, 4, 12, 15, 34, 31, 29, 5, 18] but not imposing policies on wearing masks and centralized quarantine. The U.S. has closer policies relative to Europe [39, 37, 38], except that it did not call a national lockdown yet (as of April 4th, 2020).

Due to the time-varying and heterogeneous nature of the outbreaks and the associated different NPIs across countries in the COVID-19 pandemic, it is important to borrow information from the panel data collected worldwide to help understand the impacts of different NPIs and to improve the prediction of the epidemiological developments for countries at later stages. To the best of our knowledge, there is no up-to-date analysis based on integrated infection, recovery and death data from different countries with significant variations in their NPIs and timelines on the global scale. In this paper, we perform a scenario analysis of NPIs on the COVID-19 transmission through a dynamic SIR model tailored to a panel study with data from 9 countries in three continents, which were or are currently the epicenters: Italy, Spain, Germany, France, the UK, Singapore, South Korea, China, and the United States.

2. Methodology

2.1. **SIR model with time-varying parameters.** The SIR model is a fundamental compartmental model in epidemiology [43]. The dynamic hypothesis behind the SIR model is the Kermack-McKendrick theory that predicts the number of cases of an infectious disease as it is transmitted through a population over time. In this paper, we consider a time-varying SIR model described by the following system of (non-linear) ordinary differential equations (ODEs):

$$\begin{aligned}\frac{\mathrm{d}S}{\mathrm{d}t} &= -\frac{\beta(t)I(t)}{N}S(t),\\ \frac{\mathrm{d}I}{\mathrm{d}t} &= \frac{\beta(t)S(t)}{N}I(t)-\gamma(t)I(t),\\ \frac{\mathrm{d}R}{\mathrm{d}t} &= \gamma(t)I(t),\end{aligned}$$

where $\beta(t) > 0$ is the disease transmission rate at time t and $\gamma(t) > 0$ is the recovery rate at time t. Here $S(t), I(t), R(t)$ denote the subpopulation sizes of susceptible, infected, and recovered at time t, respectively. In the absence of vaccine, we assume that the whole population size $N = S(t) + I(t) + R(t)$ is constant over time. Similar time-varying SEIR model (with an extra exposure state) was considered in [46]. The time-varying *reproduction number* is defined as

$$\mathcal{R}_t = \frac{\beta(t)}{\gamma(t)}. \tag{1}$$

In particular for $t = 0$, $\mathcal{R}_0$ is the *basic reproduction number* and $\mathcal{R}_{\text{eff}} = \mathcal{R}_0\frac{S(0)}{N}$ is the *effective reproduction number*. If $\mathcal{R}_{\text{eff}} > 1$, then $I(t)$ will first increase to its maximum and then decrease to zero, which is often referred as an epidemic outbreak. If $\mathcal{R}_{\text{eff}} < 1$, then $I(t)$ is monotonically decreasing and there would be no epidemic outbreak.

2.2. **Dynamic panel SIR model.** Suppose we have collected a panel dataset (i.e., longitudinal data) from p countries of population size $N_1, \dots, N_p$, and the data points are observed on evenly spaced time intervals such as daily data. Let $S_j(t), I_j(t), R_j(t)$ be the subpopulation sizes of susceptible, infected, recovered in country j at time t, respectively. Given initial data $\{S_j(0), I_j(0), R_j(0)\}_{j=1}^p$, the Euler method with the unit time interval gives the discretized

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version of the following *dynamic panel SIR* (DP-SIR) model determined by the system of equations: for $j = 1, \ldots, p$,

$$\begin{aligned} I_j(t+1) - I_j(t) &= \frac{\beta_j(t) S_j(t)}{N_j} I_j(t) - \gamma_j(t) I_j(t), \\ R_j(t+1) - R_j(t) &= \gamma_j(t) I_j(t), \\ N_j &= S_j(t) + I_j(t) + R_j(t), \end{aligned}$$

where $\beta_j(t) > 0$ and $\gamma_j(t) > 0$ are the rates of disease transmission and recovery in country j at time t, respectively. Denote $\Delta I_j(t) = I_j(t+1) - I_j(t)$ and $\Delta R_j(t) = R_j(t+1) - R_j(t)$. Then we may rewrite the discrete DP-SIR model as

$$\begin{aligned} \Delta I_j(t) + \Delta R_j(t) &= \frac{\beta_j(t) S_j(t)}{N_j} I_j(t), \\ \Delta R_j(t) &= \gamma_j(t) I_j(t), \end{aligned}$$

subject to the constraint $N_j = S_j(t) + I_j(t) + R_j(t)$. For simplicity, we treat $\gamma_j(t), j = 1, \ldots, p$ as constant functions, i.e., $\gamma_j = \gamma_j(t)$. To model the intervention effect on $\beta(t)$, our basic intuition is that each intervention has the same effect on the disease transmission rate (thus the reproduction numbers since $\gamma_j(\cdot)$ is constant) across countries and over time. Specifically, to borrow information cross countries, the coefficients $\beta_j(t)$ have a panel data structure:

$$\beta_j(t) = \exp\Big(\alpha_j + \sum_{k=1}^{K} \beta_k \, \mathsf{NPI}_{tjk}\Big), \tag{2}$$

where NPI_{tjk} is the k-th NPI in country j at time t, α_j is the country-level fixed (non-random) effect, and β_k is the k-th NPI effect which does not depend on j and t.

2.3. **Construction of the NPIs.** We now construct the NPIs from their intervention times. Let $t \in [0, T]$ be the time span for observing data from the DP-SIR model and t^*_{jk} be the intervention time by the k-th NPI in country j. Then NPI_{tjk} is modeled as following:

$$\mathsf{NPI}_{tjk} = \begin{cases} 1 & \text{if } 0 \leqslant t < t^*_{jk} \\ \exp\Big(-\frac{t - t^*_{jk}}{\tau}\Big) & \text{if } t^*_{jk} \leqslant t \leqslant T \end{cases}, \tag{3}$$

where $\tau > 0$ is a user-specified scale parameter controlling the time-lag effect of interventions. Specifically, for smaller τ, NPI_{tjk} is closer to the indicator function $\mathbf{1}(t \leqslant t^*_{jk})$; for larger τ, NPI_{tjk} decays to zero more slowly, which reflects the time-lag to see the intervention effect. Thus NPI_{tjk} in (3) is a smooth approximation of interventions with incorporated time-lag effect.

2.4. **Estimation.** Suppose the data $I_j(t)$ and $R_j(t)$ are observed at time points $t_i, i = 1, \ldots, T_j$ with equal spacing. With the panel structure (2) and the NPI parametrization (3), our goal is to estimate the parameter of interest $\boldsymbol{\theta} := (\alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_K, \gamma_1, \ldots, \gamma_p) \in \mathbb{R}^{K+2p}$ from the observed data. For shorthand notation, we write $I_{ij} = I_j(t_i), \Delta I_{ij} = I_j(t_i + 1) - I_j(t_i)$ for $i = 1, \ldots, T_j - 1$, and similarly for R_{ij}, S_{ij} and $\Delta R_{ij}, \Delta S_{ij}$. Denote $\mathsf{NPI}_{ijk} = \mathsf{NPI}_{t_i jk}$.

We use the ordinary least-squares (OLS) to estimate $\boldsymbol{\theta}$. The squared loss function of the DP-SIR model is given by

$$\ell(\boldsymbol{\theta}) = \sum_{j=1}^{p} \sum_{i=1}^{T_j - 1} \Big[\log\Big(\Delta I_{ij} + \Delta R_{ij}\Big) - \log\Big(\frac{S_{ij} I_{ij}}{N_j}\Big) - \Big(\sum_{k=1}^{K} \beta_k \, \mathsf{NPI}_{ijk} + \alpha_j\Big)\Big]^2 + \sum_{j=1}^{p} \sum_{i=1}^{T_j - 1} \Big(\Delta R_{ij} - \gamma_j I_{ij}\Big)^2.$$

Then the OLS estimate for $\boldsymbol{\theta}$ is given by

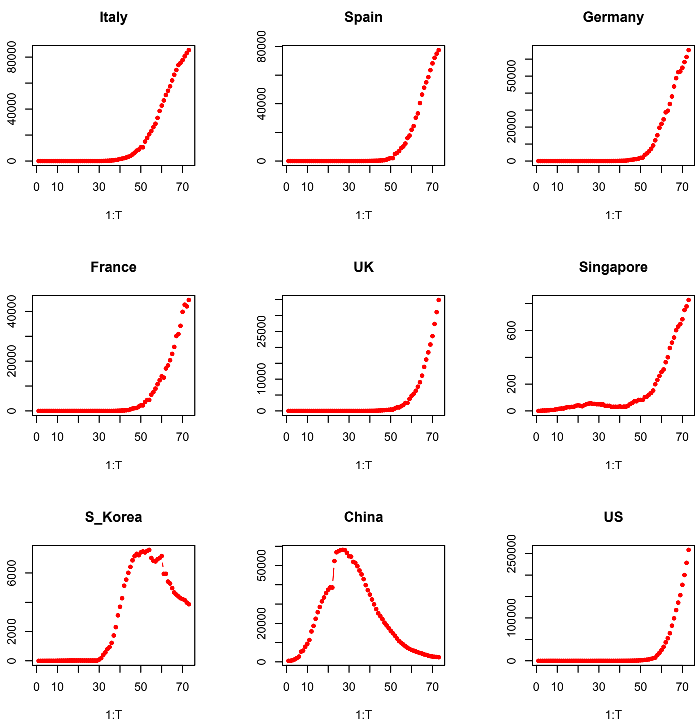
$$\hat{\boldsymbol{\theta}} = \operatorname{argmax}_{\boldsymbol{\theta} \in \mathbb{R}^{K+2p}} \ell(\boldsymbol{\theta}).$$

Based on the OLS estimate, we can also test for which intervention is statistically significant.

3. Scenario analysis on COVID-19 panel data

3.1. Data description. We collected COVID-19 data on the number of infections, recoveries and deaths of 9 countries between 1/22/2020 and 4/3/2020, including Italy, Spain, Germany, France, the UK, Singapore, South Korea, China, and the United States. The dataset is made publicly available by the Center for Systems Science and Engineering (CSSE) at John Hopkins University and it can be downloaded at [25]. In total, there are 73 days in this time span and the daily active cases (i.e., number of current infections) are plotted in Figure 1.

Figure 1. Observed data for the number of active cases from 9 countries between 1/22/20 and 4/3/20. There are $T = 73$ data points in each plot.



In addition, we reviewed the NPIs each country imposed, and we considered the following NPIs in our initial DP-SIR model: travel restriction (TR), mask wearing (MW), lockdown (LD), social distancing (SD), school closure (SC), and centralized quarantine (CQ).

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Table 1. NPIs used in our model. TR: travel restrictions; MW: mask wearing; LD: lockdown; SD: social distancing; SC: school closure; CQ: centralized quarantine. N/A means that an intervention is not implemented up to 4/3/20.

County / NPI	TR	MW	LD	SD	SC	CQ
Italy	1/31/20	N/A	3/8/20	3/8/20	3/5/20	N/A
Spain	3/16/20	N/A	3/14/20	3/14/20	3/12/20	N/A
Germany	3/15/20	N/A	3/22/20	3/12/20	3/13/20	N/A
France	3/17/20	N/A	3.17/20	3/15/20	3/16/20	N/A
UK	3/17/20	N/A	3/23/20	3/16/20	3/20/20	N/A
Singapore	1/23/20	N/A	N/A	3/27/20	N/A	1/23/20 [1]
South Korea	2/4/20	2/2/20 [2]	N/A	3/20/20	2/24/20	3/2/20
China	1/23/20	2/2/20 [3]	1/23/20	1/23/20	1/23/20	2/3/20
U.S.	2/2/20	N/A	N/A	3/16/20	3/16/20	N/A

The intervention times and descriptions of the NPIs imposed in each country were collected from local government websites, official public health authorities, and major newspapers [20, 33, 22, 21, 23, 19, 28, 32, 35, 1, 7, 30, 26, 27, 24, 9, 36, 6, 17, 13, 3, 16, 10, 11, 14, 8, 15, 4, 12, 15, 34, 31, 29, 5, 18, 39, 37, 38]. Summary of each country's NPIs with their intervention times are shown in Table 1. We choose the scale parameter $\tau = 7$ in (3) to control the time-lag effect of interventions for the COVID-19 study as a proxy for the incubation period (typically 2-14 days [2]).

3.2. **Estimation of NPI impact.** We first include all 6 NPIs from Table 1 into the DP-SIR model. The estimated coefficients with 95% confidence intervals in this full model are shown in Table 2.

Note that TR and SD are not statistically significant at the 95% confidence level. First, while many countries imposed travel restrictions for passengers coming directly from China, they did not ban travels from other international destinations, which may not be an effective policy as people who were infected could still come across the border by connecting to a third country. Second, given that SD intervention came very close to SC and LD interventions, we may view SD as a weaker intervention than LD, while it is stronger than SC. Hence the inclusion of SC and LD would be a strong proxy for SD. In addition, the coefficients for MW, LD, SC, CQ are all positive, which implies that these interventions are effective in reducing COVID-19 transmission rate. Table 2 also indicates that CQ is the most effective NPI to mitigate the COVID-19 transmission, while LD, SC and MW also play an important role. In our subsequent scenario analyses, we primarily focus on the 4 NPIs with statistically significant positive coefficients (i.e., MW, LD, SC, CQ).

While NPIs have different impacts on mitigating virus transmission, they are also associated with different degrees of costs to the overall economy. Policies such as lockdown may hurt the economy significantly by forcing non-essential businesses to close for a certain period of time, which may cause firms to go bankruptcy and employees to lose jobs. Other policy

[1]Singapore did not have a reported date for centralized quarantine. We used the earliest date for NPI as the proxy for central quarantine date.

[2]South Korea did not have a strict policy implementation date for wearing masks. We used 2/2/20 as the proxy date for wearing mask.

[3]Although mask wearing policy was imposed on 1/23/20, China had a shortage of mask supply until 2/2/20. BBC News Feburary 6th, 2020.

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such as mask wearing is the most cost-efficient due to the low cost of production and easy implementation. Understanding the benefits of different combinations of NPIs in reducing the transmission rates as well as the costs to the economy are essential for countries to choose the most appropriate combination of NPIs to balance the control of virus transmission as well as the economy performance.

TABLE 2. Estimated NPI impact.

NPI	estimated coefficient	95% CI
travel restriction (TR)	-0.343	[-0.786, 0.100]
mask wearing (MW)	0.651	[0.009, 1.294]
lockdown (LD)	1.063	[0.427, 1.699]
social distancing (SD)	-0.279	[-0.986, 0.427]
school closure (SC)	0.972	[0.339, 1.604]
centralized quarantine (CQ)	2.042	[1.493, 2.592]

In the next section, we predict the COVID-19 transmission dynamics under various policy scenarios with different combinations of NPIs.

3.3. **Scenario analysis.** To begin with, we look at the predicted active cases of the 9 countries using the strongest combination MW+LD+SC+CQ, which also has the biggest negative impact on the economy. Predicted active cases of the 9 countries for MW+LD+SC+CQ over time up to 8/9/20 (i.e., $T = 200$) is shown in Figure 2. Predicted time point and height of the epidemic peak, as well as the number of total infected cases on 8/9/20 for MW+LD+SC+CQ are shown in Table 3.

TABLE 3. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) for MW+LD+SC+CQ.

NPIs	Peak location	Peak value	Total # cases by 8/9/20	Total population
Italy	4/10/20	102,938	194,473	60,461,826
Spain	4/7/20	87,049	175,802	46,754,778
Germany	4/7/20	70,389	124,911	83,783,942
France	4/7/20	47,219	88,022	65,273,511
UK	4/11/20	43,067	67,644	67,886,011
Singapore	4/15/20	1,136	2,846	5,850,342
South Korea	3/16/20	7577	11,013	51,269,185
China	2/18/20	58,108	83,073	1,439,323,776
U.S.	4/15/20	429,641	677,801	331,002,651

From Figure 2, we see that by imposing the strongest combination MW+LD+SC+CQ of NPIs, each country can reach the turning point the soonest, with Spain, Germany and France having the peak day on April 7th, Italy on April 10th, UK on April 11th, U.S. and Singapore on April 15th. After passing the peak days, the numbers of actively infected cases will drop faster for France, Spain and Germany than for Italy, UK, U.S. and Singapore. The NPIs would not impact China and South Korea significantly given that they both have passed the peak and especially China's active cases are approaching to zero.

We notice that the MW+LD+SC+CQ scenario was indeed China's selection of NPIs during its outbreak. China took a strict implementation of all four policies, which succeeded in

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Table 4. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) for MW+SC+CQ.

NPIs	Peak location	Peak value	Total # cases by 8/9/20	Total population
Italy	4/11/20	113,933	233,740	60,461,826
Spain	4/8/20	95,805	203,657	46,754,778
Germany	4/8/20	75,893	144,758	83,783,942
France	4/8/20	50,414	98,814	65,273,511
UK	4/13/20	47,938	86,516	67,886,011
Singapore	4/18/20	1,201	3,647	5,850,342
South Korea	3/16/20	7,577	11,894	51,269,185
China	2/18/20	58,108	83,126	1,439,323,776
U.S.	4/19/20	389,914	774,269	331,002,651

significantly reducing the reproduction rate in a timely manner (cf. Figure 3). Although it is the most economically costly method in the short run, by getting the best infection control outcome in the shortest period of time, China can quickly reach a very low reproduction rate and recover the economy by releasing those strict policies sooner. Our finding is consistent with what China is doing right now: China lifts all those restrictions nationally, with Wuhan being the last city and planning to remove those policies on April 8th.

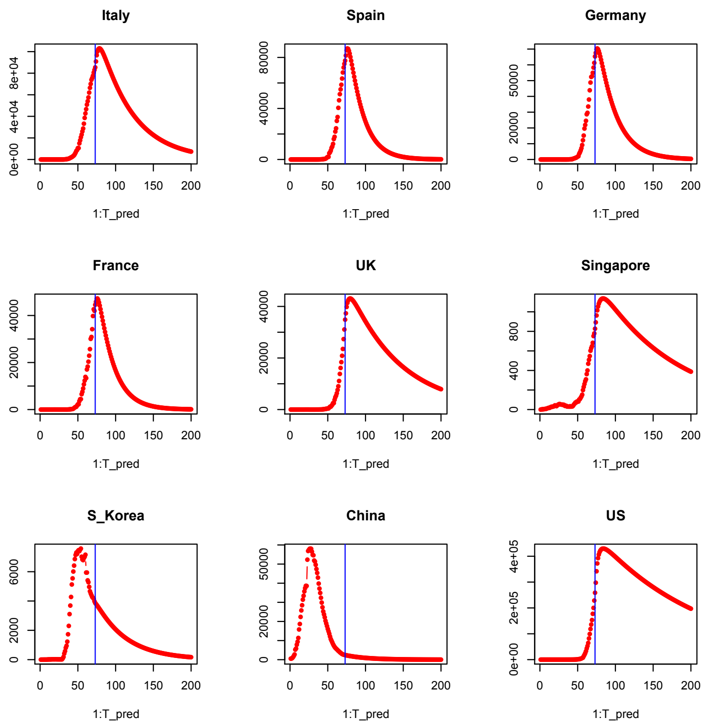
While having most strict NPIs can help each country which are experiencing outbreak to control virus transmission in the fastest way, the economy costs associated with such scenario are also the highest. Given the lockdown policy is in particular harmful to the economy, we then construct a weaker NPI combination by relaxing the lockdown policy while still imposing the other three: mask wearing, school closure, and centralized quarantine. Such NPI combination MW+SC+CQ can be economically affordable given it does not require closing businesses for all industries except for schools. The prediction is shown in Figure 4.

By comparing the results of MW+SC+CQ in Figure 4 with MW+LD+SC+CQ in Figure 3, we find that the predicted infection outcomes are very similar, which implies that lifting the lockdown policy may not substantially impact the infection outcome, provided that: (i) schools still remain closed, (ii) everyone is required to wear masks, and (iii) there is a centralized quarantine system to isolate all confirmed cases from their households. By excluding lockdown policy, the peak time is postponed for 1 day for Italy (April 11th), Spain, Germany and France (April 8th), 2 days for the UK (April 13th), 3 days for Singapore (April 18th) and 4 days for the U.S. (April 19th). Considering the significant economy harm of lockdown, this set of NPIs may be more feasible for many countries given it does not require to suspend the majority of economic activities on a national scale.

South Korea indeed took this approach MW+SC+CQ (without a national lockdown). By choosing this combination of NPIs, South Korea reached its turning point fairly quickly and successfully managed to control the COVID-19 transmission in an economically efficient way. Although it may control the virus spread slower and may require lifting those imposed policies later than what China did, it does provide a solution to keep the entire economy running even during the outbreak. This finding may provide insights for European countries, which are experiencing the negative economic consequences caused by the national lockdown, to consider imposing mask wearing and centralized quarantine so they can lift the lockdown policy.

To proceed further, we remove one more NPI from MW+SC+CQ to see whether or not any combination of two NPIs can achieve as efficient outcomes as imposing all the three, which

FIGURE 2. Predicted active cases of the 9 countries using MW+LD+SC+CQ. Date of the blue vertical line is 4/3/20. Observed number of active cases between 1/22/20 and 4/3/20 are on the left side of the blue vertical line and predicted number of active cases between 4/4/20 and 8/9/20 are on the right side of the blue vertical line.



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may be more economically efficient. While imposing two NPIs generally work for majority of the European countries (see the complete data in Appendix), we find that it may not work effectively for Singapore and the U.S. In particular, we find that by imposing only SC+CQ or MW+CQ, Singapore cannot even reach the turning points by August 9th, which implies that the transmission rate will not be below 1 and the outbreak cannot be controlled. For the U.S., although imposing two NPIs can still enable the country to reach the turning points in late April (April 25th for SC+CQ, April 25th for MW+SC, and April 22nd for MW+CQ), but after passing the turning point, the transmission rates drop very slowly, with the curve for active cases remain relative flat. It suggests that both Singapore and the U.S. may need to impose stricter NPIs relative to other countries in order to enable reaching a turning point and/or faster dropping transmission rates.

To summarize, our scenario analysis provides useful insights for countries to choose the most appropriate combination of NPIs which can balance the benefits on infection controls and the costs to the overall economy. Taking into consideration the heterogeneity across

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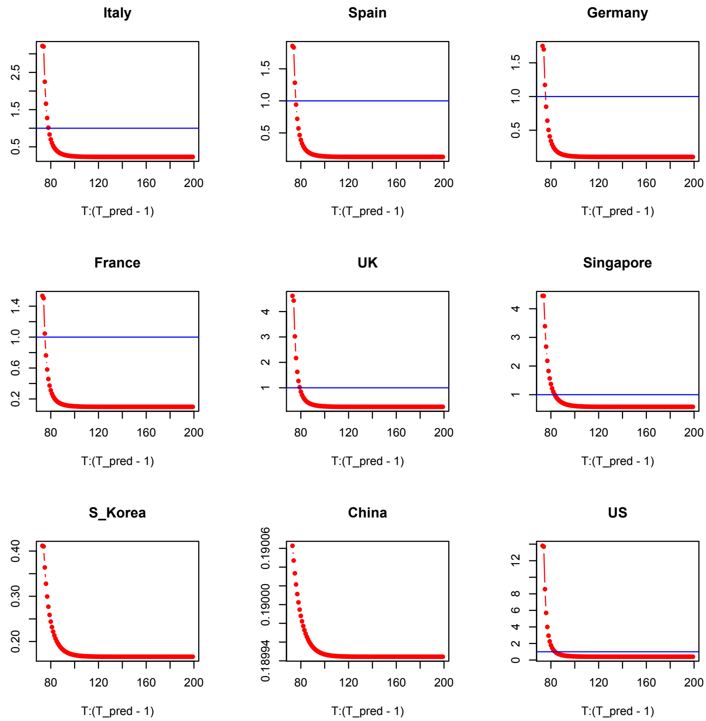
FIGURE 3. Effective reproduction numbers $\mathcal{R}_{\text{eff}}$ of the 9 countries using MW+LD+SC+CQ between 4/3/20 and 8/9/20. Blue horizontal line corresponds to $\mathcal{R}_{\text{eff}} = 1$.

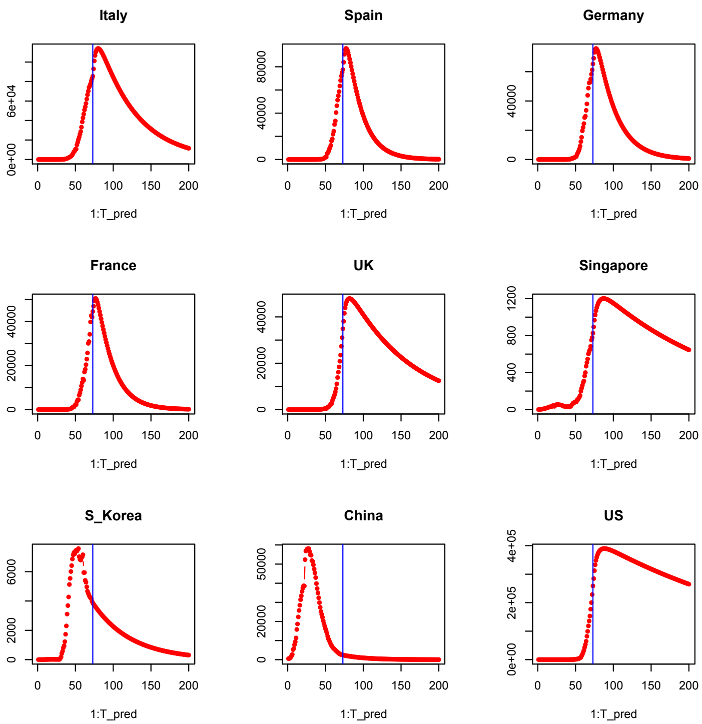


countries, each country should customize its own choices of NPIs to reach its desired goal in both infection and economy measures. As of April 4th, Singapore and the U.S. may need to impose stricter NPIs, while European countries which are about to reach the turning points in the next few days can cautiously consider to gradually lift some policy such as national lockdown. The estimation and scenario analysis results provide an empirical evidence for countries to impose mask wearing and centralized quarantines instead of a national lockdown, which can provide similar disease transmission-control outcomes and meanwhile minimize the damage to the overall economy. Our findings can also provide useful insights for other countries which have not yet and however may experience an epidemic outbreak in a future time.

4. Discussion

This paper proposes a dynamic SIR model to estimate the impact of various NPIs on the COVID-19 transmission using panel data from 9 countries across the globe. Data from these countries show significant variations in their selections and timelines of the NPIs. Our findings suggest that centralized quarantine is the most effective NPI measure, followed by

FIGURE 4. Predicted active cases of the 9 countries using MW+SC+CQ. Date of the blue vertical line is 4/3/20. Observed number of active cases between 1/22/20 and 4/3/20 are on the left side of the blue vertical line and predicted number of active cases between 4/4/20 and 8/9/20 are on the right side of the blue vertical line.



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lockdown, school closure and wearing masks. The scenario analysis shows that lockdown might be cautiously lifted if the country using the other three NPIs simultaneously (school closure, wearing masks and centralized quarantine).

Our findings provide feasible solutions for countries to use economically affordable NPIs such as mask wearing and centralized quarantine to replace the highly economically costly NPIs such as national lockdown, without significantly heightening the epidemic peak and can substantially flatten the curve of the active COVID-19 cases to reach a non-epidemic regime. This paper also suggests each country should customize its choice of NPIs by considering specific socioeconomic situations within the country. In particular, our empirical findings suggest that, as of April 4th, Singapore and the U.S. might consider imposing stricter NPIs, while European countries may cautiously consider to gradually lift the policies after reaching the turning points in a few days.

We are aware that there are likely undetected cases in the population, for instance because the testing capacity is limited and individual has no symptoms, which may cause potential

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issues such as the second-wave of the epidemic after the control policy is lifted. It is possible to calibrate such effect by ongoing random testing of the population in the SIR framework [47].

To conclude, the DP-SIR model used with panel data can provide useful insights for countries to choose the most appropriate NPIs in a timely manner to balance the desired goals between the economy performance and health consequence.

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Appendix A. Additional prediction results

This appendix presents additional prediction results.

Table 5. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in Italy. Total population size of Italy is 60,461,826.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	4/12/20	115,495	259,519
MW+CQ	4/12/20	153,948	287,300
MW+SC	4/12/20	110,310	258,353
MW+SC+CQ	4/11/20	113,933	233,740
MW+LD+SC+CQ	4/10/20	102,938	194,473

Table 6. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in Spain. Total population size of Spain is 46,754,778.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	4/9/20	95,918	214,319
MW+CQ	4/10/20	145,736	290,562
MW+SC	4/8/20	90,480	205,233
MW+SC+CQ	4/8/20	95,805	203,657
MW+LD+SC+CQ	4/7/20	87,049	175,802

Table 7. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in Germany. Total population size of Germany is 83,783,942.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	4/8/20	75,799	151,653
MW+CQ	4/10/20	110,708	205,406
MW+SC	4/8/20	72,260	145,375
MW+SC+CQ	4/8/20	75,893	144,758
MW+LD+SC+CQ	4/7/20	70,389	124,911

Table 8. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in France. Total population size of France is 65,273,511.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	4/8/20	50,338	102,452
MW+CQ	4/10/20	74,161	141,862
MW+SC	4/7/20	48,061	97,952
MW+SC+CQ	4/8/20	50,414	98,814
MW+LD+SC+CQ	4/7/20	47,219	88,022

Table 9. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in the UK. Total population size of the UK is 67,886,011.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	4/14/20	48,627	97,341
MW+CQ	4/15/20	77,132	146,285
MW+SC	4/14/20	45,537	91,453
MW+SC+CQ	4/13/20	47,938	86,516
MW+LD+SC+CQ	4/11/20	43,067	67,644

Table 10. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in Singapore. N/A means peak is not achieved by 8/9/20. Total population size of Singapore is 5,850,342.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	N/A	3,239	9,587
MW+CQ	N/A	10,290	22,792
MW+SC	4/10/20	1,121	1,861
MW+SC+CQ	4/18/20	1,201	3,647
MW+LD+SC+CQ	4/15/20	1,136	2,846

Table 11. Predicted time point and height of the epidemic peak, as well as the number of total infected cases at $T = 200$ (i.e., 8/9/20) in the U.S. Total population size of the U.S. is 331,002,651.

NPIs	Peak location	Peak value	Total number of cases by 8/9/20
SC+CQ	4/25/20	404,489	922,658
MW+CQ	4/22/20	641,340	1,315,976
MW+SC	4/25/20	378,099	874,759
MW+SC+CQ	4/19/20	389,914	774,269
MW+LD+SC+CQ	4/15/20	429,641	677,801

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FIGURE 5. Predicted active cases of the 9 countries using MW+SC. Date of the blue vertical line is 4/3/20. Observed number of active cases between 1/22/20 and 4/3/20 are on the left side of the blue vertical line and predicted number of active cases between 4/4/20 and 8/9/20 are on the right side of the blue vertical line.

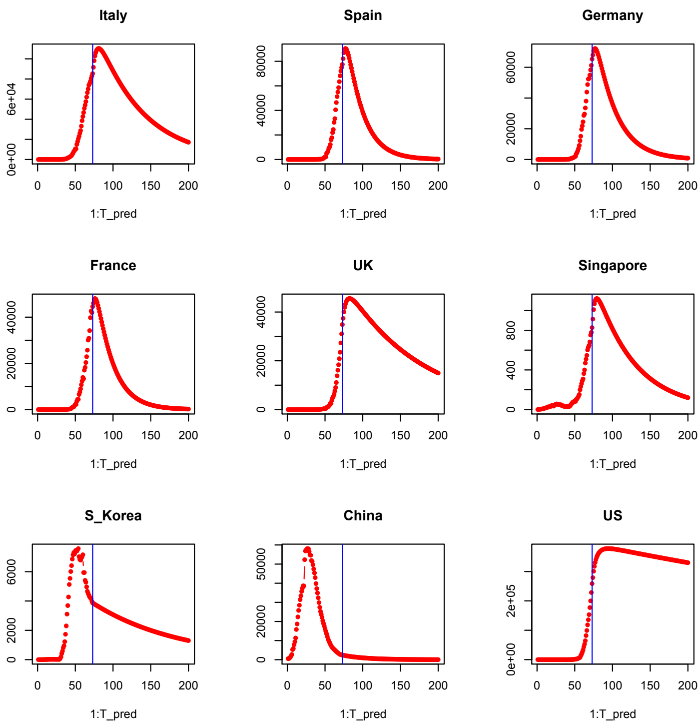

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Figure 6. Predicted active cases of the 9 countries using MW+CQ. Date of the blue vertical line is 4/3/20. Observed number of active cases between 1/22/20 and 4/3/20 are on the left side of the blue vertical line and predicted number of active cases between 4/4/20 and 8/9/20 are on the right side of the blue vertical line.

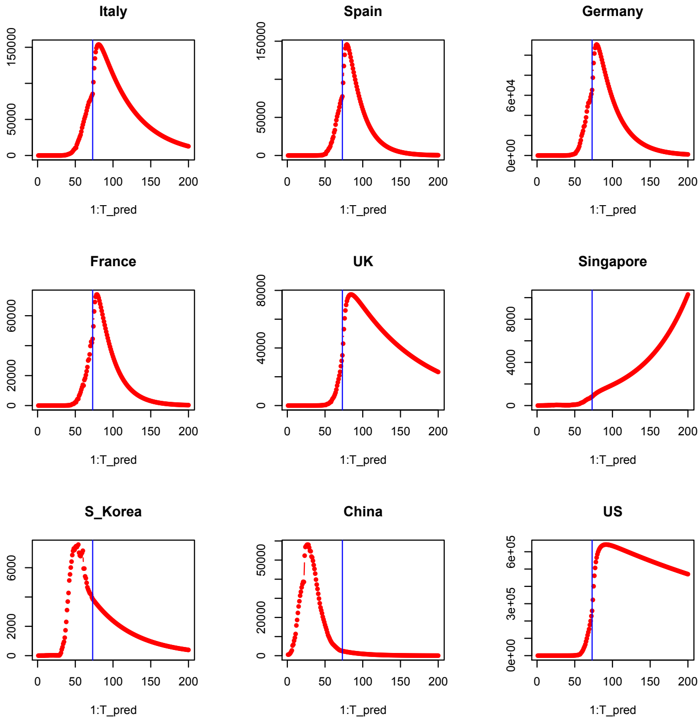

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FIGURE 7. Predicted active cases of the 9 countries using SC+CQ. Date of the blue vertical line is 4/3/20. Observed number of active cases between 1/22/20 and 4/3/20 are on the left side of the blue vertical line and predicted number of active cases between 4/4/20 and 8/9/20 are on the right side of the blue vertical line.

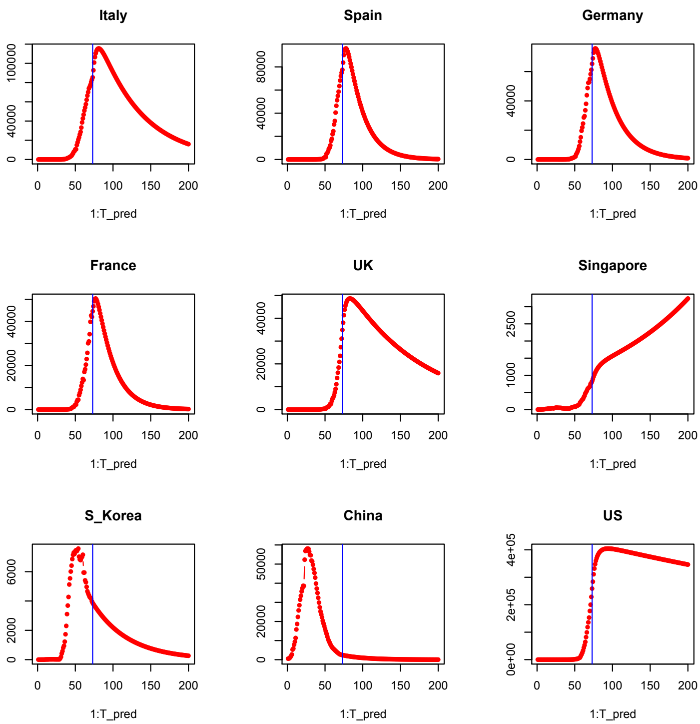

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FIGURE 8. Effective reproduction numbers $\mathcal{R}_{\text{eff}}$ of the 9 countries using MW+SC+CQ between 4/3/20 and 8/9/20. Blue horizontal line corresponds to $\mathcal{R}_{\text{eff}} = 1$.

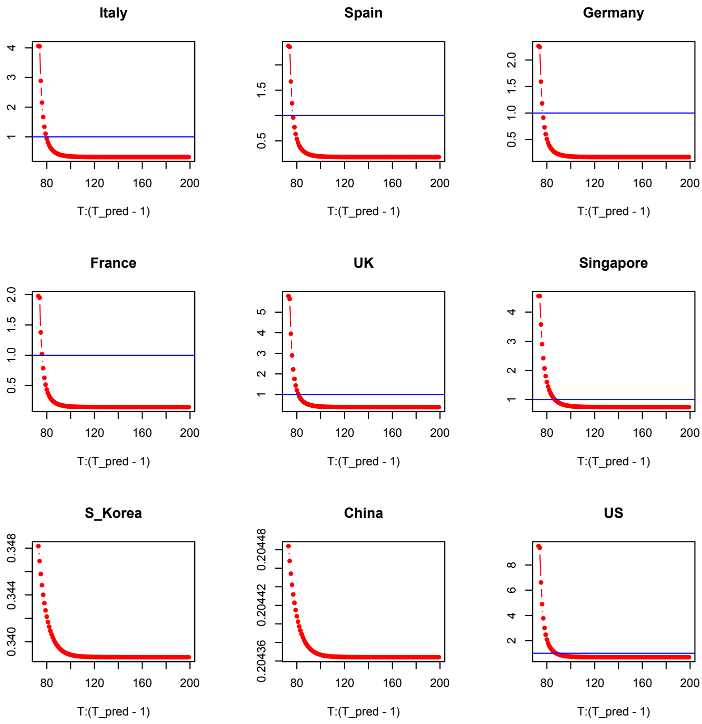

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FIGURE 9. Effective reproduction numbers $\mathcal{R}_{\text{eff}}$ of the 9 countries using MW+SC between 4/3/20 and 8/9/20. Blue horizontal line corresponds to $\mathcal{R}_{\text{eff}} = 1$.

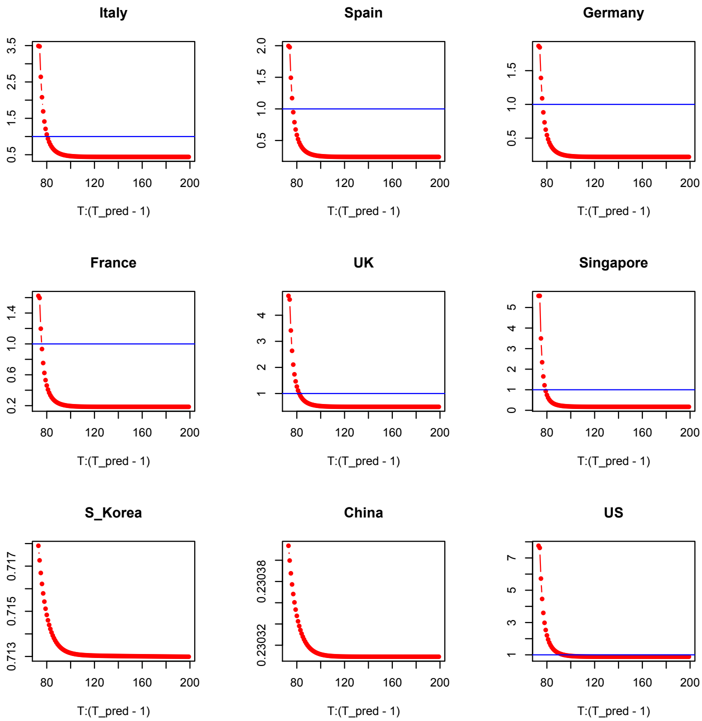

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FIGURE 10. Effective reproduction numbers $\mathcal{R}_{\text{eff}}$ of the 9 countries using MW+CQ between 4/3/20 and 8/9/20. Blue horizontal line corresponds to $\mathcal{R}_{\text{eff}} = 1$.

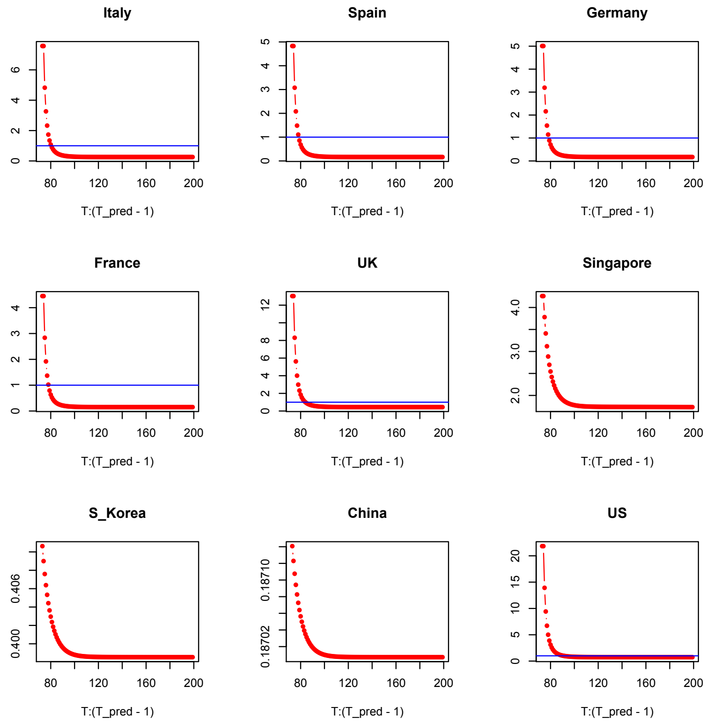
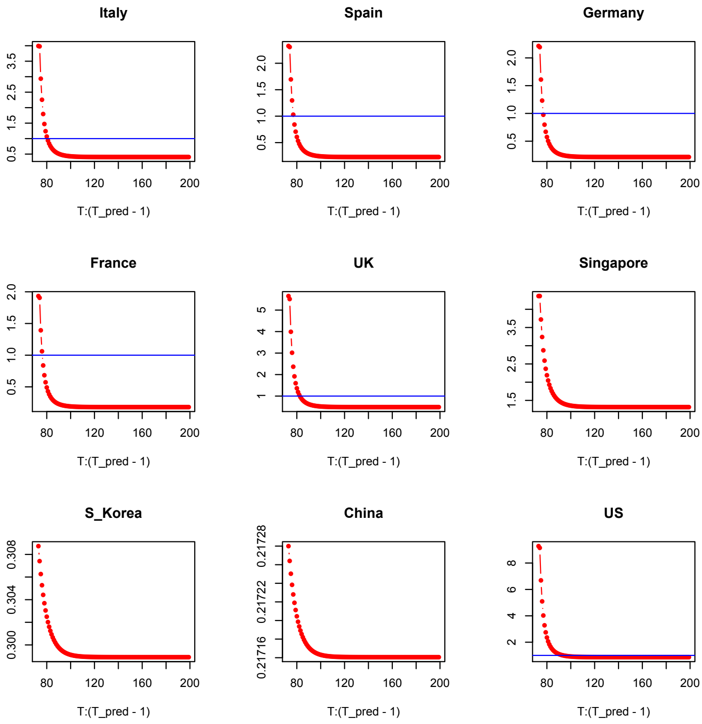


FIGURE 11. Effective reproduction numbers $\mathcal{R}_{\text{eff}}$ of the 9 countries using SC+CQ between 4/3/20 and 8/9/20. Blue horizontal line corresponds to $\mathcal{R}_{\text{eff}} = 1$.



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On the optimal 'lockdown' during an epidemic

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Date submitted: 13 April 2020; **Date accepted:** 13 April 2020

We embed a lockdown choice in a simplified epidemiological model and derive formulas for the optimal lockdown intensity and duration. The optimal policy reflects the rate of time preference, epidemiological factors, the hazard rate of vaccine discovery, learning effects in the health care sector, and the severity of output losses due to a lockdown. In our baseline specification a Covid-19 shock as currently experienced by the US optimally triggers a reduction in economic activity by two thirds, for about 50 days, or approximately 9.5 percent of annual GDP.

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1 Introduction

To "flatten the curve" of severe respiratory tract infections caused by Covid-19, policy makers around the world have imposed strict social distancing measures and partial lockdowns. In that context, a first-order policy question is how strict such measures should be and for how long they should be imposed. In this note, we propose two simple models based on the classical epidemiological framework with an embedded policy choice to address this question.

Our analysis starts from a framework with "susceptible," "infected," and "removed" (deceased or fully recovered) persons in the tradition of the classical article by Kermack and McKendrick (1927). In that framework transitions between the subgroups with different health status are governed by epidemiological parameters. We augment this framework by allowing for a policy choice—reflecting the level of economic activity—to affect infection rates. Higher activity increases production but also raises the rate of infections, causing future production shortfalls due to death as well as an overburdening of the health care system. Since current and future production shortfalls and health care costs enter society's loss function the government's program is a dynamic one: to select the optimal path for activity (or social distancing or lockdowns).

This dynamic program cannot be solved in closed form. In parallel, ongoing work Alvarez et al. (2020) therefore numerically solve for the optimal policy path. We pursue a complementary approach: We simplify the epidemiological framework slightly and build two nested, much more tractable models. One of them can be solved in closed form and the other can "nearly" be solved in closed form. Together, the two models offer transparent and easy-to-compute answers to the policy question at hand. We believe that this is valuable, in particular when information about an infectious disease—like Covid-19 now—is sparse and the task is to gain a first, basic understanding of the tradeoffs at work.

We allow the government's program to reflect several factors that prominently feature in policy discussions. For example, one of our models features convex costs of flows from the susceptible to the infected population, introducing a role for policies that flatten the curve. Similarly, our other model includes learning effects in the health care sector which introduce a role for delaying such flows. The learning effects reflect the fact that except for a few countries mostly in the Far East (that had experienced similar outbreaks

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in the past), governments and public health agencies across the globe were left scrambling after the surge in Covid-19 infections; over time, we should expect experience and more adequate supplies of equipment to relax some of the current bottlenecks.

When we calibrate the models using information about the projected death toll, health care stress, and output losses in the US due to the current Covid-19 shock we find that the optimal lockdown is quite severe and prolonged: Activity is optimally reduced by two thirds, for roughly 50 days. We conduct a series of robustness checks and find that all resulting model predictions are in the same ballbark.

As mentioned before our work is closely related to ongoing work by Alvarez et al. (2020). Other recent contributions that merge basic epidemiology and economics include Atkeson (2020), Eichenbaum et al. (2020), and Stock (2020). For discussions of the broader policy options, see for example Baldwin and Weder di Mauro (2020a; 2020b).

2 The Model

Our analysis is based on the canonical epidemiological model (the SIR model) due to Kermack and McKendrick (1927). We simplify that framework to improve tractability and imbed policy decisions that capture the severity and duration of a "lockdown." In this section we review the SIR model and introduce policy objective and instrument.

2.1 SIR Model

The SIR model specifies laws of motion in continuous time for the population shares of three groups that differ with respect to health status. The three groups are the "susceptible," the "infected," and the "removed," and their respective population shares at time $t \geq 0$ are denoted by $x(t)$, $y(t)$, and $z(t)$, where $x(t) + y(t) + z(t) = 1$. We normalize the population size to unity. Accordingly, the population shares $x(t)$, $y(t)$, and $z(t)$ correspond to the "number" of susceptible, infected, and removed persons.

At time $t = 0$ the population consists of $x(0)$ susceptible persons and a few infected persons, $y(0)$. There are no removed persons at this time, $z(0) = 0$. In each instant after time $t = 0$, the infected transmit their infection to the susceptible and a fraction of the infected either dies or develops

resistance. Formally, following Bohner et al. (2019), the change of the number of susceptible, infected, and removed persons, respectively, satisfies

$$\dot{x}(t) = -b(t)x(t)\frac{y(t)}{x(t)+y(t)}, \tag{1}$$
$$\dot{y}(t) = -\dot{x}(t) - (c^d + c^r)y(t), \tag{2}$$
$$\dot{z}(t) = (c^d + c^r)y(t). \tag{3}$$

Here, $b(t)$ denotes a possibly time-varying infection rate. As in Bohner et al. (2019) it reflects epidemiological factors which we take as exogenously given. Unlike Bohner et al. (2019) we allow $b(t)$ to also reflect government policy (see below). The extent to which susceptible persons are infected depends on their number, $x(t)$; the infection rate, $b(t)$; and the share of the infected in the susceptible or infected population.

The number of infected persons increases one-to-one with each susceptible that gets infected. At the same time, a share $c \equiv c^d + c^r$ of the infected population dies or recovers; the coefficients c^d and c^r parameterize the flow into death and recovery, respectively.

The system (1)–(3) can be solved (see appendix A) for

$$x(t) = x(0)\mathrm{e}^{\int_0^t \frac{-\kappa b(u)}{\kappa + \mathrm{e}^{\int_0^u (c-b(s))ds}} du}, \tag{4}$$
$$y(t) = y(0)\mathrm{e}^{\int_0^t \frac{b(u)}{1+\kappa \mathrm{e}^{\int_0^u (b(s)-c)ds}} - c \, du}, \tag{5}$$
$$z(t) = 1 - x(t)\left(1 + \kappa \mathrm{e}^{\int_0^t (b(s)-c)ds}\right) \text{ s.t. (4)}, \tag{6}$$

where $\kappa \equiv y(0)/x(0)$.

Figure 1 illustrates the dynamics when we let $b(t) = \beta$, the fundamental infection rate absent any policy intervention.[1] We measure time in days and let $\beta = 0.2$, $c^r = (0.05)(0.99)$, and $c^d = (0.05)(0.01)$.[2]

[1]Equation (2) implies that at the beginning of an epidemic when $x(t) \approx 1$ and $z(t) \approx 0$, rate β equals the growth rate of the number of persons who are or were infected:

$$\frac{\dot{y}(t) + \dot{z}(t)}{y(t) + z(t)} = \beta y(t)\frac{x(t)}{x(t)+y(t)}\frac{1}{y(t)+z(t)} \approx \beta.$$

[2]We take the value for β from Alvarez et al. (2020) and assume that 5 percent of the infected are removed, of which 1 percent dies.

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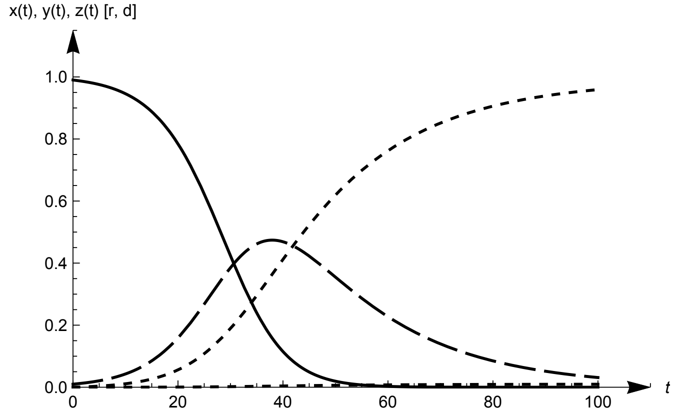

Figure 1: Dynamics in the SIR model: $x(t)$ (solid), $y(t)$ (dashed), and $z(t)$ (recovered and deceased, dotted).

2.2 Policy Objective and Instrument

The basic tradeoff we are interested in is the conflict between fostering economic activity and slowing down the spread of infections. Almost all countries that have responded to the spread of Covid-19 by imposing severe restrictions on mobility and economic activity have motivated these restrictions with the aim to delay infections or to "flatten the curve," i.e., to reduce the speed at which infections occur. The main argument for delay is to gain time in which health care providers can prepare for the higher case load. The main argument for flattening the curve is to limit the stress that Covid-19 infections impose on the health care system—specifically on intensive care units—because this stress increases fatality rates. In the SIR model outlined above, both measures to delay and to flattening the curve correspond to policy interventions that push $b(t)$ below β.

Let $a(t) \in \mathcal{A}$ denote a measure of economic activity inversely related to lockdown policies such as social distancing, forced shutdowns of businesses, etc. The maximum element of $\mathcal{A}$ is unity, representing the regular level of activity. The minimum element of $\mathcal{A}$ (which is nonnegative) represents the lower bound on activity or upper bound on lockdown policies. This minimum could be strictly positive, reflecting the fact that even during an

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extreme lockdown elementary goods and services need to be produced (e.g., in the food, energy, or health care sector) or that political constraints prevent extreme containment policies.

Activity $a(t)$ increases the spread of infections, which imposes a burden on the health care system, and it raises output. We assume that the infection rate satisfies

$$b(t) = \beta f(a(t))$$

for some smooth increasing function f. Moreover, we assume that output is a smooth increasing function g of activity which may also depend on the population shares,

$$\text{output}(t) = g(a(t), x(t), y(t), z(t)),$$

and satisfies $g(1, 1, 0, 0) = 1$ (i.e., we normalize output in "normal" times to unity). Finally, we assume that the burden that new infections impose on the health care system is a smooth increasing function h of $\dot{y}(t)$,

$$\text{burden}(t) = h(\dot{y}(t), t).$$

Let ρ denote the rate of time preference and ν the hazard rate with which a new vaccine is discovered. The policy problem then reads

$$\begin{aligned} \max_{(a(t))_{t=0}^{\infty}} \quad & \int_0^{\infty} \mathrm{e}^{-(\rho+\nu)t} \left\{ g(a(t), x(t), y(t), z(t)) - h(\dot{y}(t), t) + \nu V(1, x(t), y(t), z(t)) \right\} \, dt \\ \text{s.t.} \quad & (1), (2), (3), \quad b(t) = \beta f(a(t)), \quad a(t) \in \mathcal{A}, \quad x(0) \text{ given.} \end{aligned}$$

The last term in the integral reflects the probability weighted value, V, of exiting the lockdown due to the discovery of a vaccine.

We are interested in analytical characterizations of optimal paths for $a(t)$ and the implied paths for $x(t)$, $y(t)$, and $z(t)$. The system (1)–(3) or (4)–(6) is not suitable for such characterizations. When we leave $a(t)$ unrestricted (subject to $a(t) \in \mathcal{A}$) and form the Hamiltonian that reflects (1)–(3) and the policy objective then the Hamiltonian does not yield closed-form solutions even if we assume tractable functional forms for f, g, and h.[3] Similarly, restricting $a(t)$ to belong to a class of functions that is parameterized by a few parameters and maximizing the intertemporal objective subject to the constraints (4)–(6) very quickly becomes analytically intractable as well.

[3]See Alvarez et al. (2020) for a numerical approach to solving a related problem.

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Against this background, we simplify the epidemiological framework in order to express health dynamics in terms of a single rather than two state variables.[4] In the next section, we lay out these simplifications and solve the policy problem.

3 Analysis

We analyze two specialized models which are nested by the general model introduced above. We assume, realistically for most countries, that available tests for infection and immunity are scarce, limiting the government's options to indiscriminate lockdowns of varying intensity and duration.

3.1 Model 1

To obtain the first model we simplify along two dimensions. First, we neglect deaths and let $c^d = 0$.[5] Importantly, this does not mean that we disregard the burden that infections impose on the health care system, to the contrary. This burden depends on the outflow from susceptibles, not on the number of deceased.

Second, we blur the distinction between infected and recovered. While we maintain the feature of the SIR model that infection rates reflect the interaction between susceptible and infected persons we assume that infected persons are as productive as healthy ones. Formally, we let $c^r = 0$ such that infection is an absorbing state and $z(t) = 0$, and we assume that production does not depend on the population shares $x(t)$ and $y(t)$. Stated differently, we view $x(t)$ as the population share of the "not yet infected" and $y(t) = 1-x(t)$ as the share of the "infected but still productive." Since members of the two groups are equally productive the function g does not depend on population shares and V satisfies

$$V(1, x(t), y(t), z(t)) = \int_{j=0}^{\infty} \mathrm{e}^{-\rho j} g(1, 1, 0, 0)\ dj = g(1, 1, 0, 0)/\rho = \rho^{-1}.$$

Regarding functional forms, we let $f(a(t)) = a(t)$, output$(t) = a(t)$, and

[4] The SIR model features two state variables, $x(t)$ and $y(t)$. The third variable, $z(t)$, is implied by the former two.

[5] Recall from figure 1 that the population share of deceased is small even in the absence of any policy intervention.

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$h(\dot{y}(t), t) = h_1 \mathrm{e}^{-\lambda t} \dot{y}(t)$.[6] That is, we let activity have a proportional effect on the infection rate and on output and we assume that stress in the health care system is proportional to $\dot{y}(t)$ and a factor $h_1 \mathrm{e}^{-\lambda t}$. The parameter λ represents the speed of learning or efficiency enhancing measures in the health care sector. A strictly positive λ generates a motive to delay infections until society is better equipped to confront the stress imposed on the health care sector.[7] Finally, we let $\mathcal{A} = [\bar{a}, 1]$ with $\bar{a} > 0$. Accordingly, the government's program reads

$$\max_{(a(t))_{t=0}^{\infty}} \quad \int_0^{\infty} \mathrm{e}^{-(\rho+\nu)t} \left\{ a(t) - h_1 \mathrm{e}^{-\lambda t} \dot{y}(t) + \nu/\rho \right\} \, dt$$
$$\text{s.t.} \quad \dot{y}(t) = a(t)\beta y(t)(1 - y(t)), \quad a(t) \in [\bar{a}, 1], \quad y(0) \text{ given.}$$

When we abstract from policy model 1 is identical to the SIR model except that $c = 0$; that is, the time paths of $x(t)$ and $y(t)$ follow logistic curves. Figure 2 illustrates the dynamics when $a(t) = 1$ and when we reduce β by a factor of 0.8 relative to the value underlying figure 1 in order to better match the dynamics of $x(t)$ in the SIR model.

Note that the time paths of the shares of "infected" and "not yet infected" are very similar in the two models.

Optimal Policy To characterize the optimal policy we form the current value Hamiltonian

$$H^c(t) = a(t) - h_1 \mathrm{e}^{-\lambda t} a(t)\beta y(t)(1 - y(t)) + \frac{\nu}{\rho} + \mu(t)a(t)\beta y(t)(1 - y(t)),$$

where $\mu(t)$ denotes the co-state variable associated with the state variable $y(t)$. The derivative of $H^c(t)$ with respect to the control variable $a(t)$ yields

$$\frac{dH^c(t)}{da(t)} = 1 - \beta y(t)(1 - y(t))(h_1 \mathrm{e}^{-\lambda t} - \mu(t)). \tag{7}$$

Since this derivative does not depend on $a(t)$ the control variable typically is in a corner: either $a(t) = \bar{a}$ or $a(t) = 1$.

[6] Unlike Alvarez et al. (2020) we assume that the effect of activity on the infection rate is linear rather than quadratic. Recall from equation (1) that the infection rate $\dot{x}(t)$ depends on $x(t)$ as well as the number of infected relative to the number of infected or susceptible. The latter ratio does not change with a lockdown.

[7] In model 2, we explicitly model the motivation to flatten the curve in order to smooth convex stress in the health care system over time.

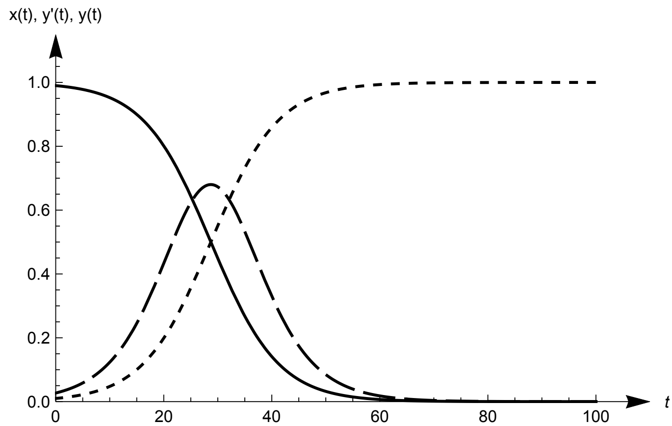

Figure 2: Dynamics in model 1 absent policy intervention: $x(t)$ (solid), $\dot{y}(t)$ (scaled, dashed), and $y(t) = (1 - x(t))$ (dotted).

The law of motion for the co-state variable is given by

$$\dot{\mu}(t) = -\frac{dH^c(t)}{dy(t)} + (\rho + \nu)\mu(t) = a(t)\beta(1 - 2y(t))(h_1 \mathrm{e}^{-\lambda t} - \mu(t)) + (\rho + \nu)\mu(t).$$

Finally, the time derivative of the effect of the control variable on the Hamiltonian equals

$$\begin{aligned} \dot{\left(\frac{dH^c(t)}{da(t)}\right)} &= -\beta(1 - 2y(t))(h_1 \mathrm{e}^{-\lambda t} - \mu(t))a(t)\beta y(t)(1 - y(t)) \\ &\quad + \beta y(t)(1 - y(t)) \left[a(t)\beta(1 - 2y(t))(h_1 \mathrm{e}^{-\lambda t} - \mu(t)) + (\rho + \nu)\mu(t) + \lambda \mathrm{e}^{-\lambda t}\right], \\ &= \beta y(t)(1 - y(t)) \left[(\rho + \nu)\mu(t) + \lambda \mathrm{e}^{-\lambda t}\right]. \end{aligned} \tag{8}$$

Note that $\mu(t)$ is the shadow value of the population share of the infected, $y(t)$. An increase in this share has no direct effect on output but *reduces* the future burden on the health care system since $\dot{y}(t)$ is strictly positive until everybody is infected.[8] Accordingly, $\mu(t) > 0$. Combining this result with equation (8) implies that the effect of $a(t)$ on the Hamiltonian is monotonically increasing over time.

[8]Recall that $\bar{a} > 0$.

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We conclude that there are two cases to distinguish: Either $dH^c(0)/(da(0)) > 0$ and the optimal policy does not involve a lockdown. For given $y(0)$ this condition is satisfied when h_1, which parameterizes the burden that infections impose on the health care system, is low. Or, if $dH^c(0)/(da(0)) < 0$ (which is the case for sufficiently high h_1) the optimal policy immediately imposes a lockdown. Such a lockdown cannot be permanent however and in fact, it ends before all persons have been infected. For as long as $\mu(t)$ is bounded the effect of the control on the Hamiltonian sooner or later becomes positive since $\lim_{t\to\infty} y(t) = 1$ and therefore $\lim_{t\to\infty} dH^c(t)/da(t) = 1 > 0$.[9]

3.2 Model 2

To obtain the second model we simplify along different dimensions. First, we neglect recovery ($c^r = 0$) and assume a strictly positive death rate ($c^d > 0$) such that everyone who transits from susceptible to infected eventually dies. Second, we blur the distinction between susceptible and infected assuming that the two groups are equally productive and that only their total share, $x(t) + y(t) = 1 - z(t)$, is relevant for the economy's dynamics. That is, we assume that $x(t)$ and $y(t)$ can be characterized by a single state variable.

Given the laws of motions (1) and (2) this requires that the relative share $x(t)/(x(t) + y(t))$ remains constant over time. Since $y(0)/x(0) = \kappa$ this implies $y(t)/(x(t) + y(t)) = \kappa(1 + \kappa)^{-1}$ and consistency with the laws of motion then entails $c^d = \beta$, which we assume to hold.[10] Absent policy, the system (1)–(3) therefore simplifies to

$$\begin{aligned} (1 - \dot{z(t)}) &= -\tilde{\beta}(1 - z(t)) \quad (= -\beta y(t)), \\ \dot{z}(t) &= \tilde{\beta}(1 - z(t)) \quad (= \beta y(t)), \end{aligned}$$

where $\tilde{\beta} \equiv \beta\kappa/(1+\kappa)$ denotes the fatality rate. Constancy of the fatality rate is an unreasonable feature over longer periods, due to the eventual slowdown of infections; we therefore view model 2 as a useful approximation only for the short run.

Since susceptible and infected persons are equally productive and the

[9] This requires that $\bar{a} > 0$ as we assumed. If $a(t)$ fell to zero the economy would shut down and infections would no longer spread.

[10] When we introduce the policy choice $a(t)$ we disregard the fact that this would in principle also affect the condition $c^d = \beta$ and thereby modify the laws of motion.

deceased do not contribute to production we have

$$V(1, x(t), y(t), z(t)) = \int_{j=0}^{\infty} \mathrm{e}^{-\rho j} g(1, 1 - z(t), 0, z(t))\ dj = (1 - z(t))\rho^{-1},$$

where we assume that productivity returns to normal levels once the vaccine is discovered. Regarding the (other) functional forms, we let $f(a(t)) = a(t)$, $\text{output}(t) = a(t)(1 - z(t))$, and

$$h(\dot{y}(t)) = \frac{h_2}{2}\left(\dot{y}(t)\right)^2 \left(\frac{1+\kappa}{\kappa}\right)^2 = \frac{h_2}{2}\left(\dot{\overline{(1 - z(t))}}\frac{\kappa}{1+\kappa}\right)^2 \left(\frac{1+\kappa}{\kappa}\right)^2 = \frac{h_2}{2}\left(\dot{z}(t)\right)^2.$$

That is, we let activity have a proportional effect on the infection rate and on per-capita output and we assume that the stress in the health care system is quadratic, with coefficient $h_2/2$.[11] Finally, we let $\mathcal{A} = [\bar{a}, 1]$. The government's program thus reads

$$\begin{aligned} \max_{(a(t))_{t=0}^{\infty}} \quad & \int_0^{\infty} \mathrm{e}^{-(\rho+\nu)t} \left\{ a(t)(1 - z(t)) - \frac{h_2}{2}\left(\dot{z}(t)\right)^2 + \frac{\nu}{\rho}(1 - z(t)) \right\} dt \\ \text{s.t.} \quad & \dot{z}(t) = a(t)\tilde{\beta}(1 - z(t)), \quad a(t) \in [\bar{a}, 1], \quad z(0) \text{ given.} \end{aligned}$$

Optimal Policy The current value Hamiltonian now reads

$$H^c(t) = a(t)(1-z(t)) - \frac{h_2}{2}a(t)^2\tilde{\beta}^2(1-z(t))^2 + \frac{\nu}{\rho}(1-z(t)) + \mu(t)a(t)\tilde{\beta}(1-z(t))$$

and its derivative with respect to the control variable $a(t)$ is given by

$$\frac{dH^c(t)}{da(t)} = (1 - z(t))(1 + \tilde{\beta}\mu(t)) - h_2 a(t)\tilde{\beta}^2(1 - z(t))^2.$$

We conjecture that $a(t)$ is interior and thus satisfies

$$a(t) = \frac{1 + \tilde{\beta}\mu(t)}{h_2\tilde{\beta}^2(1 - z(t))}. \tag{9}$$

The product $a(t)(1 - z(t))$ then does not directly depend on $z(t)$ and the same holds true for all terms in the Hamiltonian except the third one.

[11] This implies that lockdown is motivated by the aim to flatten the curve.

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The law of motion for the co-state variable is given by

$$\dot{\mu(t)} = -\frac{dH^c(t)}{dz(t)}+(\rho+\nu)\mu(t) = a(t)(1+\tilde{\beta}\mu(t))-h_2a(t)^2\tilde{\beta}^2(1-z(t))+\frac{\nu}{\rho}+(\rho+\nu)\mu(t).$$

With an interior choice of $a(t)$ the first two terms in this law of motion cancel. The resulting differential equation integrates to

$$\mu(t) = \left(\mu(0) + \frac{\nu}{\rho(\rho+\nu)}\right) \mathrm{e}^{(\rho+\nu)t} - \frac{\nu}{\rho(\rho+\nu)}. \tag{10}$$

Recall that $\dot{z}(t) = a(t)\tilde{\beta}(1-z(t)) = (1+\tilde{\beta}\mu(t))/(h_2\tilde{\beta})$ where we use equation (9). From condition (10) we therefore have

$$z(t) = z(0)+\left(\frac{1}{h_2\tilde{\beta}} - \frac{\nu}{h_2\rho(\rho+\nu)}\right) t+\left(\mu(0) + \frac{\nu}{\rho(\rho+\nu)}\right) \frac{1}{h_2(\rho+\nu)} \left(\mathrm{e}^{(\rho+\nu)t} - 1\right). \tag{11}$$

To find $\mu(0)$ we compute the value of the objective function under the optimal policy, W say, and differentiate it with respect to $z(0)$. Under our conjecture that the $a(t)$ path is interior, all terms in the objective that are proportional to $a(t)(1-z(t))$ do not directly depend on $z(0)$, so we can neglect them. Moreover, from condition (11) the integral over $\mathrm{e}^{-(\rho+\nu)t}\nu(1-z(t))/\rho$ only depends on $z(0)$ through the term

$$\int_0^\infty \mathrm{e}^{-(\rho+\nu)t}\frac{\nu}{\rho}(1-z(0))\ dt = (1-z(0))\frac{\nu}{\rho}\frac{1}{\rho+\nu}.$$

We conclude that

$$\mu(0) = \frac{dW}{dz(0)} = -\frac{\nu}{\rho}\frac{1}{\rho+\nu}$$

and thus, from condition (10), $\mu(t) = \mu(0)$.

This implies that the optimal path of $a(t)$ satisfies

$$a(t) = \frac{1 - \frac{\tilde{\beta}\nu}{\rho(\rho+\nu)}}{h_2\tilde{\beta}^2(1-z(t))}$$

provided that this solution lies in $[\bar{a}, 1]$. That is, during the short term (when the number of dead increases from $z(t) \approx 0$ to a small population share) the optimal size of the lockdown approximately equals

$$\left(1 - \frac{\tilde{\beta}\nu}{\rho(\rho+\nu)}\right) / (h_2\tilde{\beta}^2).$$

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Higher values for $\tilde{\beta}$ or h_2, that is, a higher fatality rate or higher costs in the health care sector thus increase the optimal severity of the lockdown. A more likely discovery of a vaccine (higher ν) increases the stringency of the optimal containment measures because it renders $\mu(0) = \mu(t)$ more negative; this lowers $\dot{z}(t)$ and shortens the expected duration of the lockdown.

The implied solution for $z(t)$ is given by

$$z(t) = z(0) + \frac{1}{h_2} \frac{\rho(\rho+\nu) - \nu\tilde{\beta}}{\tilde{\beta}\rho(\rho+\nu)} t,$$

which is a valid solution only if $\rho(\rho+\nu) > \nu\tilde{\beta}$. Under this restriction $a(t)$ is indeed interior.[12]

Recall that in the absence of policy $z(t) = 1 - (1 - z(0))\mathrm{e}^{-\tilde{\beta}t}$ and thus $\dot{z}(t) \approx \tilde{\beta}\mathrm{e}^{-\tilde{\beta}t}$. Comparing this expression with the time derivate of the preceding equality we conclude that the optimal policy reduces the number of new deaths at time t by

$$\tilde{\beta}\mathrm{e}^{-\tilde{\beta}t} - \frac{1}{h_2} \frac{\rho(\rho+\nu) - \nu\tilde{\beta}}{\tilde{\beta}\rho(\rho+\nu)}.$$

3.3 Taking Stock

Model 1 takes the exogenous lower bound $\bar{a}$ as given and predicts the optimal duration of a lockdown. When the burden that infections impose on the health care system is sufficiently high then the optimal policy immediately imposes a lockdown and abandons it before everybody is infected. If the burden is low, in contrast, then the optimal policy never imposes a lockdown.

Model 2 predicts an interior path for the control variable when a parametric condition is satisfied. When the fatality rate or the cost of stress in the health care sector are higher, or discovery of a vaccine is more likely then the optimal lockdown is tighter. Over time the lockdown is slowly relaxed as the number of deaths decreases.

We view the predictions of the two models as complementary. In the next section we calibrate the two frameworks and generate quantitative predictions.

[12]Plugging the expression for $z(t)$ into the expression for the optimal value of $a(t)$ derived above yields the duration until $a(t)$ reaches the activity level 1—the duration of the lockdown. Since we view the model is a model of the short run we do not emphasize this implied duration.

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4 Calibration and Quantitative Results

We calibrate the model such that one period in the model corresponds to one day. Following Alvarez et al. (2020) we assume an annual discount rate of five percent, which translates into a daily rate of $\rho = -\ln(0.95)/365$.[13] Also following Alvarez et al. (2020) we let $\nu = 0.0018$; this corresponds to a probability of roughly 28 percent that a vaccine is discovered during half a year,[14] or to an expected time until discovery of about one and a half years.

For model 1, we assume that the fundamental infection rate, β, equals $(0.2)(0.8)$. Alvarez et al. (2020) assume that this value equals 0.2; we reduce it to correct for the simplified law of motion (see the discussion relating figures 1 and 2). Moreover, we assume that $\lambda = -\ln(0.5)/182$ such that the cost of stress in the health care sector (conditional on $\dot{y}(t)$) falls by one half after half a year.

To calibrate the parameter h_1 we rely on estimates according to which an unchecked Covid-19 infection wave would have caused costs in the U.S. of 13 trillion dollars, corresponding to roughly 61 percent of annual U.S. GDP (Scherbina, 2020).[15] Consistent with Alvarez et al. (2020) and Scherbina (2020) we assume that this damage would have occurred within half a year. In light of the model this implies

$$h_1 \int_0^{182} \mathrm{e}^{-(\rho+\nu)t} \mathrm{e}^{-\lambda t} \dot{y}(t) dt = 0.61 \cdot 365,$$

where the right-hand side accounts for the fact that daily output equals one in normal times. Letting $y(0) = 0.01$ and evaluating the integral numerically we find that $h_1 \approx 265$.

For model 2, we calibrate the fatality rate, $\tilde{\beta}$, based on estimates according to which an unchecked Covid-19 infection wave would have caused 1.9 million deaths in the U.S., corresponding to roughly 0.58 percent of the U.S. population (Scherbina, 2020).[16] Consistent with Alvarez et al. (2020) and Scherbina (2020) we assume that most of this death toll would have occurred within half a year. This yields an estimate of $\tilde{\beta} = -\ln(1 - 0.0058)/182$. To calibrate the parameter h_2 we again use the cost estimate of 61 percent of annual U.S. GDP (Scherbina, 2020). From this cost, we subtract the present

[13] $0.95 = \mathrm{e}^{-\rho 365}$.
[14] $1 - 0.28 \approx \mathrm{e}^{-\nu 182}$.
[15] $13/21.4 \approx 0.6075$ (BEA data).
[16] $1.9/330 \approx 0.0058$ (Census data).

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value of the permanent output losses due to lost lives after the end of the transition. The remainder of the cost estimate is what we attribute to the cost due to health care stress. Formally, we solve

$$\int_0^{182} \mathrm{e}^{-(\rho+\nu)t} \frac{h_2}{2} \tilde{\beta}^2 (1 - z(t))^2 dt = 0.61 \cdot 365 - \mathrm{e}^{-\rho 182} z(182) \int_0^{\infty} \mathrm{e}^{-\rho t} dt$$

or

$$\int_0^{182} \mathrm{e}^{-(\rho+\nu)t} \frac{h_2}{2} \tilde{\beta}^2 (1-z(0))^2 \left(\mathrm{e}^{-\tilde{\beta}t}\right)^2 dt = 0.61 \cdot 365 - \frac{\mathrm{e}^{-\rho 182}}{\rho} \left(1 - (1 - z(0))\mathrm{e}^{-\tilde{\beta}182}\right).$$

Letting $z(0) \approx 0$ and solving for h_2 yields $h_2 \approx 2.34 \times 10^9$. With these values the parametric condition discussed in subsection 3.2 is satisfied.

Quantitative Predictions We use the formula from model 2 to compute the optimal activity level during lockdown, $a^\star(0)$ say. We find that the optimal lockdown is severe: activity is reduced to roughly 33 percent of normal. Not surprisingly this depends on the health care cost parameter, h_2. As figure 3 illustrates $a^\star(0)$ increases substantially (the lockdown is less extreme) when the cost is lower (and we keep the other parameter values unchanged).

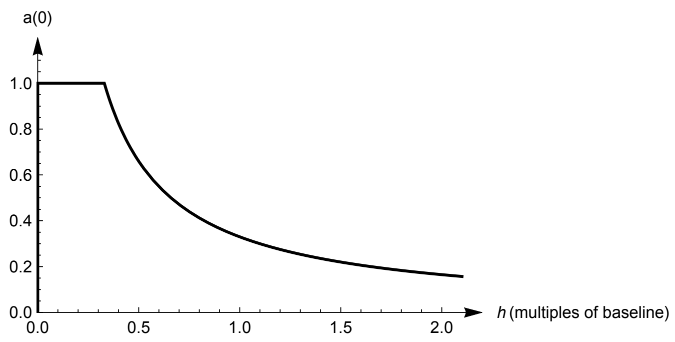

Figure 3: Predicted optimal activity level, $a^\star(0)$, for different costs due to stress in the health care system.

Next, we set $\bar{a}$ in model 1 equal to $a^\star(0)$ and numerically solve for the optimal duration of the lockdown, $T^\star$ say. We find that this duration equals

nearly 52 days. After the lockdown, roughly 13 percent of the population are infected. Figure 4 illustrates how the objective of the government varies with the duration of the lockdown. The cost of getting T wrong is asymmetric: Setting T a bit smaller than $T^{\star}$ is less costly than setting it a bit higher. If the lockdown is kept in place over a very long period (longer than roughly 90 days) then this policy generates a lower value than no lockdown at all.

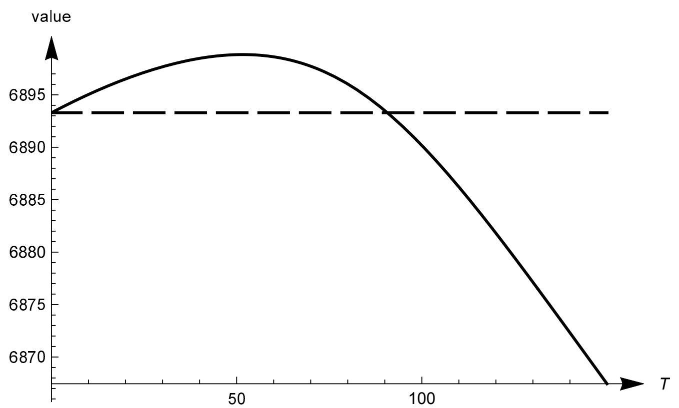

Figure 4: Value of the program for different durations of the lockdown, T. The dashed line indicates the value when there is no lockdown, $T = 0$.

Figure 5 illustrates how the optimal policy changes the dynamics of infections. The solid line in the figure depicts the optimal path: it is relatively up to the optimal exit time and increases quickly thereafter. The dashed line depicts the path of $y(t)$ in the absence of policy.

The first line in table 1 summarizes these baseline results. The other lines in the table report how the predictions change when we alter the calibration. When we assume a lower discount rate then $a^{\star}(0)$ falls and $T^{\star}$ rises slightly: a more patient planner reduces activity by more, for longer. The same holds true when we assume a higher discovery rate for a vaccine. When we double ν to 0.0036 then $a^{\star}(0)$ falls to roughly 28 percent and $T^{\star}$ rises to roughly 83 days.

Changes in β do not affect the optimal severity of a lockdown. However, they do affect $T^{\star}$. A reduction in β by 20 percent increases $T^{\star}$ to nearly 61 days, and an increase in β by 20 percent lowers it to 45 days. Lowering $\tilde{\beta}$ by

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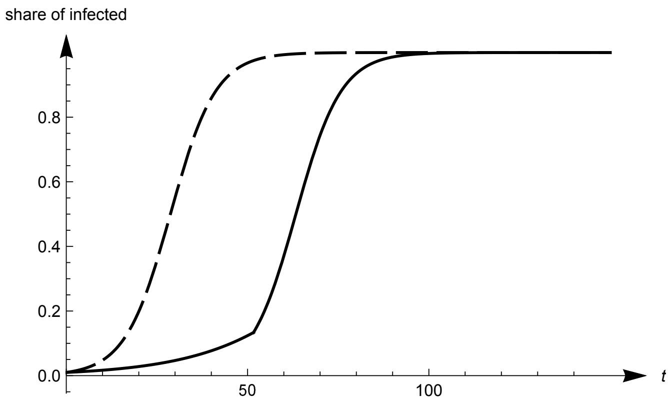

Figure 5: Share of infected under the optimal policy (solid) and in the absence of policy intervention (dashed).

20 percent increases $a^{\star}(0)$ to 33.32 and reduces $T^{\star}$ to 51.32, while increasing it by 20 percent implies $a^{\star}(0) \approx 32.62$ and $T^{\star} \approx 51.98$. The model predictions thus are fairly robust to changes in the fatality rate.

Finally, when we increase λ by 10 percent such that after half a year, efficiency in the health care sector has increased by roughly 53 percent (for instance because preparations for the wave of infections have been particularly bad), then the optimal duration rises to more than 56 days. When we strongly reduce λ, however, the optimal policy eventually involves no lockdown at all. That is, when the health care system is adequately prepared to deal with a pandemic such that there is no role for learning or efficiency improvements over time then it is optimal not to impose a lockdown.

5 Conclusion

We embed a lockdown choice in a simplified epidemiological model and derive formulas for the optimal lockdown intensity and duration. The optimal policy reflects the rate of time preference, epidemiological factors, the hazard rate of vaccine discovery, learning effects in the health care sector, and the severity of output losses due to a lockdown.

In our baseline specification a Covid-19 shock as currently experienced

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Table 1: Optimal Lockdown

Calibration	$a^{\star}(0)$ (in percent)	$T^{\star}$ (in days)
Baseline	32.98	51.64
Annual discount rate 3%	31.50	51.83
ν twice as high	28.12	82.83
β 20% lower	32.98	60.87
β 20% higher	32.98	44.70
$\tilde{\beta}$ 20% lower	33.32	51.32
$\tilde{\beta}$ 20% higher	32.62	51.98
λ 10% higher	32.98	56.31

Table 2: Quantitative predictions under different calibration assumptions. $a^{\star}$ denotes the optimal activity level relative to normal and $T^{\star}$ the optimal duration of the lockdown.

by the US optimally triggers a reduction in economic activity by two thirds, for about 50 days. On an annual basis, this corresponds to a drop in GDP by 9.5 percent.

We hope that future research can build on our simplified frameworks.

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A Solving the SIR Model

The system (1)–(3) can be solved as follows (Bohner et al., 2019): Let $\xi(t) \equiv x(t)/y(t)$ for $y(t) \neq 0$. We have

$$\dot{\xi}(t) = \frac{\dot{x}(t)y(t) - x(t)\dot{y}(t)}{y^2(t)} = (c - b(t))\xi(t),$$

such that

$$\xi(t) = \xi(0)\mathrm{e}^{\int_0^t (c-b(s))ds} \quad \Leftrightarrow \quad y(t) = x(t)\kappa\mathrm{e}^{\int_0^t (b(s)-c)ds}$$

where $\kappa \equiv y(0)/x(0)$. Substituting into equation (1) yields

$$\dot{x}(t) = -b(t)x(t)\frac{\kappa\mathrm{e}^{\int_0^t (b(s)-c)ds}}{1 + \kappa\mathrm{e}^{\int_0^t (b(s)-c)ds}},$$

which has the solution

$$x(t) = x(0)\mathrm{e}^{\int_0^t \frac{-\kappa b(u)}{\kappa + \mathrm{e}^{\int_0^u (c-b(s))ds}} du}. \tag{4}$$

Accordingly, we can solve equation (2) for

$$y(t) = y(0)\mathrm{e}^{\int_0^t \frac{b(u)}{1+\kappa\mathrm{e}^{\int_0^u (b(s)-c)ds}} - c \; du} \tag{5}$$

and equation (3) for

$$z(t) = 1 - x(t)\left(1 + \kappa\mathrm{e}^{\int_0^t (b(s)-c)ds}\right) \text{ s.t. (4)}, \tag{6}$$

where we use the fact that the population size equals unity.

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Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data[1]

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This paper uses transaction-level customer data from the largest bank in Denmark to estimate consumer responses to the COVID-19 pandemic and the partial shutdown of the economy. We find that aggregate card spending has dropped sharply by around 25% following the shutdown. The drop is mostly concentrated on goods and services whose supply is directly restricted by the shutdown, suggesting a limited role for spillovers to non-restricted sectors through demand in the short term. The spending drop is somewhat larger for individuals more exposed to the economic risks and health risks introduced by the COVID-19 crisis; however, pre-crisis spending shares in the restricted sectors is a much stronger correlate of spending responses.

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1 We are extremely grateful to key employees at Danske Bank for their help. We note that all individual data has been anonymized and no individual customers can be traced in the data. All data processing has been conducted by authorized Danske Bank personnel, following the bank's strict data privacy guidelines.,
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1 Introduction

The COVID-19 pandemic represents a grave risk to public health and most governments have attempted to contain the virus by shutting down parts of the economy (e.g. Kraemer et al., 2020). Beyond the direct health consequences, the economic costs have been staggering: millions of workers have lost their jobs and trillions of dollars of stock market wealth has been destroyed.

A key concern for firms and policymakers is the size and the nature of the consumer response. While some highlight that the shutdown is, in essence, a supply shock with possible spill-overs to the demand side (Guerrieri et al, 2020), others stress that the pandemic may also affect demand directly because the health risk of going to public spaces like shops, restaurants and hairdressers deters consumption (Eichenbaum et al, 2020). In either case, the dynamics on the demand side may lead to a recession that persists long after the epidemic has ended and restrictions on economic activity have been lifted (Gourinchas, 2020). If consumers respond to mass lay-offs, falling asset prices (Gormsen and Koijen, 2020) and an uncertain financial outlook (Baker et al., 2020a) by slashing private consumption, the epidemic may mark the beginning of a demand-driven economic meltdown. In the face of this risk, governments have initiated massive programs, including fiscal, monetary and regulatory measures, to support businesses and households.

In this paper, we use transaction data for card spending in Denmark to study consumer responses to the COVID-19 crisis. The crisis has unfolded in Denmark as in many other developed countries in Europe and North America: the first case of COVID-19 was confirmed on 28 February 2020 and the government announced a partial shutdown of the economy on 11 March to get the virus under control and a series of interventions to sustain the economy in the following days. At the time of writing, the cumulative mortality is comparable to Germany and the United States (John Hopkins, 2020) whereas fiscal stimulus is somewhat larger than in the United Kingdom but lower than in the United States (Bruegel, 2020).[1]

Our analysis proceeds in three steps. First, we estimate the change in aggregate consumer spending since the onset of the crisis. Consumer spending is the largest component of private demand and therefore of immediate interest to governments designing policy responses in the form of fiscal and monetary stimulus. Second, we study heterogeneity in spending responses across categories of expenditure. As entire sectors of the economy are effectively shut down,

[1] As of 7 April 2020, the cumulative mortality in Denmark stood at 3.5 per 100.000 inhabitants compared to 2.4 in Germany and 3.9 in the United States (John Hopkins, 2020). The immediate fiscal stimulus in Denmark is estimated at 2.1% of GDP compared to 1.4% in the United Kingdom and 5.5% in the United States (Bruegel, 2020).

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consumer spending on the goods and services produced in those sectors is bound to decline. Guided by recent theory (Guerrieri et al, 2020), we conduct a simple test of spill-overs to the demand-side by estimating the change in consumer spending on categories that are not constrained on the supply-side. Third, we study heterogeneity in spending responses across individuals with different characteristics. We investigate the mechanisms underlying the drop in consumer spending by estimating how the spending drop varies with measures of income risk, wealth losses, health risk and *ex ante* spending on supply-constrained goods and services.

Our analysis uses transaction data for about 760,000 individuals who hold their main current account at Danske Bank, the largest retail bank in Denmark with a customer base that is roughly representative of the Danish population. For each individual, we observe every purchase made by cards through accounts at the bank from 1 January 2018 through the shutdown of large parts of the Danish economy on 11 March to the end of our sample period on 5 April 2020. This allows us to construct a customer-level measure of total spending at the daily frequency and, exploiting a standardized classification of merchants, a breakdown of total spending by expenditure category. The dataset also contains basic demographic information such as age and gender and allows us to construct a measure of income based on the bank's algorithm for categorizing account inflows.

Our aim is to estimate the drop in consumer spending relative to a counterfactual without the pandemic and without the shutdown. The main empirical challenge is the strong cyclicality of spending over the week, the month and the year. We address the cyclicality by comparing consumer spending on each day in 2020 to consumer spending on a reference day 364 days earlier, which is always the same day of the week and almost exactly the same place in the monthly and annual spending cycle. We first compute *excess spending* as the difference between spending on a given day in 2020 and spending on the reference day in 2019. We then compute the consumer response as the difference between excess spending in the post-shutdown period (11 March - 5 April) and excess spending in the pre-shutdown period (1 January - 15 February).[2] The identifying assumption is that the year-over-year growth in consumer spending observed in the pre-shutdown period would have continued in the post-shutdown period absent the COVID-19 crisis.

Our main finding is that aggregate card spending dropped by around 25% relative to the counterfactual trajectory. This estimate reflects that excess spending averaged 2% over the pre-shutdown period and -23% over the post-shutdown period. The dynamics supports a causal

[2]We do not include the days immediately before the shutdown (15 February - 10 March) to avoid that anticipation effects affect the counterfactual.

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interpretation: aggregate spending remained remarkably similar to the reference period until the shutdown and then fell sharply. The magnitude of the estimated response is enormous compared to consumer responses to other types of shocks. For instance, two recent studies using similar data find that job losses are associated with spending drops of around 5-10% (Ganong and Noel, 2019; Andersen et al., 2020).

The responses vary widely across sectors and correlate strongly with the severity of the restrictions imposed by the government. On the one hand, spending increased modestly in grocery stores and pharmacies, which remained open throughout the shutdown. On the other hand, spending dropped dramatically on items where restrictions were particularly severe such as travel, restaurants and personal services. In aggregate, we find that spending increased by around 10% in sectors where supply was totally unconstrained by government interventions (around half of the economy) while it dropped by almost 70% in sectors where supply was most constrained (around one quarter of the economy). Our results suggest that the partial shutdown had negative spill-overs on certain open sectors through the demand side (Guerrieri et al, 2020). For instance, spending on fuel and commuting plummeted although gas stations remained open, presumably because shopping centers and work places shut down. More generally, however, our results suggest a limited role for negative spillovers of supply shocks through the demand side, at least within the relatively short time frame covered by our analysis.

To investigate the causal mechanisms, we provide estimates for subsamples that are heterogeneous in one dimension (e.g. age) while re-weighting observations to make the subsamples homogeneous in other dimensions (e.g. income). Consistent with an important role for *supply constraints*, a high spending share on items such as travel and restaurants before the shutdown is associated with a differential spending decrease of around 12 percentage points. It seems that *economic risks* play a smaller role as the differential spending cut for individuals working in closed sectors (exposure to job loss) and for individuals holding stocks (exposure to bleeding stock markets) is modest. The evidence that the direct *health risks* associated with shopping deter spending is mixed: individuals above 65 years (exposure due to age) reduce spending more than others whereas spending in pharmacies before the shutdown (exposure due to pre-existing condition) is almost uncorrelated with the spending response.

In summary, our results document that the closed sector of the economy is at the heart of the drop in consumer spending. There are two possible interpretations. Either, the drop in spending is caused directly by the shutdown, e.g. consumers do not go to restaurants because they are closed. Or, the drop in spending is caused by the health risks that motivated the shut-

down, e.g. consumers would not go to restaurants if they were open because it would expose them to the virus. Our results provide some support for both of these interpretations. Within the relatively short time frame of our analysis, economic risks such as income and wealth losses play a limited role, but this may change over longer horizons.

Our analysis contributes to a growing empirical literature on the economic consequences of the COVID-19 crisis. Two papers make predictions about the likely macro-economic effect of the pandemic using forward-looking indicators: uncertainty measures based on stock market data, newspaper articles and business expectation surveys (Baker et al., 2020a) and price information for dividend futures (Gormsen and Koijen, 2020). Other papers draws lessons for health and economic outcomes by comparing to epidemics in the past (e.g. Barro et al., 2020; Correia et al., 2020). The most closely related paper is Baker et al. (2020b) who describe spending dynamics in the U.S. in the early weeks of the COVID-19 epidemic based on a sample of 5,000 users of a financial app.

Our paper also contributes to the broader literature on consumption dynamics. Many papers have studied how household consumption responds to macro-economic events such as *financial crisis* (e.g. Mian et al., 2013; Andersen et al., 2016; Jensen and Johannesen, 2017), *economic policies* (e.g. Shapiro and Slemrod, 2003; Johnson et al., 2006; Parker et al., 2013; Di Maggio et al., 2017) and idiosyncratic changes in *income* (e.g. Baker, 2018; Kueng, 2018; Ganong and Noel, 2019), *wealth* (e.g. Di Maggio et al., 2018; Aladangady, 2017), *health* (e.g. Mohanan, 2013) and *uncertainty* (e.g. Carroll, 1994). We relate to this literature by, first, quantifying the aggregate spending response to an immense shock encompassing income losses, wealth destruction, health risks and financial uncertainty and, next, assessing the importance of each of these elements by comparing samples with different exposure to the different shocks. While most papers rely on consumption data from household surveys (e.g. Shapiro and Slemrod, 2003) or imputed consumption from administrative data on income and wealth (Browning and Leth-Petersen, 2003), we follow a recent wave of papers using transaction data (e.g. Gelman et al., 2014; Baker, 2018).

The paper proceeds in the following way. Section 2 briefly accounts for the Danish context. Section 3 describes the data sources and provides summary statistics. Section 4 develops the empirical framework. Section 5 reports the results. Section 6 concludes.

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2 Background

The first case of COVID-19 in Denmark was confirmed on 28 February 2020 and more cases quickly followed. Initially, all cases were related to travelling in the most affected areas of Europe, but the virus soon started spreading within the country. So far, the dynamics has resembled the experience of the United States, as illustrated in Figure 1, and that of many developed countries. As of 7 April 2020, cumulative mortality per 100.000 inhabitants due to COVID-19 stood at 3.5 in Denmark and 3.9 in the United States compared to 28 in Italy, which has the highest recorded per capita mortality in the world together with Spain (European Centre for Disease Prevention and Control, 2020).

The Danish authorities initially attempted to contain the virus by placing COVID-19 patients as well as individuals with recent contact to the patients in home quarantine and by discouraging travel to the most affected areas in the world. However, on 11 March, the Prime Minister announced a national lockdown in a televised speech: all non-essential parts of the public sector were shut down (including schools, libraries and universities); private sector employees were urged to work from home; borders were closed for foreign nationals and air traffic therefore virtually closed; the population was generally encouraged to avoid social contact. On 18 March, the government announced further restrictions banning congregations of more than 10 individuals, shutting down shopping centers, hairdressers and nightclubs and restricting restaurants to take-away service. The timing and severity of the measures were generally comparable to most of Northern Europe (such as Germany, Netherlands and Norway), but less restrictive than in Southern Europe where the virus spread more rapidly (such as Italy, France and Spain).

The Danish shutdown was accompanied by massive government programs to mitigate the financial damage to businesses and households. First, to help firms overcome temporary liquidity problems, deadlines for making tax payments were postponed and regulatory constraints on bank credit were loosened. Second, to prevent mass lay-offs, the government committed to pay 75% of the salary of private sector employees who were temporarily sent home as long as the employer committed to keep them on the payroll at full salary. Third, to mitigate business failures, separate policies offered partial compensation to all firms for fixed costs and to self-employed for lost revenue. These programs were all proposed by the government within the first week after the shutdown and received unanimous support in the Danish Parliament. The programs were similar in scale and scope to those launched by many other governments in Europe (Bruegel, 2020).[3]

[3]For instance, the immediate fiscal stimulus in Denmark is estimated at 2.1% of GDP compared to 1.2% in

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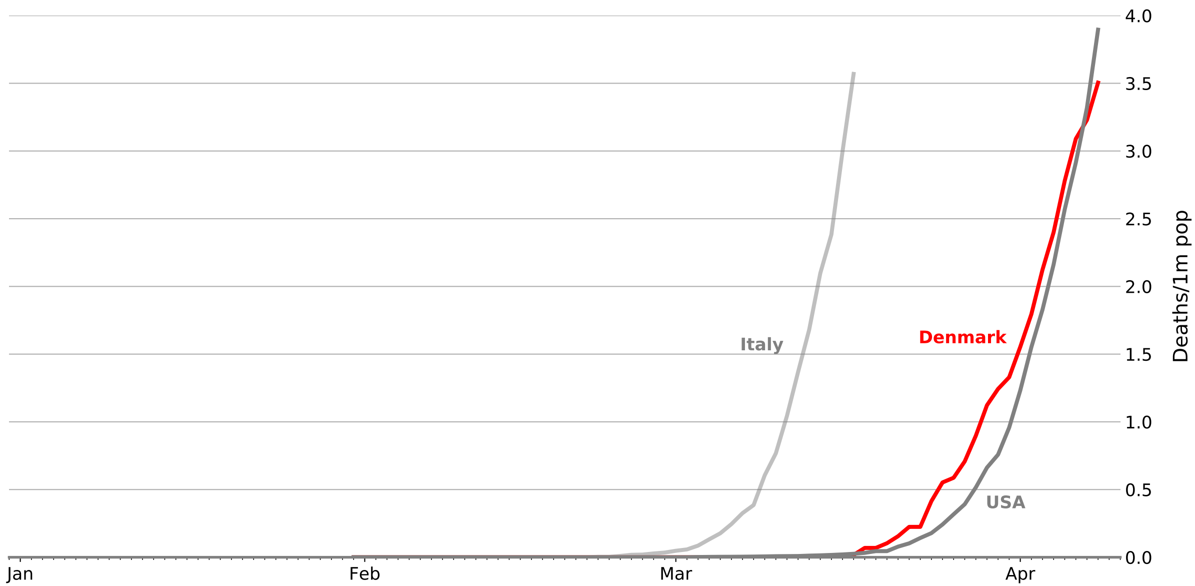
Figure 1: COVID-19 mortality. The figure shows cumulative mortality due to COVID-19 for Denmark, Italy and the United States over the period 1 January 2020 - 8 April 2020. Numbers for Italy are only shown until 17 March 2020. Source: European Centre for Disease Prevention and Control (2020).



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3 Data

We measure consumer spending with transaction data from Danske Bank, the largest retail bank in Denmark. We have information about every purchase made with payment cards (credit cards and debit cards): the date and the amount as well as the branch code and location of the shop. Moreover, we extract information on income using the bank's own algorithm for classifying money flows coming into accounts. Finally, we obtain basic demographic information such as age and gender from the bank's customer records.

We use two criteria to define a sample of adult individuals who consistently use Danske Bank as their main bank and for whom we measure their income relatively well. First, we require that customers have held their main current account at Danske Bank between 1 January 2018 and the end of the sample period.[4] Second, we require that customers made at least one card payment in each month between 1 January 2018 and 31 December 2019. We do not impose a spending requirement in 2020 as we want to allow that card spending falls to zero in response to the crisis.[5] With these restrictions, our sample consists of around 760,000 individuals.

We create a measure of *aggregate spending* by summing the card payments by all individuals in the sample on a given day.[6] Further, we create measures of specific *spending categories*, such as groceries, travel and restaurants, based on a standardized coding of the type of goods and services each shop provides.[7] Finally, we create three composite spending categories that aggregate individual spending categories based on the extent to which the supply was constrained by government restrictions. At one extreme, we consider travel, restaurants, personal services (e.g. dentists, hairdressers and beauty salons) and entertainment (e.g. cinemas, theatres and bars) as *closed sectors*. These sectors were, in principle, shut down although there were exceptions. For instance, restaurants were not allowed to seat guests, but could sell take-away food; dentists

France, 1.4% in the United Kingdom, 4.4% in Germany and 5.5% in the United States.

[4]In Denmark, all citizens need to register a bank account for monetary transactions with the public sector, e.g. tax refunds, child subsidies, pensions, student loans, unemployment benefits, housing support and social welfare payments. We assume that this "EasyAccount" is also the main current account.

[5]We make two additional sample restrictions, both very minor. First, we require that individuals have active joint accounts with at most one other individual. We define couples as individuals who share a joint account and live on the same address, however, this definition is ambiguous for individuals sharing accounts with multiple others. Second, we require that the ratio of total spending to disposable income is below two. When individuals seemingly spend many times their disposable income, the most likely explanation is that we do not measure their income well. The two restrictions jointly reduce the sample size by 2%.

[6]Card payments account for around 75% of total spending in our sample while other payment methods (e.g. bills, wire transfers, cash) account for the remaining 25%.

[7]Following the emerging literature that uses transaction-data from banks and financial apps to study consumer spending (Ganong and Noel, 2019), we categorize spending by four-digit Merchant Category Code, which is an international standard for classifying merchants by the type of goods and services they provide.

were closed, but could take emergency patients; international travel was virtually impossible as borders were closed, but domestic tourism was possible. At the other extreme, we consider online retail (except airlines etc), groceries and pharmacies to be *open sectors*. These sectors faced only very mild constraints. For instance, the government instructed consumers to limit the number of shopping trips and to keep distance in the stores. As an intermediate case, we consider retail (except online), fuel and commuting to be *constrained sectors*. Within the retail sector, malls were shut down but high-street shops were generally allowed to remain open. In the public transport sector, trains and buses continued to operate but at much reduced frequencies. We provide more detail on the coding of supply constraints in Table A1 in the Appendix.

Finally, we divide the full sample into various subsamples in order to compare spending responses across individuals who are exposed to the epidemic in different ways. Here, it becomes important to account for household structure. Since economic resources are usually pooled within households, it is generally not meaningful to assign spouses to different income groups based on their individual incomes. Similarly, since one spouse often buys items for other members of the household when shopping, it is not meaningful to divide spending across spouses based on their individual purchases. We address this issue by assigning individuals to households based on the information available in the bank's records: when two individuals live on the same address and have a joint bank account, we assume that they are cohabiting partners and divide each income flow and each purchase equally between them.[8] Averaging income and spending across cohabiting partners has no bearing on the main analysis in the full sample.

We split the sample along a number of dimensions. First, to capture differences in the distortions created by *supply constraints*, we split the sample by the ratio of supply constrained spending to total spending measured in 2019 before the supply constraints kicked in. Second, to capture differences in *health risk*, we split the sample by age (above and below 65 years) and by pharmacy spending in 2019 reflecting that COVID-19 is much more dangerous for the elderly and for individuals with pre-existing medical conditions. Third, to capture the differences in *wealth losses*, we create subsamples of stockholders and non-stockholders in 2019 reflecting that stock markets both in Denmark and elsewhere plunged around the shutdown (Gormsen and Koijen, 2020). Finally, to capture differences in the exposure to *job losses*, we split the sample by the income level in 2019 reflecting that low-income jobs constitute a large share of total employment in the closed sectors.[9] We also study exposure to job losses in an alternative way

[8]For instance, when one spouse spends DKK 200 at the pharmacy, we consider that each spouse has spent DKK 100 and when the other spouse receives a DKK 20,000 pay check, we consider that each spouse has received income of DKK 10,000.

[9]In the United Kingdom, employees in the shut-down sectors constituted 35% of all individuals in the bottom

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Table 1: Summary statistics. This table presents summary statistics for our analysis sample of Danske Bank customers (Column (1)) and the approximate population of Denmark from which they are drawn (Column (2)). Statistics in Column (1) are calculated on an annual basis as of December 2019. Population figures are sourced from the Danish Statistics Agency's (DST) online Statistics Bank for the most comparable population available: 18+ year olds in 2018. Some differences between variable construction are explained below.
* Individual-level measure constructed for the 14+ years population in 2018.
** Individual-level measure for the 14+ years population in November 2018, without any tenure requirement. Details on the construction of the income, industry and spending measures for the analysis sample (Column (1)) can be found in the Appendix.

	Sample	Population
	(1)	(2)
Female	51.6%	50.6%
Age:		
18-29 years	21.5%	19.9%
30-44 years	22.1%	22.5%
45-64 years	33.0%	32.9%
65+ years	23.4%	24.7%
Disposable income (USD)	37,554.6	34,615.4*
Stockholder	27.8%	25.2%*
Industry:		
At-risk, Private	4.2%	6.8%**
Other, Private	33.4%	36.7%**
Public	19.5%	18.2%**
Total card spending (USD)	16,900.60	-
Spending by category, %Total:		
Groceries	30.3%	-
Pharmacies	1.7%	-
Retail	20.3%	-
Entertainment	3.8%	-
Fuel & commuting	8.1%	-
Prof. & pers. svcs	5.5%	-
Food away from home	8.6%	-
Travel	6.2%	-
Online spending, %Total:		
All online	26.7%	-
Groceries	1.3%	-
Retail	8.7%	-
Food away from home	0.9%	-
Travel	5.0%	-
Spending by shutdown effect, %Total:		
Closed	26.1%	-
Constrained	26.6%	-
Open	47.2%	-
N	760,571	4,670,227

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by splitting the sample by employer industry: public sector where employees should not expect to be laid off, private sector firms directly affected by the shutdown (e.g. restaurants, hotels, personal care) and other private sector firms. We provide more detail on the coding of industries in Table A2 in the Appendix.

Table 1 reports summary statistics for our estimating sample (Column 1) and compare to socio-economic information for the full adult population obtained from government registers (Column 2). Our sample of 760,000 individuals is largely representative of the adult population of 4,670,000 individuals in terms of gender, age, income and stock market participation. This reflects that Danske Bank is a broad retail bank present in all parts of the country and catering to all types of customers. Our sample seemingly includes a smaller fraction of individuals working in at-risk sectors than the full population. This may reflect that we impose a 3-month tenure requirement when assigning individuals to industries combined with the fact that at-risk sectors generally have a higher turnover. By comparison, the industry distribution in population-wide statistics is a snapshot with no tenure requirement.

4 Empirical strategy

The main aim of the empirical analysis is to measure the change in consumer spending induced by the corona crisis: the COVID-19 epidemic, the shutdown of the economy and the various stimulus policies.

To capture the sharp change in behavior around the shutdown, we use spending information at the daily level. The high frequency creates empirical challenges as spending exhibits strong cyclicality over the week, the month and the year. We address the cyclicality by comparing consumer spending on each day in 2020 to consumer spending on a reference day 364 days earlier. The reference day is always the same day of the week and almost exactly the same place in the monthly and annual spending cycle. For example, we compare 8 February 2020 (a Saturday) to the reference day 9 February 2019 (also a Saturday). While the method does not account for the fact that spikes in spending due to pay days (Gelman et al., 2014; Olafsson and Pagel, 2018) may fall on different weekdays in different years, this will not affect our key estimates as explained below.[10]

For each day of our window of analysis, 1 January 2020 – 5 April 2020, we thus compute the

decile of the income distribution compared to 5% of the individuals in the top decile (Joyce and Xu, 2020). We expect that a similar relationships exists in Denmark.

[10]We refer to the notion of pay days in a loose way. While there is no uniform pay day in Denmark, most salary payouts in a given month typically fall on a few days around the end of the month.

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difference between aggregate spending on the day itself and aggregate spending on the reference day the year before. Scaling with average daily spending over a long period before the window of analysis, we obtain a measure of excess spending on a given day expressed as a fraction of the normal level of spending:

$$excess\ spending_t = \frac{spending_t - spending_{t-364}}{average\ spending}$$

where $spending_t$ is spending on day t and $average\ spending$ is average daily spending taken over all days in 2019.

Equipped with this machinery, we measure the effect of the crisis as the difference between average excess spending in the post-shutdown period, 11 March – 5 April, and average excess spending in the early pre-shutdown period, 1 January – 15 February:

$$\Delta spending = \underbrace{E[excess\ spending_t | t \in post]}_{\substack{\text{average excess spending} \\ \text{post-shutdown}}} - \underbrace{E[excess\ spending_t | t \in pre]}_{\substack{\text{average excess spending} \\ \text{pre-shutdown}}}$$

We effectively use excess spending in the pre-shutdown period as a counterfactual for excess spending in the post-shutdown period. In plain words, we assume that year-over-year spending growth between 2019 and 2020 would have been the same after 11 March as before absent the epidemic and the shutdown. However, we exclude 16 February - 11 March from the pre-shutdown period as early restrictions (e.g. on air travel to Asia) and anticipation of the broader crisis may have affected spending prior to the shutdown. While pay day spending creates spikes in excess spending on individual days - positive when we compare a pay day to a normal day and negative when we do the opposite - they do not affect $\Delta spending$ because both its terms average over the same number of positive and negative pay day spikes.

While $\Delta spending$ remains our summary measure of the spending response, we also show plots that compare spending on each day in the window of analysis to spending on the reference day the year before. The plot allows us to visually assess whether consumer spending behaved similarly in the pre-shutdown period as on the same days the year before (except for a level shift). This is key to assessing the credibility of our identifying assumption that consumer spending would have behaved similarly in the post-shutdown period as on the same days the year before (except for the same level shift) absent the epidemic and the shutdown.

To assess the importance of the various mechanisms that may be driving the aggregate change in spending, we study heterogeneity in spending responses across groups that were exposed differentially in a particular dimension. For instance, we compare the spending response of

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young and old to assess the importance of health risk. Correlations across different dimensions of exposure is an important caveat. For instance, the old are more likely to hold stocks and therefore also more exposed to stock market losses than the young. We address that concern by reweighting observations so that the subsamples we compare are balanced in other dimensions of heterogeneity. For instance, if stockholders are underrepresented in the young sample, we put more weight on individuals with this characteristic when we estimate the spending response for the young.

Formally, let individuals differ in N observable dimensions (age, income, and so on) and let $m_n = 1, ..., M_n$ denote the possible characteristics within dimension n (e.g., young and old in the age dimension). Suppose we want to compare spending responses for individuals who differ in dimension N. We then define a type as a combination of characteristics in the $N-1$ other dimensions, summarized by the vector $\mathbf{m} = (m_1, ...m_{N-1})$. Let $\lambda(\mathbf{m})$ denote the share of individuals with characteristics $\mathbf{m}$ in the full sample and let $\beta(\mathbf{m}, \widetilde{m}_N)$ denote the spending response for individuals of this type with characteristic $\widetilde{m}_N$ in the dimension of interest (e.g. the young). We define the re-weighted spending response for individuals with this characteristic as:

$$(\Delta spending | m_N = \widetilde{m}_N) = \sum_{\mathbf{m}} \lambda(\mathbf{m}) \cdot \beta(\mathbf{m}, \widetilde{m}_N)$$

This is effectively a weighted average of the type-specific responses $\beta(\mathbf{m}; \widetilde{m}_N)$ where the weights ensure that characteristics in other dimensions than N match those of the full sample. To implement the formula, we replace the sample shares $\lambda(\mathbf{m})$ with their empirical analogues and replace the spending responses $\beta(\mathbf{m}; \widetilde{m}_N)$ with estimates obtained by applying equation (4) to the sample of individuals of type m with characteristic $\widetilde{m}_N$.

5 Results

Figure 2 illustrates our findings concerning the drop in aggregate card spending. The left side of the figure plots spending on each day of the window of analysis (red line) and spending on the reference day one year earlier (gray line), both scaled by average daily spending in 2019. Both series exhibit a pronounced weekly cycle with spikes around weekends as well as a pay day cycle with spikes around the end of the month. Until the shutdown on 11 March 2020, both the level and the dynamics of spending are strikingly similar to the reference period. After 11 March 2020, spending is generally below the level in the reference period as indicated by the

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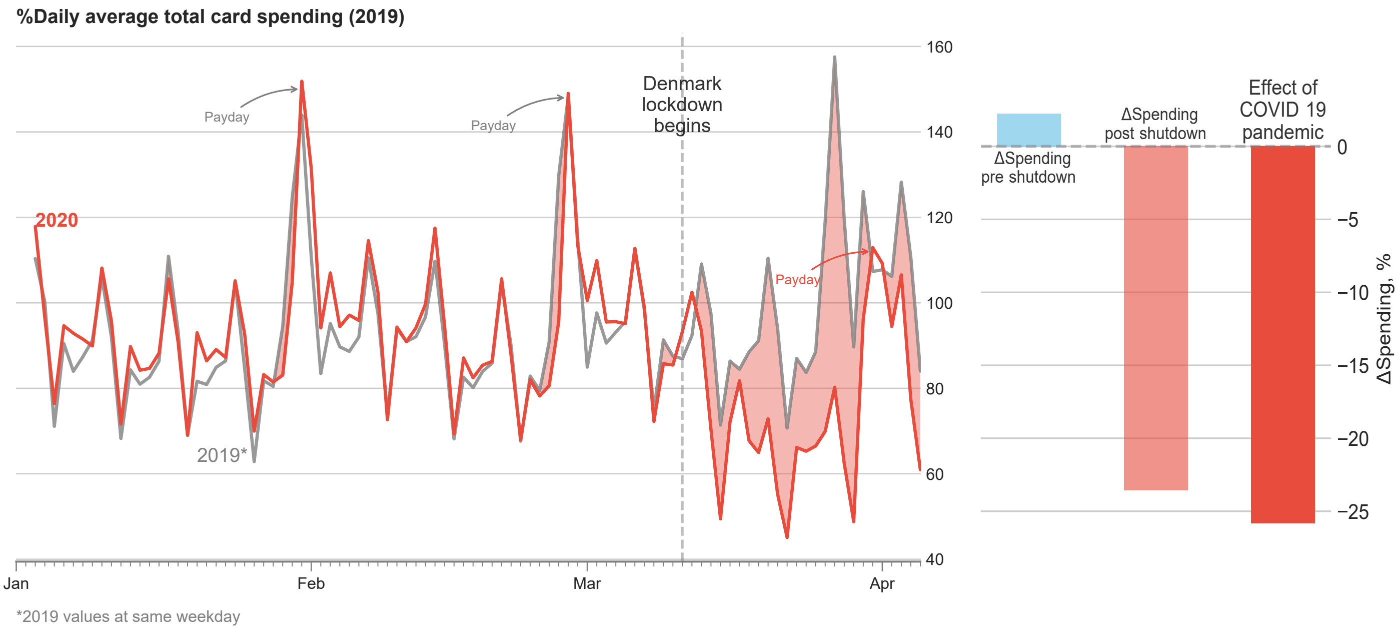
Figure 2: Aggregate card spending. The figure shows the drop in household spending on credit and debit cards associated with the COVID-19 crisis. The left panel shows the evolution of daily average card spending in 2020 (red line) and on equivalent days in 2019 (gray line), where each series is shown as a percentage of average daily card spending throughout 2019. Labelled "paydays" are the final bank day of the month, when the majority of individuals in Denmark receive their salary and/or government transfers. The right bar chart summarises our approach to estimate the impact of the crisis and provides our headline estimate of the drop in card spending.



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shaded differences.

Our headline estimate is that spending dropped by around 25% in response to the pandemic and the shutdown. The right side of the figure illustrates the mechanics underlying this estimate. The blue bar indicates average excess spending over the pre-shutdown period 1 January – 15 February 2020: consumers spent around 2% more over these days than over the reference days in 2019. The black bar indicates average excess spending over the post-shutdown period 11 March – 5 April 2020: consumers spent around 23% less over these days than over the reference days in 2019. Under the identifying assumption that the year-over-year growth between 2019 and 2020 would have continued to be 2% absent the epidemic and the shutdown, we estimate the spending response at -25%.

Figure 3 shows similar estimates for selected expenditure groups. The left side plots scaled daily spending in the window of analysis (red lines) and the reference days (gray line) whereas the right side shows the estimated spending response. In all categories, spending in 2019 and 2020 followed similar patterns until the shutdown. Spending responses to the shutdown, however, varied widely across categories: spending in grocery shops and pharmacies increased modestly relative to the counterfactual (blue bars and blue shading) whereas spending on restaurant meals, travel, retail , personal services, fuel and entertainment exhibited pronounced decreases (red bars and red shading).

Spending responses are closely linked to the restrictions on mobility and activity imposed by the government to prevent the spreading of the virus. Grocery shops and pharmacies where spending increased are both in the open sector whereas travel, restaurants and personal services were spending plummeted are all in the closed one. Figure 4 makes this point more formally by showing estimates of the spending response by sector. In all three sectors, spending in the pre-shutdown period tracked spending in the reference period closely. After the shutdown, the three sectors fared very differently: our estimates of the spending responses are around 10% for the open sector (roughly half of the economy), around -40% for the constrained sector (roughly one quarter of the economy) and almost -70% for the closed sector (roughly one quarter of the economy).

The pandemic and the partial shutdown of many economies have been presented as a golden opportunity for online retail: with high-street retail shops being partly shut down and associated with health risks to the extent that they remained open, the conditions for online substitutes should be ideal. While total online spending decreased considerably less than traditional offline spending (15% verus 30 %), as shown in Figure 5, these overall responses do not provide support

Figure 3: Spending categories. The figure shows the impact of the COVID-19 crisis on spending at different categories of merchant, identified using Merchant Category Codes associated with card payments. The graphs follow the same format as Figure 2: the left panel shows the evolution of spending in each category in 2020, relative to the reference period in 2019, and the right panel summarises our estimate of the effect on spending in each category. Blue shading and bars identify categories of spending that increase; red shading and bars identify categories of spending that decrease.

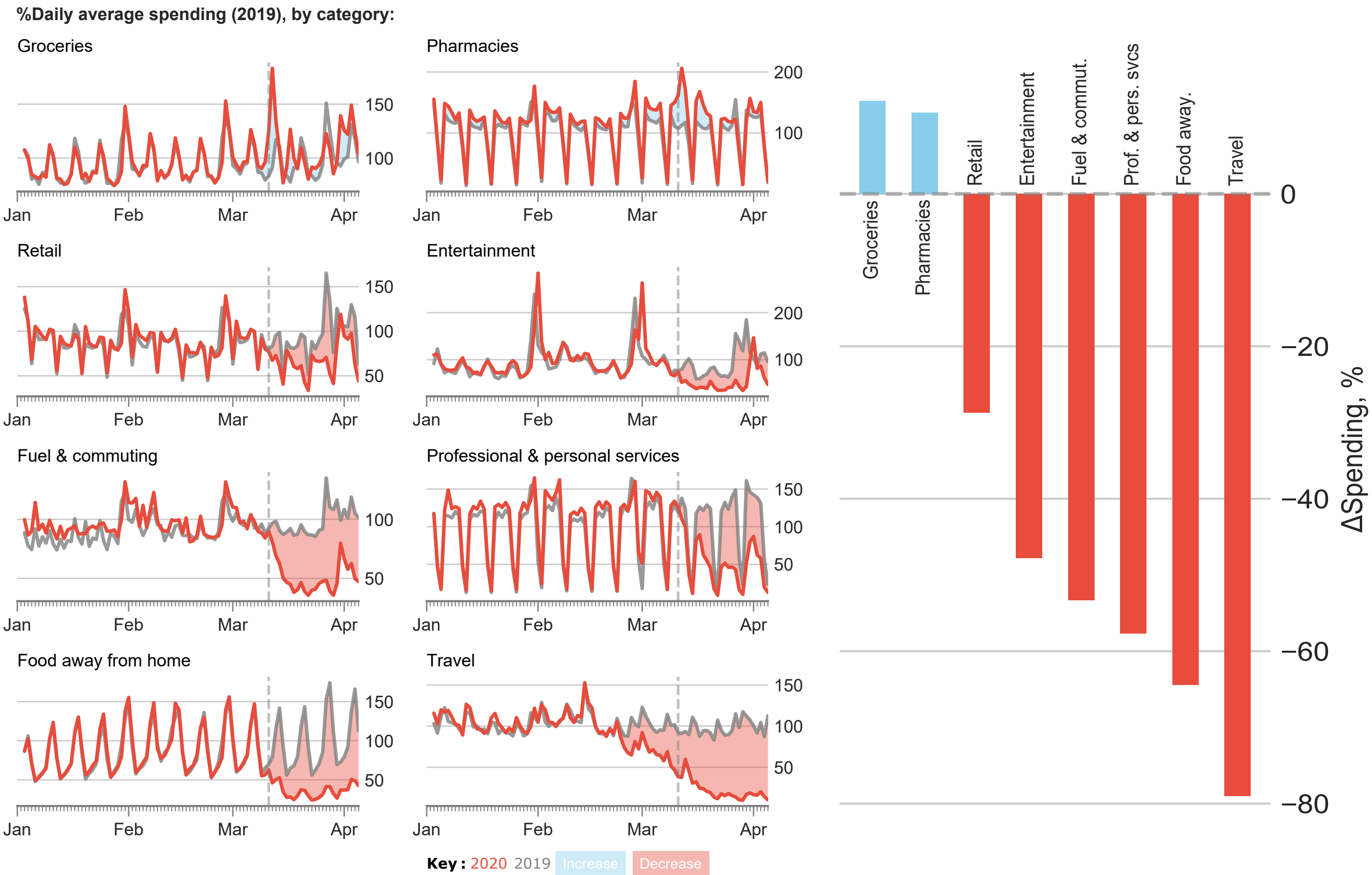

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Figure 4: Supply constraints. The figure shows the impact of the COVID-19 crisis on consumer spending in the Open, Constrained and Closed sectors of the economy under the government controls. Appendix Table A1 contains the crosswalk of spending categories into each group of supply constraints.

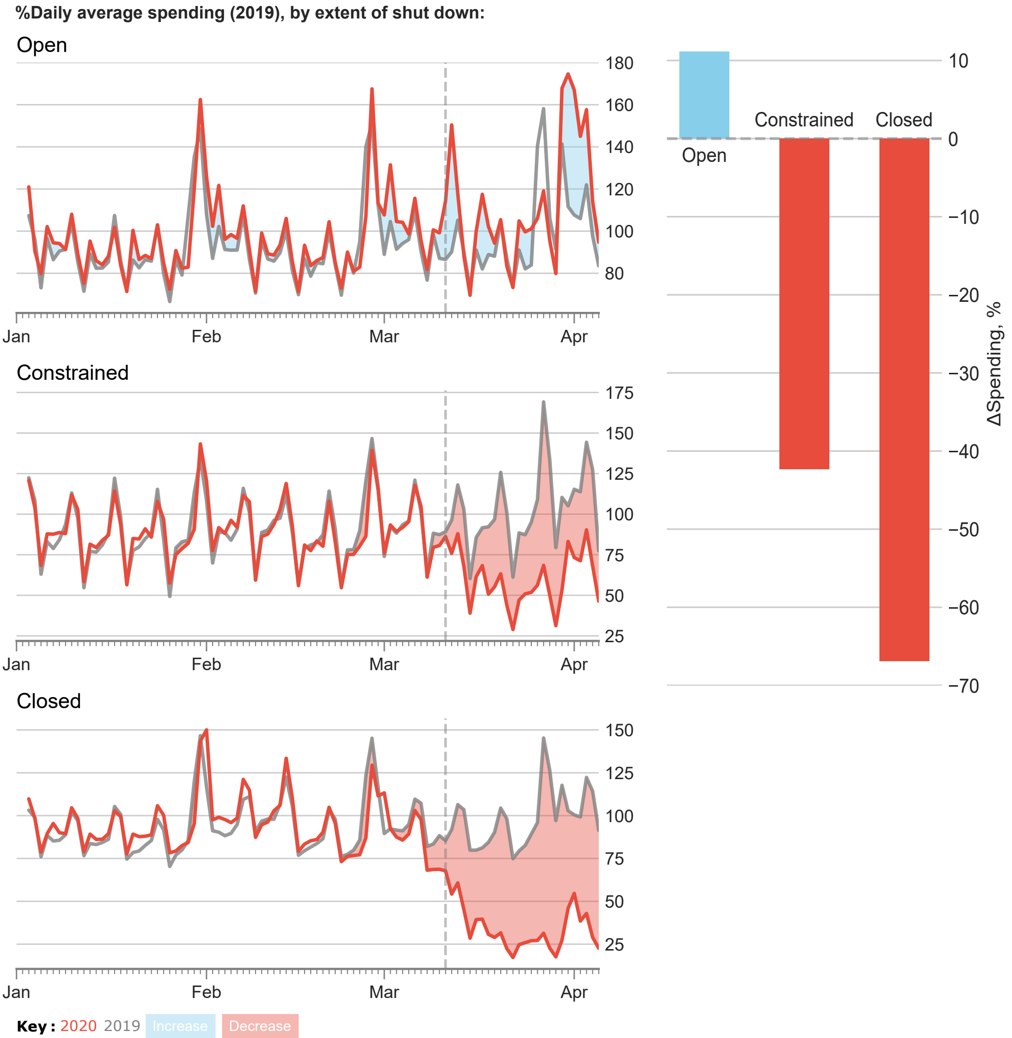

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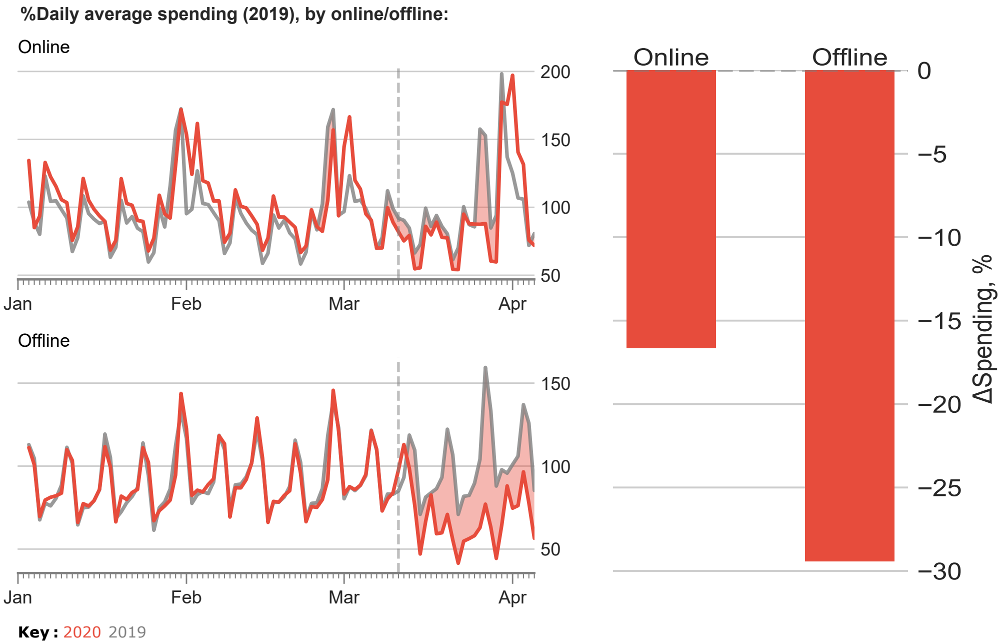
Figure 5: Online vs offline spending. The figure shows the impact of the COVID-19 crisis on online and offline consumer spending. We identify whether a payment takes place online or offline based on payment metadata associated with each transaction.



for a massive substitution into online retailing. However, Figure 6 shows that the modest decrease in overall online spending conceals enormous heterogeneity: online spending on travel almost disappeared whereas online spending on groceries almost doubled.

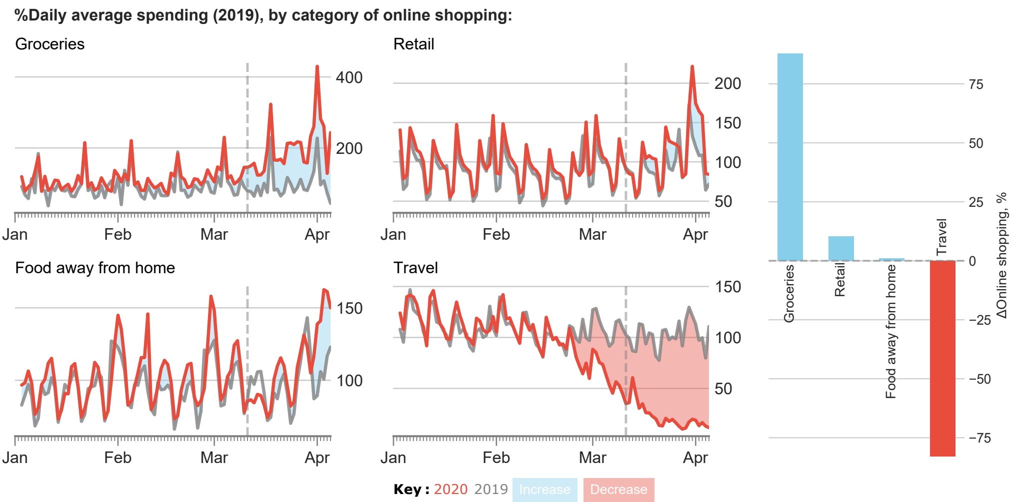
Finally, we study heterogeneity in spending responses across groups that were exposed differentially to the pandemic and the shutdown of the economy. Figure 7 illustrates the estimated drop in card spending for various subsamples. Observations are weighted so that the bars can be interpreted as the spending response for a subsample that has the same characteristics as the full sample in all other observable dimensions *except* in the highlighted dimension.[11].

We first compare individuals facing different income risk as a result of the crisis: those working in private businesses in the closed sector where lay-offs were frequent and those working in the public sector where jobs remained secured.[12] The results indicate that the spending

[11]Specifically, types are defined as combinations of the following characteristics: Age (indicators for ages 18-35, 35-64, 64+), Gender (binary indicator), Spending in closed sector in 2019 (binary indicator for being above or below median), Pharmacy spending in 2019 (binary indicator for being above or below median), Public sector employee (binary indicator), Stockholder (binary indicator), Income level in 2019 (indicators for income quartile

[12]The sample of private sector employees at risk of unemployment covers passenger transportation (air and sea), hotels, restaurants, cafes, bars, travel agents, entertainment, personal care services and retail.

Figure 6: Categories of online spending. The figure shows the impact of the COVID-19 crisis on online and offline consumer spending in a number of key categories: Groceries, a sector that remains open throughout; Retail, including all purchases of consumer goods such as clothes, electronics, etc., Food away from home, which includes online and app based purchases of takeaway/prepared food; and Travel, including all purchases of flights, hotels, and rental cars.



response is slightly larger (+3 percentage points) for individuals with higher income risk.

We then compare individuals with different exposure to wealth losses: stockholders who were exposed to the global stock market bust and non-stockholders who were not. The results suggest a somewhat larger spending response (+5 percentage points) for individuals with exposure to stock markets.

We provide separate results for individuals at different positions in the income distribution: those in the bottom quartile where the risk of job loss following the shut-down is relatively large and those in the top quartile where this risk is limited (Joyce and Xu, 2020). The results suggest a smaller spending response (-5 percentage points) for individuals with more exposure to job losses as proxied by their income level.

We proceed to split the sample by two measures of exposure to health risk. We first compare elderly individuals (above 65 years) who are the most likely to suffer serious health consequences if infected with the virus to the young and the middle-aged (below 65 years). The results indicate a larger spending response (+7 percentage points) for individuals with more exposure because of their age. We also compare individuals who generally spend a lot in pharmacies before the pandemic, an indication of a pre-existing condition that raises the health risks associated with the virus, to individuals who generally spend little in pharmacies. The results suggest a slightly

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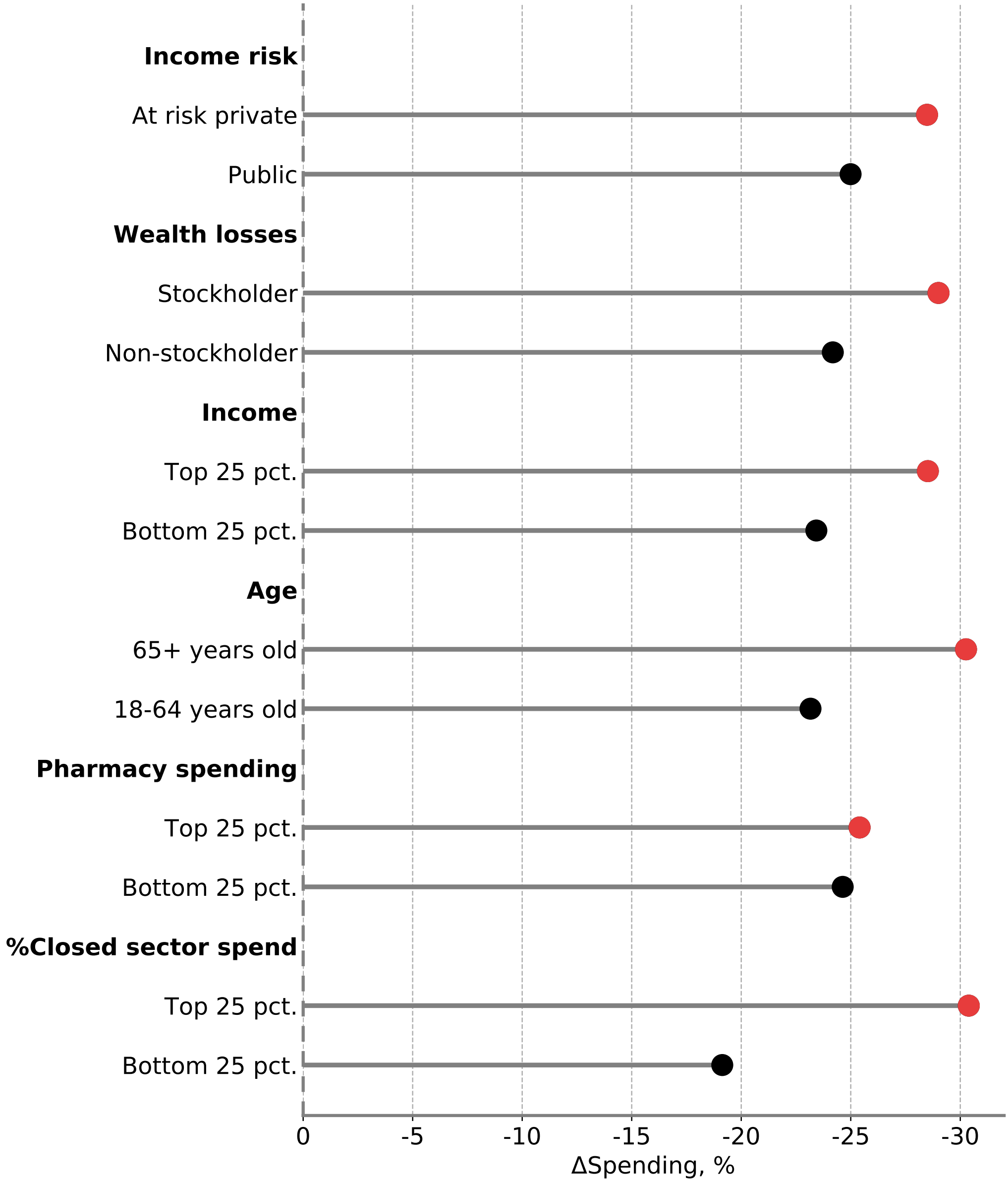
Figure 7: Individual heterogeneity. The figure quantifies heterogeneity in the impact of the COVID-19 crisis on consumer spending. We focus on comparing the impact across individuals who differ in exposure to different risks associated with the crisis and the shutdown.



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larger spending response (+1 percentage points) for individuals with more exposure due to pre-existing health problems.

We finally compare individuals with different exposure to the shut-down of economic sectors such as restaurants and international travel: individuals who spent most in these sectors before the shutdown to those who spent the least. The results indicate a much larger spending response (+12 percentage points) for individuals with more exposure to the shut-down because of their inherent spending patterns.

The results provide some insights into the mechanisms underlying the massive drop in aggregate spending. Differential exposure to economic risks and health risks can account for some of the variation in spending responses but not nearly all of it. Pre-crisis spending shares on goods and services provided by the closed sector is clearly the strongest correlate of spending responses.

6 Conclusion

This paper uses transaction-level bank account data from the largest Danish bank to study consumer responses to the COVID-19 crisis. We present three key results. First, the drop in aggregate spending is around 25%. Second, the spending response varies widely across expenditure categories and correlate strongly with the severity of government restrictions. Third, the spending responses correlate moderately with exposure to economic risks and health risks while pre-crisis spending shares on supply-constrained goods and services is the strongest correlate of spending responses.

Our results consistently indicate that the closed sector of the economy is at the heart of the drop in consumer spending. This may reflect that the drop in spending is caused directly by the shutdown, e.g. consumers do not go to restaurants because they are closed, or that the drop in spending is caused by the health risks that motivated the shut-down, e.g. consumers do not go to restaurants because it exposes them to the virus. Economic risks such as income and wealth losses appear to play a limited role over the short horizon studied in this paper.

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ONLINE APPENDIX

Table A1: Aggregation of spending categories This appendix explains how spending categories obtained from MCCs are aggregated to measures of spending in open, constrained and closed sectors.

Sector	Description
Closed:	Travel: All expenditures on flights, hotels, travel, rental cars, etc.
	Food away from home: Any in-person expenditures at restaurants, cafes, bars, etc.
	Personal care: All expenditures on personal and professional services, including dentists, phyiotherapists, hairdressers, etc.
	Entertainment: All expenditures on entertainment, including cinema tickets, sporting events, etc.
	Department stores: Any in-person expenditures at department stores
	Auto: Any in-person expenditures on auto equipment or servicing in malls
	Home improvements: Any in-person expenditures on home improvements and furnishings in malls
	Retail: Any in-person expenditures on retail durables, non-durables and miscellaneous durables in malls
Constrained:	Fuel & commuting: Any expenditures on fuel or commuting, including payments at petrol stations, public transport passes, etc.
	Auto: Any non-mall, in-person expenditures on auto equipment or servicing
	Home improvements: Any non-mall, in-person expenditures on home improvements and furnishings
	Retail: Any non-mall, in-person expenditures on retail durables, non-durables and miscellaneous durables
Open:	Pharmacies: Any expenditure in pharmacies
	Groceries: Any expenditures at grocery stores
	Insurance: Any insurance purchases
	Television & communication: Any expenditures on television entertainment packages or phone and internet
	Utilities: Any utilities expenditures, including gas, electricity, etc.
	Department stores: Any online expenditures at department stores
	Auto: Any online expenditures on auto equipment or servicing in malls
	Home improvements: Any online expenditures on home improvements and furnishings in malls
	Retail: Any online expenditures on retail durables, non-durables and miscellaneous durables in malls

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Table A2: Aggregation of industries This appendix explains how industries of employment are aggregated to at-risk private, other private and public sectors.

Industry	Classification by NACE industry codes/DB07 Danish section codes
At-risk, Private:	Passenger flight and sea transportation, including support services: 501000, 511010, 511020, 522300 Hotels: 551010, 552000, 553000, 559000 Restaurants, cafes, bars, etc: 561010, 561020, 562100, 562900, 563000 Travel and reservation agents: 791100, 791200, 799000 Entertainment, sports, recreation services, etc: 900110, 900120, 900200, 900300, 900400, 931100, 931200, 931900, 932100, 932910, 932990, 855100, 855200, 855300, 855900 Personal care services: 960210, 960220, 960400, 960900, 869020, 869030, 869040, 869090
Other, Private:	DB07 Sections A, B, C, D, E, F, G, H (excluding workers in passenger flight and sea transportation, above), J, K, L, M, T (excluding personal care services, above): Includes farming, manufacture, logistics, utilities, building and construction, retail, information and communication, financial services, real estate, professional and technical services
Public:	DB07 Sections N, O and P (excluding private sector activities grouped in recreation services, above), Q and 9101, 9102, 9103, 9104

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The COVID-19 pandemic: Government versus community action across the United States[1]

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Date submitted: 12 April 2020; **Date accepted:** 14 April 2020

Are lockdown policies effective at inducing physical distancing to counter the spread of COVID-19? Can less restrictive measures that rely on voluntary community action achieve a similar effect? Using data from 40 million mobile devices, we find that a lockdown increases the percentage of people who stay at home by 8% across US counties. Grouping states with similar outbreak trajectories together and using an instrumental variables approach, we show that time spent at home can increase by as much as 39%. Moreover, we show that individuals engage in limited physical distancing even in the absence of such policies, once the virus takes hold in their area. Our analysis suggests that non-causal estimates of lockdown policies' effects can yield biased results. We show that counties where people have less distrust in science, are more highly educated, or have higher incomes see a substantially higher uptake of voluntary physical distancing. This suggests that the targeted promotion of distancing among less responsive groups may be as effective as across-the-board lockdowns, while also being less damaging to the economy.

1 We thank SafeGraph for generously providing their data and support. We also thank Rick Van der Ploeg, Doyne Farmer, Blas Kolic, Moritz Absenger, the Complexity Economics Group at the Institute for New Economic Thinking and seminar participants at Bocconi University for support and helpful discussions.

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1 Introduction

The outbreak of COVID-19 has caused an unprecedented healthcare crisis and a major disruption to the global economic system across the world. Political leaders in many countries have taken measures to limit the contagion rates in order to relieve the pressure on health care systems and prevent excess deaths. While epidemiological uncertainty about the virus and its spread remains (Anderson et al., 2020), research on China and South Korea shows that early governmental action and cooperation by the population can stem the uncontrolled spread of the pandemic (Kraemer et al., 2020; Wilder-Smith and Freedman, 2020; Wu and McGoogan, 2020).

In this paper, we provide estimates of how government action influences community behavior along several dimensions, and in turn is itself influenced by decisions made by the population at large. From a policy perspective, understanding whether and how communities respond to government actions is crucial. To the best of our knowledge, we are the first to leverage high-resolution big data on people's movements and whereabouts in combination with causal econometric methods in order to analyze the interdependence between government and community action.

Using staggered difference-in-differences (DiD) approaches and an instrumental-variable (IV) analysis, we show that physical distancing measures pick up after the implementation of government lockdown policies. In particular, in our first approach, we estimate that the introduction of a lockdown policy increases the proportion of people who stay completely at home by around 8%, over and above any community action taken. For our difference-in-differences instrumental variable approach, we group states together by the date on which the first within-state COVID death occurs. The evidence suggests that the effect size can be as large as 39% for certain states, once we account for endogeneity due to treatment selection. However, we document that communities take action even in the absence of government policies. Moreover, we find that the more communities take independent action to limit social interactions, the less likely it is that state governments implement restrictive lockdown measures. Our conclusion is that government policies can further amplify measures already taken at the community level, but that the need for restrictive policies is reduced the more the community takes independent action. Finally, our analysis suggests that non-causal econometric approaches to measure the uptake in physical distancing following lockdown policies will yield biased results, as we provide evidence for a two-way interaction between physical distancing and such policies.

These result shed further light on the role of public health policies in combating the COVID pandemic. In general, governments can take two distinctive strategies according to Ferguson et al. (2020): mitigation and suppression. The former aims at lowering maximum healthcare demand by reducing contagion rates through non-pharmaceutical interventions, while the latter approach adopts very restrictive measures to push down the prevalence of new cases to zero. Most researchers argue that only a mix of suppressive measures such as mandatory home isolation and lockdown policies can be successful in mitigating the spread of the virus. These interventions may need to be maintained over several years (Kissler et al., 2020) and complemented with

school and business closures (Ebrahim and Memish, 2020; Ferguson et al., 2020; Hellewell et al., 2020). Yet, even though lockdown policies have been crucial in slowing down infection rates during the early phases of the disease (Stoecklin et al., 2020; Wu et al., 2020; Xiao and Torok, 2020; Zu et al., 2020), the 'Swedish solution' of voluntary physical distancing has gained increased support in balancing the burden on health systems and the economy in the medium run (Krueger et al., 2020). Our findings reveal that both approaches may help to promote physical distancing. Nonetheless, the evidence we provide for differential outbreak response along socioeconomic lines calls for a more nuanced discussion paired with policies targeted at less responsive groups. Our findings align closely with earlier findings in the epidemiology literature that the distribution of individual infectiousness around the basic reproductive number – R(0) – is often highly skewed in epidemics, making that targeted control measures generally outperform population-wide ones (Lloyd-Smith et al., 2005).

So far, first steps have been taken to analyze social distancing under lockdown policies. Using mobility statistics from Unacast, Engle et al. (2020) find state-wide stay-at-home orders to be correlated with a reduction in mobility of 7.9%. Mediated by perceived risk, this correlation is stronger in counties with lower vote shares of the Republican party, higher population density and relatively more people over age 65. Painter and Qiu (2020) exploit SafeGraph data to show that the introduction of shelter-in-place policies is associated with a 5.1 percentage point increase in the probability of staying home. They also document smaller correlations in Republican states and in case a county is politically misaligned with the governor of the state. Qualitatively similar results have been obtained by Andersen (2020) and Allcott et al. (2020). We add to this literature by providing a detailed examination of the two-way causality and the overlooked endogeneity of lockdown policies.

More broadly, our research speaks to the field studying the behavioral impact of major crises such as natural disasters or pandemics. A host of papers deal with the long-run effects of the Spanish Flu in 1918-19, showing persistent decreases in human capital (Beach et al., 2018), generalized trust (Aassve et al., 2020) and old-age survival (Myrskylä et al., 2013). In terms of economic outcomes, pandemics have been associated with subsequent reductions in returns to assets (Jorda et al., 2020) and slight increases in real wages (Barro et al., 2020). In addition, our findings inform the debate about the role of formal and informal institutions in times of crisis (Stiglitz, 2000). In the past, both types of institutions have been shown to contribute to economic development individually and in a complementary (Guiso et al., 2004; Williamson, 2009) or substitutive manner (Ahlerup et al., 2009). Finally, several studies indicate that informal institutions are vital in promoting behavior that helps mitigate the spread of infectious diseases (Chuang et al., 2015; Rönnerstrand, 2013, 2014).

We find support for these results in that more informed (highly educated and high trust in science) areas react more strongly to the outbreak of the virus itself by voluntarily practicing physical distancing. In contrast to previous studies by Painter and Qiu (2020) and Engle et al. (2020) we do not find evidence for heterogeneity in response to lockdown policies, except for rural and urban areas – neither in that more privileged people show a stronger additional reaction nor

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in a catch-up effect of disadvantaged communities. Nevertheless, socioeconomic inequalities may enter the COVID crisis along several dimensions. First, it is likely that disadvantaged groups will be affected more strongly by the crisis due to lower levels of health coverage, higher prevalence of pre-existing health problems, mass lay-offs and unfavorable living conditions.[1] Second, existing income and education differences income and education are likely to be exacerbated through the disruption of economic and educational systems (Armitage and Nellums, 2020; Glover et al., 2020; Van Lancker and Parolin, 2020). Third, tackling inequality could be crucial in mitigating the spread of the virus (Ahmed et al., 2020). Combining data on testing and incidences in New York City with demographic characteristics, Borjas (2020) shows that people residing in poor or immigrant areas were less likely to be tested. Yet, once a test was carried out in these neighborhoods, it was more likely to be positive. These counteracting factors dilute the importance of socioeconomic characteristics, making simple correlations between household income and the number of incidences prone to underestimating the asymmetric effects of the pandemic. Our result that less well-off areas tend to respond less to the outbreak of the crisis implies an important role for formal institutions in reaching out to such areas through welfare programs and information campaigns and for bolstering the informal institutions in place.

The remainder of this paper is structured as follows: Section 2 discusses our data sources, in particular our measures of physical distancing and lockdown policies.[2] Section 3 discusses our empirical approach and presents the results. Section 4 concludes.

[1]See e.g. www.vox.com

[2]The state-level policy dataset can be accessed here.

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2 Data

We compile a dataset on government policies and physical distancing for the period between February 1, 2020 and March 31, 2020 from various sources. In this section, we briefly discuss each of the sources and describe the variables we construct from them.

2.1 SafeGraph Physical Distancing and Foot Traffic Data

Our main dataset comes from SafeGraph, a California-based company that provides data on over 4 million points of interest (POI) across the United States, along with the associated foot traffic at those places, collected from up to 40 million mobile devices. The data was made available to academic researchers by SafeGraph to study the COVID-19 pandemic. Here, we provide a concise discussion of the two main datasets that we use.[3] Both datasets build on SafeGraph's core database of ~4 million POIs in the US, which they compile from thousands of diverse sources in an exhaustive 6-step process designed to guarantee reliability, granularity and accuracy. We aggregate this data to the state and county level to estimate the effect of lockdown policies targeted at reducing social interactions implemented by state governments to combat the spread of the virus.

Weekly Patterns. A temporary data product especially introduced for the study of the COVID-19 pandemic, Weekly Patterns, provides weekly updates of visitor and demographic aggregations for ~3.6MM POIs across the United States. It is based on an underlying panel of up to 40MM mobile devices with home addresses in all 200,000+ census block groups (CBG) across the United States.[4] Geographic bias of the sample is limited, with the absolute difference between the panel's density and true population density as measured by the US census never exceeding 3% at the state level. The correlation between both densities is 0.98. At the county level, the overall sampling bias is larger, with the correlation dropping to 0.97, although the bias for each separate county drops, to never exceed 1%.[5] In addition to this low geographic sampling bias, the panel also has a low degree of demographic sampling bias. Although device-level demographics are not collected for privacy reasons, average demographic patterns can be studied using panel-weighted, CBG-level Census data. Here again, the frequency of salient race, demographic and income groups in the panel closely tracks the same frequency in the Census. To obtain a measure of **daily state-level foot traffic**, we sum up the total number of visits each day to all POIs in each state. We consider overall foot traffic the best-suited measure to study movement patterns, since it smooths out industry-specific idiosyncrasies in

[3] For a more detailed exposition of SafeGraph's data products, see `https://safegraph.com`.

[4] CBGs with less than 5 devices are excluded for privacy reasons.

[5] CBGs, expectedly, are marked by larger sampling bias, mostly due to technical errors in determining devices' home locations and so-called sinks. Since we restrict our analysis to the state and county level, this does not pose a serious issue. For a detailed exposition of SafeGraph's panel bias, see here.

foot traffic that arise from the particular nature of the policies imposed – with traffic to airports, for example, temporarily increasing after the travel ban on European countries.

Social Distancing Metrics. To facilitate the study of how people adhere to COVID-related social distancing arrangements, SafeGraph introduced a new data product that provides direct information on the movements of the smartphone devices in its panel.[6] Based on GPS pings from the devices, the common nighttime location of each mobile device over a 6 week period is narrowed down to a Geohash-7 (153m $\times$ 153m) granularity, which is denoted the device's home. Aggregate device metrics are then reported at the CBG level.

For our analysis, we further aggregate these metrics to the county and state level. Specifically, we measure, on a daily basis[7]:

- **Median distance traveled from home** for each state and county by taking the median of the same measure for all CBGs.
- **Median home dwell time**, constructed in a similar way.
- **The percentage of devices that spent all day at home** is obtained by summing a count of such devices at the CBG level and dividing it by the total number of devices observed in that CBG.

For the county-level analysis, our preferred measure is the percentage of devices that spent all day at home, because it is constructed from a raw count of the numbers of devices. Thus, this variable exhibits the most detailed variation, and no information is lost by repeatedly extracting moments from it, as is the case for the other variables. At the same time, the measure is less well-suited to state-level analysis, since we expect state-level policies to be more strongly related to movements in the entire state-wide distribution of physical distancing – captured well by the median dwell time –, rather than to the highly detailed movements of single individuals which show up in the percent at home variable.

SafeGraph guarantees privacy preservation of the subjects whose data is collected in at least three ways. First, the data was not collected directly from people's smartphones, but from a secondary source; it contains only aggregate mobility patterns. Second, SafeGraph excluded CBG information if fewer than five devices visited a place in a month from a given CBG so as to further enhance privacy. Third, the data products and maps derived from the mobility patterns are again aggregate results. No human subjects have or can be re-identified using these derived results.

[6]See here for detailed information on this product.
[7]Detailed descriptions of each variable can be found in Appendix A, Table 5.

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2.2 Government Measures

Government Measures. Data on government measures implemented to combat the COVID-19 spread has been retrieved from the National Association of Counties (NACO)[8] and the National Governors' Association.[9] For each state and county, we obtained data on whether and when they declared a state of emergency (SOE) and implemented business or school closures and safer-at-home polices.[10] The business closure order requires all non-essential businesses to close down, while the safer-at-home order calls for all citizens to stay at home. Essential needs (such as grocery shopping, exercise and medical emergencies) are the only exceptions to safer-at-home orders. People working in essential businesses are still allowed to go to work. Additionally, all 50 states implemented school closures. The dates for school closures were obtained from the official websites of the administrations of the 50 states and the District of Columbia.

2.3 Instruments and Controls

Instruments: Weather and Ventilators Needed. To account for the potential endogeneity of government policies with respect to the community response measures obtained from the SafeGraph data, we construct an instrument based on the daily number of ventilators required for each state. This variable is based on official estimates from the Institute for Health Metrics and Evaluation (IHME) that publishes COVID-19 projections under the assumption of full social distancing throughout May 2020.[11] While a current or predicted need of ventilators increases pressure on politicians to impose lockdown policies, these information are hardly disclosed to the public, or only with a lag. Therefore, we expect a need of ventilators to influence politicians' decisions without any direct effect on physical distancing in the population.

As to the converse endogeneity, we construct an instrument for community response measures from weather data, based on the deviations of temperature and precipitation from their 10 year-averages in the capital of each state. The data is taken from the National Centers for Environmental Information website.[12] Temperature and precipitation in the capitals are based on measurements from the main weather station of the capital's airport. We match these to our community response measures for the capital cities in question.

Hospital Capacity. Data on hospital capacity is provided by Definitive Healthcare[13] through the ESRI's Disaster Response Program[14], which gathers useful data to understand the spread of COVID-19 in the United States. We use daily forecasts on the number of hospital beds and ventilators needed for COVID patients at the state level.

[8]For details, see `https://ce.naco.org/?dset=COVID-19&ind=State%20Declaration%20Types`. We thank NACO for sharing the underlying data with us.

[9]The underlying data from the NGA can be found under `https://www.nga.org/coronavirus/#states`

[10]In this paper, we use the terms shelter-in-place and safer-at-home interchangeably.

[11]See www.covid19.healthdata.org for a current version of the data.

[12]The historical weather data is available under www.ncdc.noaa.gov.

[13]www.definitivehc.com

[14]www.coronavirus-disasterresponse.hub.arcgis.com

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COVID-19 Statistics. The data on COVID-19 cases and deaths in the United States is collected from three different sources: the official US Government COVID-19 dedicated page[15], the Johns Hopkins Coronavirus Research Center[16] and the COVID Tracking Project.[17] We collect measures on positive tests, negative tests and number of deaths; and this for both cumulative count and day-on-day increases.

Socio-Economic Statistics. Most demographic variables are sourced from the American Community Survey 2018 (Ruggles et al., 2018), a 1 % random sample of the American population. Population estimates for 2018 come from the official Census Statistics. [18] Next, data on county-level employment and education were drawn from the Quarterly Census of Employment and Wages (2019Q3) and the United States Department of Agriculture's Economic Research Service. As a proxy for belief in science, we leverage data on county-level opinions on climate change from Howe et al. (2015). Data on party vote shares in the 2016 presidential election by county was obtained from the MIT Election Lab.[19] Lastly, we use the institutional health index from the United States Congress Joint Economic Committee.[20] The index combines information on the rate at which citizens cast ballots in the 2012 and 2016 presidential elections; the rate at which residents returned the 2010 census through the mail; and the confidence of adults in corporations, the media and public schools.

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3 Results

We now turn to the results of this paper. In particular, we pose four sets of questions. First, to what extent do people practice physical distancing, such as staying at home, in the absence of government policies? Second, how do people adapt their behavior following a policy change? Third, how is the implementation of lockdown policies influenced by previous community behavior? And fourth, to what extent do socioeconomic and political factors matter in shaping community responses to COVID-19?

In order to answer these questions, we first review the data descriptively in subsection 3.1. The descriptive statistics point towards the conclusion that people stay at home even in the absence of lockdowns after the virus takes hold in their area, but that their response is stronger if policies are implemented. Building upon this analysis, in subsection 3.2 we employ a staggered difference-in-differences (DiD) approach and a DiD instrumental variables (IV) methodology in order to estimate the causal effect of lockdown policies. We then turn to the question of reverse causality in subsection 3.3, where we use an IV strategy to show that persistent inaction on the side of the community can trigger the government to implement policies.

[15] www.COVID19.healthdata.org
[16] www.coronavirus.jhu.edu
[17] www.COVIDtracking.com
[18] www.bea.gov
[19] www.electionlab.mit.edu
[20] www.jec.senate.gov

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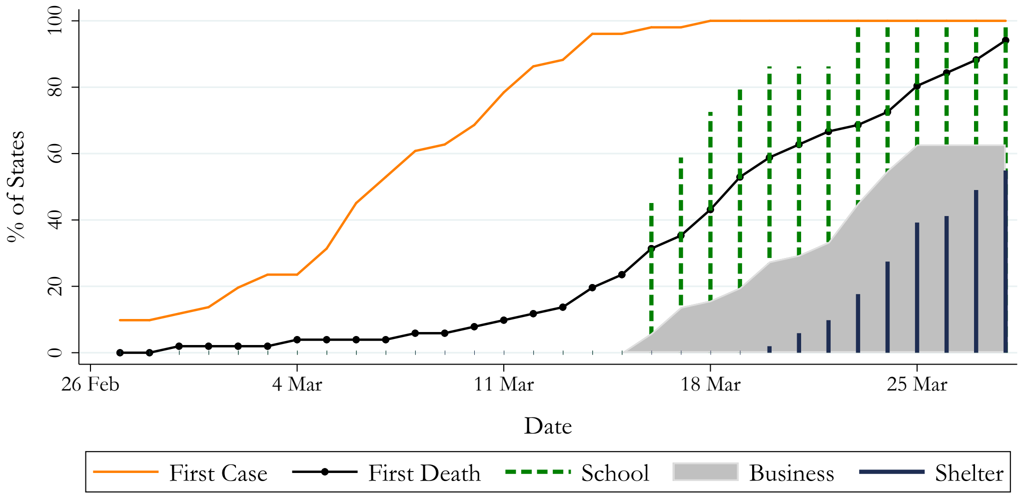
Finally, we document substantial heterogeneity in community responses across socioeconomic groups in section 3.4. After discovering stark differences between groups in their reaction to the outbreak of the virus, we show that the same heterogeneity is not evident in the additional response to lockdown policies, but is rather due to differences in the degree of voluntary physical distancing. Our analysis suggests that cross-county differences in socioeconomic variables, such as income, belief in science or education, can have as much of an effect on the level physical distancing as the imposition of a lockdown. In the medium run, this implies that governments can decrease the need for damaging lockdowns by expanding cohesive policies.

3.1 Descriptive Statistics

Figure 1 shows the series of events that occurred over the course of February and March 2020 in the United States. The first cases and deaths were confirmed in late February while the spread of the disease officially only gained momentum during the middle of the month. Lockdown policies were imposed across states during the weeks after these incidents. As of end March, all states have adopted school closure policies and roughly half of them have gradually been introducing business closures and shelter-in-place measures, i.e. orders to stay home.

Figure 1: Timeline of Contagion and Lockdown Policies, Feb-Mar 2020



Notes: The orange solid line represents the percentage of states with at least one confirmed case; the black connected line shows the percentage of states that have recorded a first death due to the virus. The dashed (solid) spikes refer to school closures (shelter-in-place policies). he grey shaded area depicts business closures.

Figure 2 and Figure B.4 in the Appendix depict trajectories for selected states from each US region by plotting the percentage of devices that stayed home all day and the foot traffic, respectively, alongside national and state-level lockdown policies. For all states, the variables seem to be stationary until the first week of March, when traffic starts to drop and the percentage

that stayed home increases. The upward trend seems to continue regardless of national and state-level policies, though the nation-wide state of emergency declaration (first dashed grey line) appears to cause a significant acceleration of this trend, as do several of the state-wide policies. Not only does the timing of the outbreak of the pandemic differ across states, but so do the community reaction as well as the timing and scope of lockdown policies. This variation allows us to explore the interplay between community behavior and government action around the time of the enactment of the lockdown policies.

Our analysis reveals that outbreaks of COVID-19 are significantly associated with uptakes in physical distancing. Figure 3 shows how three types of distancing measures respond to the first death in a state, alongside 95% confidence intervals. The estimates illustrate how the variable changes on each day after the first COVID death compared to no death having occurred, where we control for state fixed effects. Note that all three variables change in the expected way: compared to no death having occurred, the percentage of people who stay at home all day and the median dwell time at home go up (panels (a) and (b)), while the median distance from home decreases (panel (c)). Moreover, the estimated effects are large: the percentage of people staying at home all day increases by around 8 percentage points one day after the first death compared to the period before the first death.

At the state-level, the downward trends in traffic observed in Figure B.4 seem to hold both in the presence and in the absence of policy interventions. Figure 4 expands on this point by showing the community response before a policy has been implemented. In the left panel, the y-axis presents the percentage change in traffic between the date of the tenth confirmed case and the enactment of the first lockdown policy, while the x-axis shows the number of days between these two events. The right panel plots equivalently the difference in percentage stayed home. For the majority of states, lockdown policies were implemented several days after the first death as indicated by the positive values on the x-axis. The figure illustrates that once a state is affected by COVID-19, individuals start to reduce their daily foot traffic and spend relatively more time at home even before any lockdown policy is implemented. Hence, we conjecture that calls for physical distancing and information on the virus's spread are taken seriously and individuals voluntarily modify their behaviour even in the absence of fast-moving policies. This association is by no means negligible in size: in our sample, foot traffic decreases by up to 50% 10 days after the tenth confirmed case, while the share of individuals staying home increases by up to 16 percentage points.

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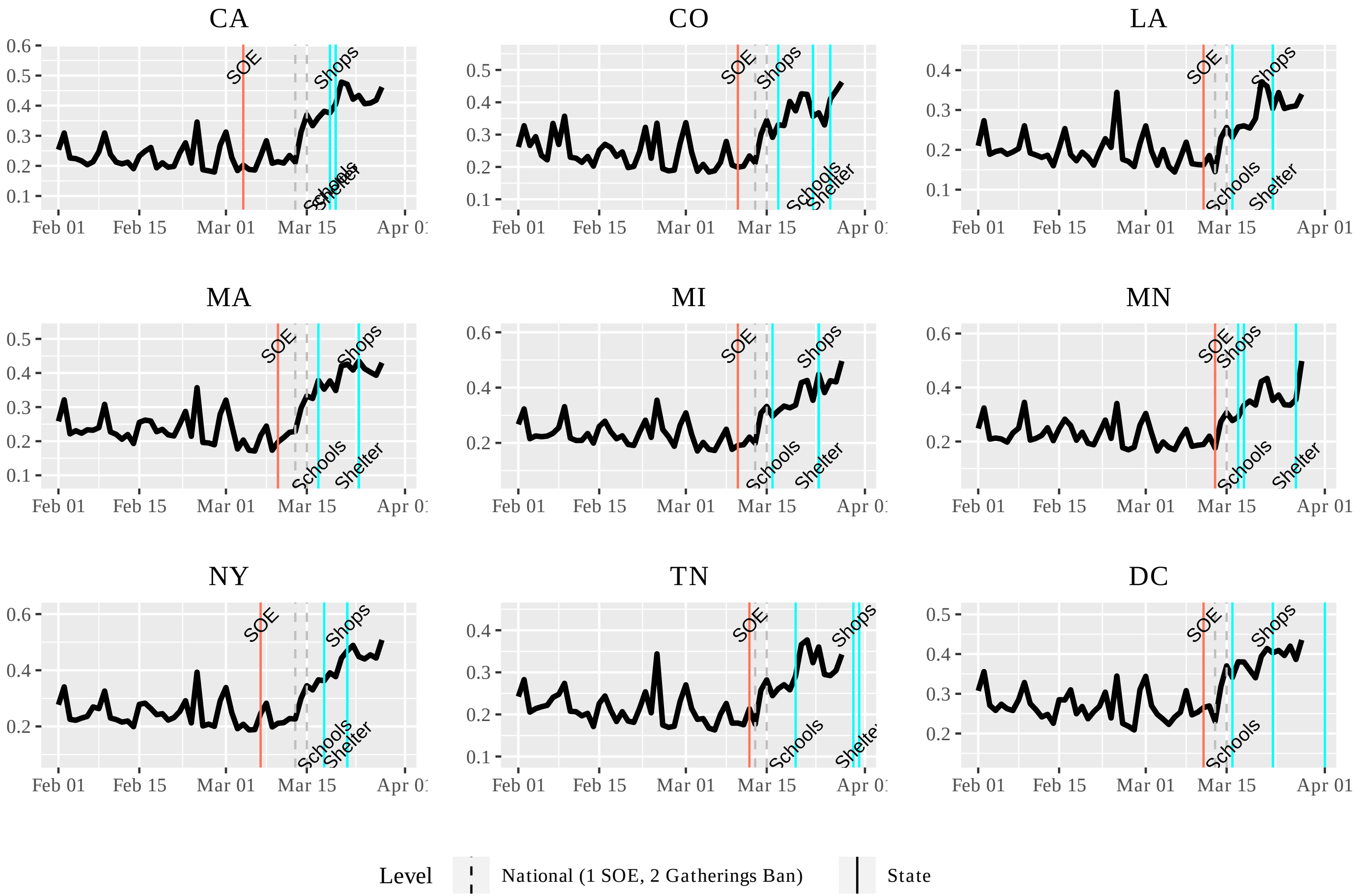
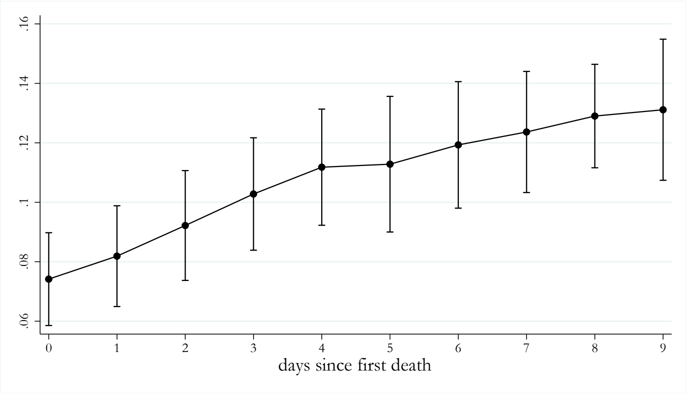
Figure 2: Percentage Completely at Home and Lockdown Policies in Selected States

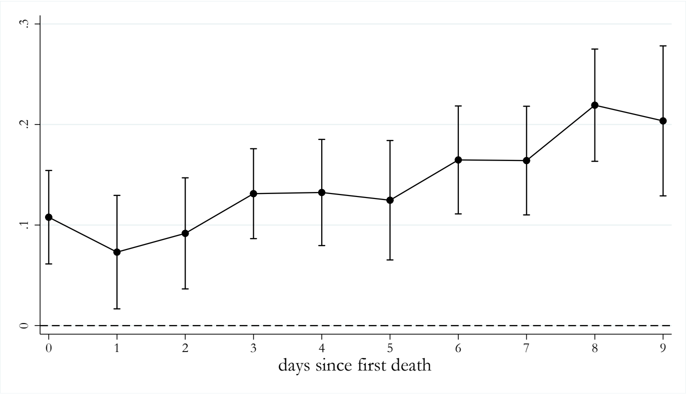


Notes: The plots show daily foot traffic and the percentage of devices that stayed home in selected states over time. The dashed vertical lines indicate national measures (SOE, Gatherings Bans) and the solid lines represent state-level SOEs and lockdown policies.

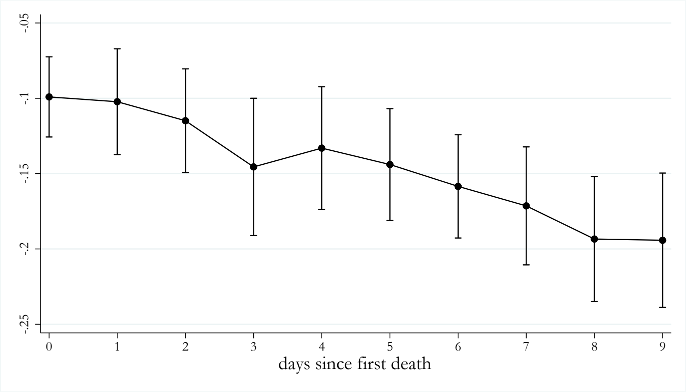
Figure 3: Physical Distancing Change Since First Death from COVID-19, Relative to No Death



(a) Percent Completely at Home



(b) Log of Median Time Spent at Home



(c) Log of Median Distance from Home

Note: The graphs plot the coefficients on days-since-first-death dummies, controlling for state fixed effects.

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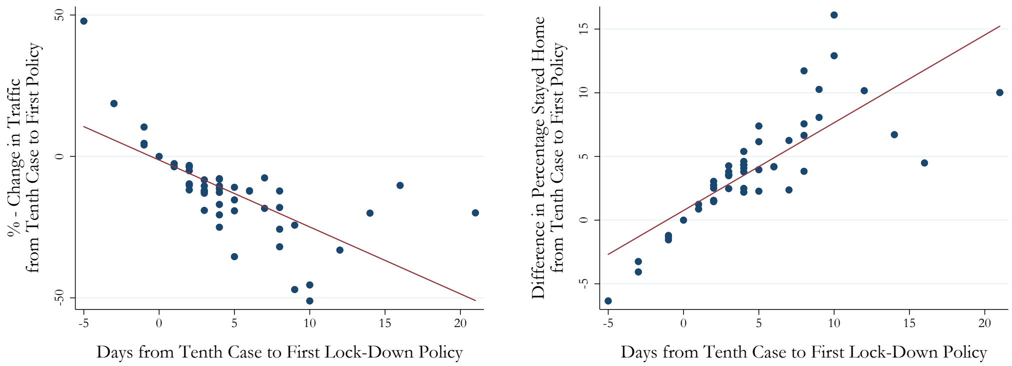
Figure 4: Change in Outcome Variables Before Enactment of Lockdown Policies



Notes: The graphs plot the change in outcome variables over the period between the tenth confirmed case in the state and the implementation of the first lockdown policy against the count of the days between the two events. The left panel shows the percentage change in foot traffic, while the right panel plots percentage point increase in the share of all devices that stayed home. Both variables are smoothed over a 7 day window.

However, it is clear that the community response will differ once states have implemented policies targeted at inducing people to take physical distancing measures. In order to disentangle independent community reaction to COVID-19 from the response to policy measures, we estimate the following model:

$$comm_{i,t} = \alpha_i + \sum_{j=0}^{28} \beta_j \, j\text{-}days_{i,t} + \rho LDP_{i,t} + \sum_{j=0}^{28} \gamma_j \, j\text{-}days_{i,t} \times LDP_{i,t} + u_{i,t}, \tag{1}$$

where $comm_{i,t}$ is the community response variable for state i at time t, i.e. either percent of people who stay at home for the whole day, median time spent at home or median distance from home; $j\text{-}days_{i,t}$ takes the value of 1 if j periods have passed since the first death; $LDP_{i,t}$ is a dummy equal to 1 if the government has implemented the respective lock-down policy at or before period t; and α_i are state-fixed effects. Thus, the coefficient β_j estimates the community response on day j after the first death in case the government action has not been taken, relative to no death having occurred; and $\rho + \gamma_j$ estimates the additional community response if the government action is in place during that period, compared to the case when no death has occurred and no policy action has yet been implemented.

Figure 5 plots the resulting estimates from Equation 1, alongside 95% intervals, for the introduction of lock-down policies. The upper panel illustrates the change in the physical distancing measure in case that no such policy was in place (i.e. β_j for each $j \in \{0, 1, ..9\}$ from Equation 1), while the lower panel shows the additional change in the measure when the policy is in place (i.e. $\rho + \gamma_j$ for each $j \in \{0, 1, ..9\}$). The upper panel documents that even in the absence of government policies, communities take physical distancing actions in response to COVID-19, controlling for differences between states. However, the lower panel suggests that the community responses are stronger if the government also takes action. The estimates in

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Figure 5 show that in states with lock-down policies in place, on the day after the first death the percent of people who stay completely at home is approximately 3 percentage points higher than in states without the policy. Similar responses are found for other measures of physical distancing (see Figures B.1 and B.2 in the Appendix). The response is also very similar when using county-level rather than state level data, where we use county instead of state fixed effects (see Appendix Figure B.3). Note that each estimate after the day of the first death pools together both states that have had the policy in place for multiple days as well as states that implemented the policy on the day of the estimate.

We can summarise two main findings so far. Firstly, people do respond to the COVID pandemic even in the absence of state-level policies. Secondly, state-level policies coincide with increased responses of the community in terms of physical distancing measures. However, our estimates do not yet yield insights about the causal response to policies. One issue is that an absence of community action can make the implementation of policies more likely, as we explore in section 3.3. Another issue is that there might be common factors that drive both physical distancing measures as well as the inclination of states to take action – such as the progression of the disease. In order to counter these potential endogeneity issues, in the next subsection we employ causal econometric methods to estimate the effect of shelter-in-place policies on physical distancing.

3.2 Effect of Government Action on Community Action

In order to account for potential endogeneity, we pursue two approaches in estimating the community response to the lockdown policies: first, we estimate a saturated staggered DiD specification where we use a rich set of controls for factors that might influence both community action and the implementation of policies. Moreover, we conduct the analysis at the county level and exclude the capitals of each state, arguing that county-level changes in foot-traffic outside of state capitals do not affect state-level policies. This combats the potential reverse causality problems which are explored in section 3.3. Second, we use a DiD-IV approach for groups of states that have experienced the first death on the same day. As an instrument, we use the number of required ventilators at the state level. We argue that, conditional on controlling for the spread of the virus, our instrument only affects community action by changing the probability of the policy being implemented.

3.2.1 Staggered Difference-in-Differences

As we have shown in subsection 3.1, communities respond to the pandemic even in the absence of any policy. Thus, our identification strategy requires that we control for the progression of the virus in each state in order for the common trends assumption to hold. Put differently, we need to guarantee that, conditional on our controls, counties in states that have not (yet) implemented a policy are a viable counterfactual for those that have. Another potential source of bias comes from non-random treatment assignment or time-varying treatment effects, as several recent

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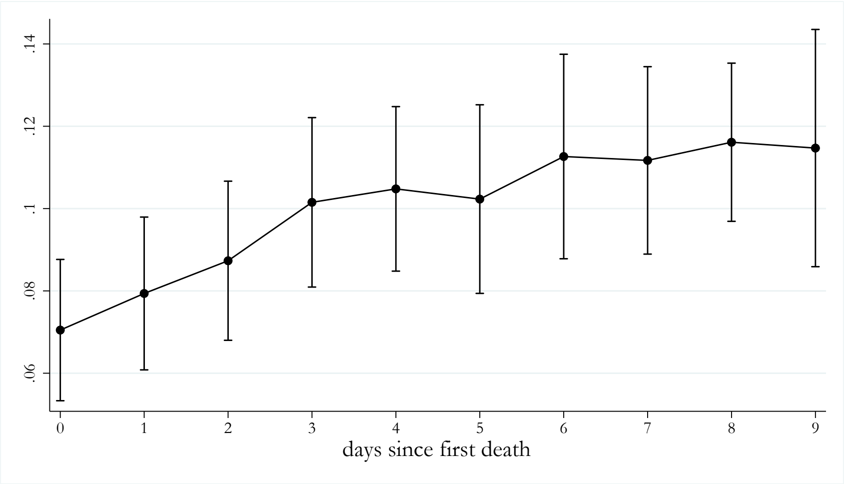
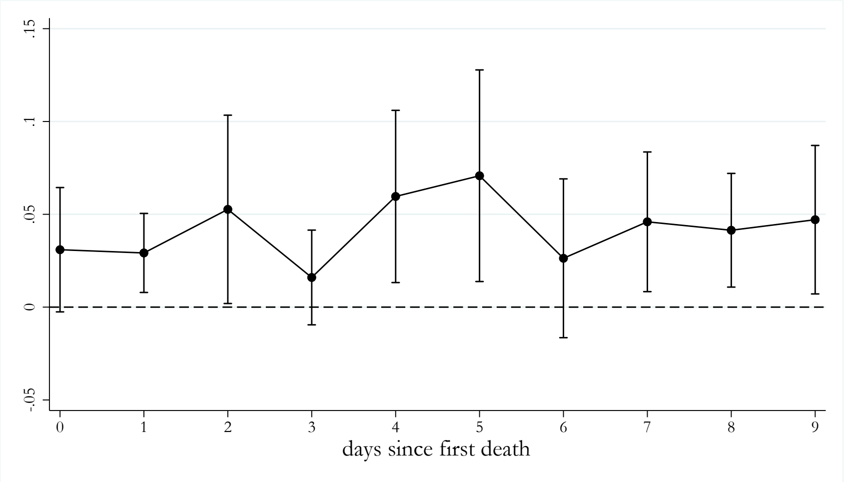
Figure 5: Percentage Point Change in Percent Completely at Home, Conditional on Lockdown



(a) Change if no Lockdown Enacted



(b) Additional Change if Lockdown Enacted

[1] **Top panel**: plots the estimated response of percent of devices at home by day since the first death in the state if no lockdown policy is in place, i.e. the β_js from Equation 1.
[2] **Bottom panel**: plots the estimated additional response of percent of devices at home by day since the first death if a lockdown policy was in place on that day, i.e. the $\rho+\gamma_j$s from the same Equation.

papers have demonstrated (Athey and Imbens, 2018; Goodman-Bacon, 2018). In what follows, we account for the stage of the pandemic each county is in by including days-since-first-case dummies and controls for the number of deaths and cases. We then assume that, conditional on controlling for the progression of the pandemic as well as county and time invariant factors, treatment assignment is indeed random. In that case, the staggered DiD estimates give an unbiased estimate of a weighted average causal effect.

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With these caveats in mind, we proceed by estimating the following saturated staggered DiD model:

$$comm_{i,j,t} = county_i + \delta_t + \beta_{i,t} + \sum_{k=-5}^{11} \rho_k \, P_{j,t+k} + \mathbf{\Psi x_{i,t}} + u_{i,t}, \tag{2}$$

where $comm_{i,j,t}$ is the community physical distancing action under analysis in county i, state j and day t; $county_i$ are county-level fixed-effects; δ_t are day fixed-effects; $\beta_{i,t}$ are day-since-first-case fixed effects[21]; $P_{j,t+k}$ is a state-level policy dummy that is equal to 1 at time $t+k$ and 0 otherwise, where $k=0$ when state j implements the policy at time t; and $\mathbf{x_{i,t}}$ comprises the numbers of deaths and confirmed cases as controls. Note that we include the effect of the policy on previous community response as a placebo check on whether we control sufficiently for pre-policy implementation trends. We also exclude capital counties in order to further combat potential reverse causality issues.

Figure 6 shows the resulting estimates for this specification. The pre-implementation responses are insignificant. Once the policy is enacted, however, there is a marked increase over the subsequent days in the percentage of people who stay at home. We find that the implementation of a shelter-in-place policy increases the time spent at home by approximately 2 percentage points one day after its implementation, once taking account of any community responses due to the county-specific COVID-19 incidence and country-wide developments. Compared to a base of approximately 25.7% at the end of February, this amounts to a 8% increase in the time spent at home. Perhaps more importantly, the effect stays significant for subsequent days.

As a robustness check, we also estimate Equation 2 at the state level, with state instead of county fixed effects and using days-since-first-death instead of days-since-first-case fixed effects. The results are presented in Figure B.5 in the Appendix with the estimated effects being very similar, albeit somewhat larger.

3.2.2 Difference-in-Differences IV

As a further step to counter endogeneity issues, we group states by the day on which their first death occurred. This allows us to run difference-in-differences IV regressions for states that have experienced the first death on the same day. Grouping states by the incidence of the first death yields the advantage that it explicitly controls for part of the overall evolution of COVID-19 and thus makes the common trends assumption more viable.

We have seen in Figure 1 that there is a lot of variation across states in the timing of the first death caused by the coronavirus. Nevertheless, there are a number of states that share the date of the first death. Table 1 shows the occurrence of the first COVID-related deaths for dates at which at least three states experienced their first death. On six dates we observe a first death for three or more states on the same day. We will concentrate on the first four

[21]The categorical variable employed here takes the same value for all time periods before the first case. Hence, it is an additional control to distinguish between periods before the outbreak of COVID with those thereafter.

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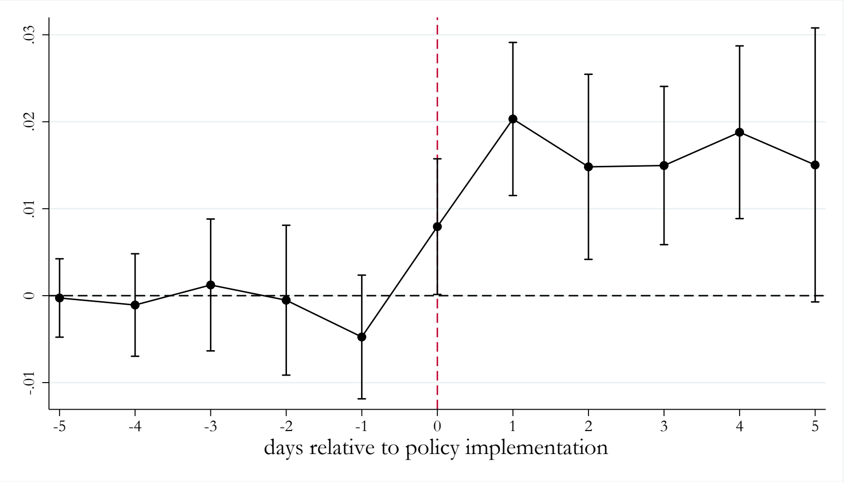
Figure 6: Staggered DiD Estimates of the Policy Impact on Percent of Devices at Home



Note: The figure plots the ρ_k-coefficients and 95% confidence intervals from Equation 2 against the days relative to the implementation of a shelter-in-place policy.

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of these, since the last two happen too close towards the end of our sample for a meaningful analysis. Note that there are early and late adopters for the groups of states with first deaths on March 14, 16 and 18. In contrast, the two states with first deaths on March 19 that do adopt safer-at-home measures implement those on the same date, March 25.

Table 1: Groups of States by Days since First Death

Date of first death	Number of states	State-ID
March 14	3	LA, NY, VA
March 16	4	IN, KY, NV, SC
March 18	4	CT, MI, MO, PA
March 19	5	MD, MS, OK, VT, WI
March 20	3	MA, OH, TN
March 25	4	AL, IA, NC, NM
Total until March 28	48	

Figure 7 shows the evolution of the median time spent at home since the first death occurred for each group of states. Panels (a) to (c) compare early adopters to never adopters, while in panel (d) both states that adopt a policy did so on the same day. For all groups under analysis, we can draw two broad conclusions: first, even unconditionally, states exhibit parallel trends before the implementation of the policy. Second, within a few days after states impose the shelter-in-place policy, their dwell-at-home time increases relative to states with the same first death date that do not adopt the policy.

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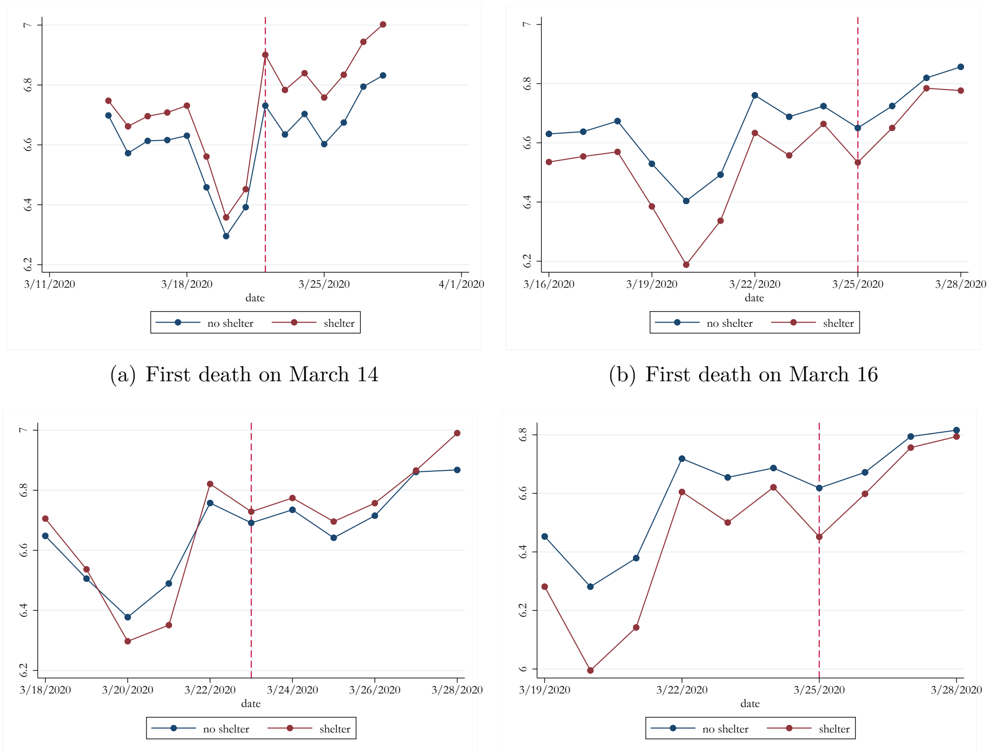
Figure 7: Dwell Time at Home (Log), by Date of First Death from COVID-19



(a) First death on March 14

(b) First death on March 16

(c) First death on March 18

(d) First death on March 19

Note: The graph plots the log of median home dwell time for groups of states that had the same date of first death from COVID-19, by whether they implemented shelter-in-place policy early (red) or not at all during the sample. The red vertical lines indicate the first policy implementation date.

We now proceed to a difference-in-differences IV regression for states with the first death occurring on March 19. This date is particularly suitable for our analysis for two reasons. Firstly, it is the date on which most states share their first death. Secondly, the two states that implement a shelter-in-place policy do so on the same date, March 25. This helps to eliminate any remaining potential bias arising from the staggered DiD specification due to time heterogeneity in treatment effects and gives us the unweighted average treatment effect for the treated.

In order to estimate the causal effect of policy adoption, we estimate the following standard DiD specification in the second stage:

$$comm_{i,t} = \alpha_i + \delta_t + \rho LDP_{i,t} + \mathbf{\Psi x_{i,t}} + u_{i,t}, \tag{3}$$

where all variables are defined as before. Thus, ρ is the standard DiD estimate that captures the effect of implementing the policy.[22]

In the first stage, we instrument $LDP_{i,t}$ by the number of ventilators needed in a given state. Note that time-invariant differences across states will be eliminated by the fixed effects α_i. We argue that, conditional on controlling for the number of COVID-related cases and deaths, the number of ventilators needed will be driven by idiosyncratic factors that only affect community action through government measures. This is because the population can observe general statistics capturing COVID-related cases and deaths and respond to them, but cannot in real time observe the number of ventilators needed due to COVID-19. However, a higher need for ventilators will increase the pressure on governors to implement preventive shelter-in-place policies to mitigate the spread of the disease.

Note that for the IV specification, our estimates should be interpreted as those for 'compliers' – i.e. states that will only adopt measures if there is an experienced or projected shortage of ventilators, but would not do so otherwise. Given that there is a long time lag between the COVID-19 outbreak and the implementation of policies for many states, we believe that the existence of 'compliers' is highly likely. Nevertheless, there could also be some 'always takers' – states that would have adopted the policy even if there was no experienced or forecast pressure on their healthcare system.

Tables 2 and 3 report the estimation results for median dwell-time and median distance from home, respectively. In each table, the first column shows the simple DiD result without instrumenting the government action, while the second one contains the baseline IV results. Note that for the latter, the F-statistic in the first stage on the excluded variable is large at 80.6, indicating that our instrument is relevant. Moreover, the sign of the coefficient for our excluded instrument is intuitive: an increase in the amount of ventilators needed increases the probability of introducing a shelter-in-place policy. The number of deaths and of confirmed cases enters our DiD estimation results generally insignificantly; columns 3 and 4 show that our results are robust to excluding either of these controls.

Across both the standard DiD and the IV specifications, there is a large positive and significant effect of the government policy on the community response. According to our favoured IV specification in Table 2, the government response increases the dwell-at-home time by $exp(0.33) - 1 = 39\%$. Without the instrument, the effect is reduced to a still substantial $exp(0.134) - 1 = 14\%$. Given that the median dwell time across states from February 1 to February 15 was 12 hours (including sleep), this would mean that the shelter-in-place policy causes an average increase of 1.7 to 4.7 hours in daily time spent at home.

Note that the size of the results as well as their significance is strikingly similar when analyzing the response of the median distance from home (see Table 3). Again, we find that

[22]Note that we do not include treatment indicators (whether a government has ever implemented a policy) since these are captured by fixed effects. Moreover, we do not incorporate post-treatment time indicators since we include the more flexible date dummies instead.

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Table 2: DiD-IV Estimates of Effect on (Log) Home Dwell Time

	(1) DiD	(2) DiD-IV	(3) DiD-IV	(4) DiD-IV
Lockdown	0.134**	0.329***	0.311**	0.363***
	(0.0412)	(0.0244)	(0.0707)	(0.0736)
COVID deaths	-0.00815*	-0.0140	-0.0130	
	(0.00346)	(0.00790)	(0.00773)	
COVID known cases	2.14e-05	2.34e-05		-3.29e-05
	(9.12e-05)	(9.76e-05)		(0.000198)
State FEs	X	X	X	X
Date FEs	X	X	X	X
First-stage F (excl.)		80.60	14.12	17.99
Observations	285	260	260	260
R^2	0.887			

Note: This table reports various DiD estimates at the state level for those states that experienced their first COVID-related death on March 19, 2020.

Table 3: DiD-IV Estimates of Effect on (Log) Home Distance

	(1) DiD	(2) DiD-IV	(3) DiD-IV	(4) DiD-IV
Lockdown	-0.102***	-0.228**	-0.249**	-0.264*
	(0.0197)	(0.0640)	(0.0665)	(0.104)
COVID deaths	0.0107***	0.0145*	0.0157	
	(0.000772)	(0.00607)	(0.00960)	
COVID known cases	3.71e-05	2.75e-05		8.56e-05
	(0.000106)	(8.43e-05)		(0.000197)
State FEs	X	X	X	X
Date FEs	X	X	X	X
First-stage F (excl.)		80.60	14.12	17.99
Observations	285	260	260	260
R^2	0.921			

Note: This table reports various DiD estimates at the state level for those states that experienced their first COVID-related on March 19, 2020.

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the estimated effect is larger once pursuing an IV strategy.[23] Our findings from Tables 2 and 3 suggest that the omission of an IV approach can lead to a downwards bias for the estimated causal effect of a shelter-in-place policy. There are two reasons to expect this result. First, it is likely that there are states which would always implement the policy, regardless of whether ventilators are lacking (i.e. 'always takers'). If such states also have a population that reduces traffic even in the absence of government policies, then the implementation of the policy will appear to have a small causal effect on traffic. In contrast, the IV estimates would be larger since they are only based on states which are 'compliers', and not on those who are 'always takers'.

Second, states with people who do not change their behaviour might be more inclined to introduce shelter-in-place policies. If people who are less likely to take action on their own are also less likely to change their behaviour following government action, then the estimated effect of state action will appear smaller than it truly is. In the following subsection, we will show that there are good reasons to believe that this line of argumentation holds true: states are indeed more likely to implement a policy if their population does not reduce foot traffic on their own.

3.3 Effect of Community Action on Government Action

In this section, we examine to what extent independent community action affects the probability of state governments introducing lockdown policies. From a theoretical point of view, the predicted sign of the effect is rather unclear. As shown in the previous section, people practice physical distancing even before the imposition of restraining measures, be it to minimize individual risk, to limit contagion within the community or because they anticipate the lockdown policies. Under this scenario, governors can introduce extensive measures to suppress the spread of the pandemic at fairly low political cost, yet the additional health effects from these lockdown policies would be comparatively small. The lower political cost would suggest stronger independent community action triggers stronger government action; the smaller effect on public health would suggest the opposite. By contrast, if the population refuses to sufficiently comply with non-compulsory calls for social distancing due to denial, defiance or to take advantage of free movement before an anticipated lockdown, governors' suppressive actions may be more effective in terms of health policy but come at higher political costs.

To evaluate the impact of community action on the probability of governors introducing lockdown policies, we estimate the following equation:

$$LDP_{i,t} = \alpha_i + \delta_t + \beta_j \; comm_{i,t-8} + \mathbf{\Psi x_{i,t}} + u_{i,t} \tag{4}$$

[23]In contrast, we do not find significant results when employing the percent of devices that stay at home as an outcome variable instead. We conjecture that this is due to the nature of the variable, which is a raw count of the number of devices that stay completely at home, divided by the total number of devices in the state. Thus, this variable will capture some unrelated variation, and potentially be more prone to sampling biases at the CBG level. In contrast, the distance from home and dwell time at home variables capture movements in the median CBG of the median county for each state, and thus are less prone to these problems.

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where $LDP_{i,t}$ is 1 on the day of state i's announcement of the lockdown policy in question– after which the state drops out of the sample – and 0 before; and $comm_{i,t-j}$ denotes the j^{th} lag of the physical distancing measure in question. We alternatively capture community action by total foot traffic, percentage of devices staying completely at home, and by median home dwell time, and find similar results across the board. In addition, the regression includes state and days fixed effects, α_i and δ_t, along with a vector of covariates $\mathbf{x_{i,t}}$ that controls for the cumulative number of confirmed cases and deaths by state.

We adopt an Instrumental Variables (IV) strategy to assess how community action affects the probability of lockdown policies being imposed. For policymakers, the most visible indicator for compliance with the call to physical distancing is public foot traffic. However, if the community anticipates the imposition of a lockdown policy, then lagged community action will also be affected by the future imposition of any such policies. As a result, Ordinary Least Squares (OLS) estimates of the effect of independent community action on the imposition of suppressive government-imposed lockdown policies will be biased. To account for this effect, we estimate the J different β_js by means of two-stage least squares, where we instrument the physical distancing measures with the maximum temperature, minimum temperature, precipitation and interaction of max temperature and precipitation in the state capital. If the temperature is high or precipitation low, individuals are more likely to leave their homes. Governmental intervention, though, should not be directly affected by weather, except insofar as it impacts individual behavior. Therefore, the instruments $TMAX$ and $PRCP$ should be relevant and satisfy the exclusion restriction.

To meaningfully interpret the results from Equation 4, we restrict the sample as follows. First, states only enter the panel from the moment they have 10 confirmed cases of COVID-19 onward. We do this because community response before this point is unlikely to affect future government interventions much – or vice versa, for that matter. In other words, we assume that people only start anticipating a state government lockdown policy from the moment the virus has gained foothold in their state. Second, we drop states after they announce the lockdown policy. The measures we consider – school closure, shelter-in-place and business closure – are all implemented for a predetermined period, with a fixed future reevaluation date. Therefore, the decision to implement them is a one-off decision, and leaving states in the panel after announcement would lead to spurious identification, as community action after announcement ceases to affect the probability that governors implement the lockdown policy after that point. Note that in this section, we use the announcement date as the government policy variable, instead of the date of implementation, because we care about the governors' *decision* to implement, not when the implementation is actually followed through.

Table 4 reports estimates for the second-stage regression of the shelter-in-place dummy on our physical distancing measures. As a first caveat, note that we are estimating a linear probability model (LPM). It is well-known that the estimates of a LPM are biased and inconsistent whenever any of the predicted probabilities lie outside the unit interval (Horrace and Oaxaca, 2006). Nonetheless, the marginal effects can be consistently estimated. Moreover, we are not necessarily

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Table 4: Second Stage: Regression of Shelter-in-Place on Physical Distancing

	Dependent variable:		
	Shelter in Place		
	~Traffic Capital	~Traffic State	~%Home All Day
	(1)	(2)	(3)
L8.y	2.075**	2.459***	−2.060**
	(0.940)	(0.943)	(0.966)
State FEs	X	X	X
Day FEs	X	X	X
F-Stat 1st Stage	7.526	16.898	13.569

[1] Dependent variable is shelter-in-place dummy, independent variables are various physical distancing measures. Controls include nr. of deaths and number of positive cases.
[2] * p<0.1; **p<0.05; ***p<0.01

interested in the precise magnitude of our estimates, but rather in their sign. That said, we find a significant and positive effect of increased social traffic on the probability that state governments will move to announce a shelter-in-place policy a week later. In other words, if people engage less in physical distancing by themselves, state governments are more likely to impose compulsory measures to that effect. For example, a 1% increase in state-level foot traffic increases the probability of the imposition of a lockdown policy by 2.5%. The magnitude and significance of this coefficient are robust to alternative specifications with different combinations of lags, while the other lag coefficients remain insignificant across various specifications. The week-long lag of community action on government action seems to conform with the delay that usually marks data collection and policy decision-making. We can thus conclude that, not only do state lockdown policies affect people's social distancing behavior, but the prevalence of such behavior before the implementation of a shelter-in-place policy also decreases the probability of that policy being introduced.

3.4 County Analysis: Heterogeneity in Virus Response and Treatment Effects

We now dig deeper into the data by looking at government and community action at the county level. While many county and most state governments similarly recurred to drastic lockdown policies such as shelter-in-place policies as they came under pressure from the rapid spread of the virus, it is less clear that all subgroups of individuals responded to the spread of the virus and the policies implemented in similar ways. In this paragraph, we, therefore, exploit the variation coming from daily data for the more than 3,000 counties to explore the heterogeneity in outbreak and treatment response among different demographic, cultural and economic lines. In what follows, we focus on the percentage of people who stay completely at home as the main measure of social distancing, and shelter-in-place as the lockdown policy of interest. Note that

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the interpretation of the dependent variable's response is in percentage points (p.p.) throughout the analysis.

Figure 8 plots the evolution of the outcome variable over time, for quantiles of the distribution of several variables of interest. Specifically, it shows the estimates of the regression coefficients on a set of time dummies referring to the 10 days before and 15 days after the first confirmed COVID-19 case in the county, interacted with the variables of interest evaluated at their 10th (light blue), and 90th percentile (dark blue). Also included in the regression are state-day fixed effects and county fixed effects. These allow us to control for state-specific time-varying shocks, as well as any county-level characteristics that remain constant over the period considered, apart from the characteristic we are interacting with. In other words, when considering differences in outbreak response by income group, we are at the same time controlling for time-invariant occupational differences, such that our results cannot be attributed solely to, for example, the fact that lower income groups are less able to work from home (unless the two features exactly overlap). As such, we can neatly disentangle the specific subgroup-level social distancing response to the spread of the virus and to the county-level policies from other factors merely correlated with the social distancing behavior of these groups. Note that we do not control for the policy implementation, so the estimated effects are average effects for counties that did not implement lock-down policies as well as those who did. This means that the reported subgroup heterogeneity can be both due to different voluntary distancing across the subgroups, as well as different frequency of policy implementation. For example, highly educated counties might see residents engage more in voluntary distancing, but might also see county governments implement lockdown policies more often. As a general measure of heterogeneity in outbreak response, both effects are of interest. However, we also further disentangle these effects below.

The figure shows stark differences in the evolution of the physical distancing behavior of the various subgroups as the virus spreads. The top left graph plots this evolution for the cross-county shares of Democratic votes in the 2016 presidential election.[24] The divide between those counties that voted strongly for Clinton and those that did not starts opening up a few days after the first confirmed case. After 15 days, the difference is 3 p.p., which means the percentage of devices that stayed home increases by 8% more for Clinton counties compared to the February mean of ~23% of devices. A similar difference can be observed in the middle left graph when we look at the evolution of counties with different shares of people who do not believe in global warming, which we consider a proxy for distrust in science. While these findings are in line with well-documented dividing lines of trust in science by political party – with 69% of Republicans saying global warming is exaggerated compared with 4% of Democrats (Gallup, 2018) – it is striking how strong of a role they seem to play even during a pandemic whose effects are starkly visible in daily life. At the same time, even counties with very low values of trust in science see social distancing increase by up to 4 p.p., or ~6% compared to the February mean. A further remarkable difference is the one between counties with lower and higher median

[24]Note that subplot a) and c) only plot the 10th and 90th percentile, as the confidence intervals overlap with the plot for the median.

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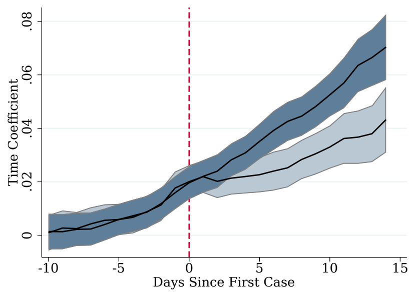
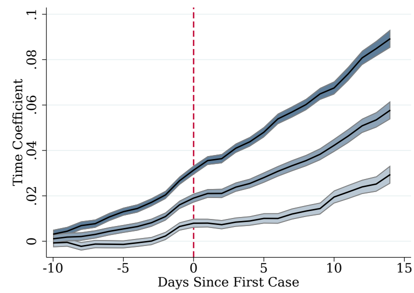
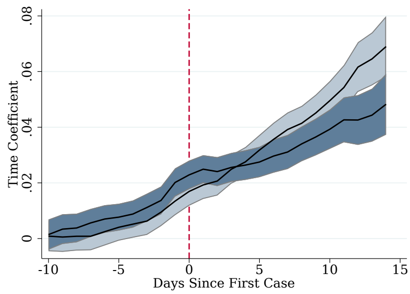
Figure 8: Heterogeneity in Community Outbreak response Over Time, % At Home



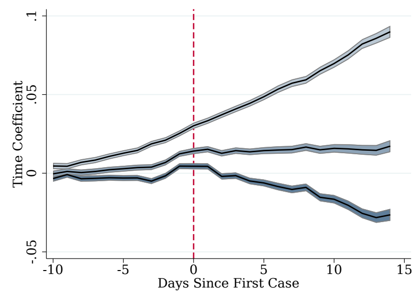
(a) Share of Votes Democratic 2016



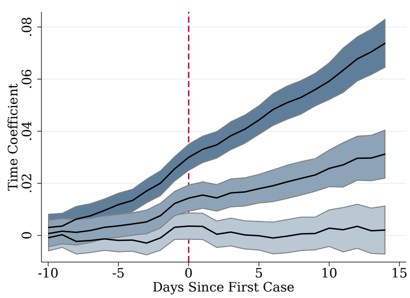
(b) Institutional Health Index (2010-2016)



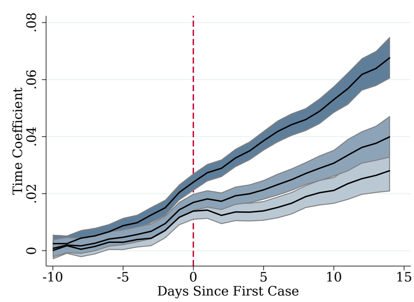
(c) Percent Who Do Not Believe in Global Warming



(d) Rural-Urban Continuum



(e) Median Household Income 2019Q3



(f) Percent with Bachelor's Degree

[1] Light blue: 10th percentile; blue: median; dark blue: 90th percentile - for variable of interest across counties. Dependent variable: percentage of devices fully at home.
[2] Shaded area is 95% confidence interval. Observations: 114,580.
[3] Figure plots estimates of dummies for days since 1st confirmed COVID-19 case interacted with variables of interest in panel regression with state-day fixed effects and county fixed effects.

household incomes. Not only do high-income counties ramp up their physical distancing by up to 8 p.p., or almost 30%, more than low-income counties when the virus gains foothold in the county; they also strongly anticipate the arrival of the virus. The median-income counties respond moderately, while low-income counties barely see an increase in the share of people

staying home. The results in counties with higher and lower shares of college-educated people follow a similar trajectory, though the differences are less stark, and groups with less education still engage in increased physical distancing. As expected, more urban areas experience a much stronger increase than rural areas, with the most rural counties actually seeing a decrease in the percentage of devices staying completely home.[25] A last conspicuous pattern, in the top right graph, is that counties where institutions are in better standing see a markedly larger increase in physical distancing both before and after the virus takes hold.

To further assess how these different subgroups respond to lockdown policies, we re-estimate the staggered difference-in-differences model with state-day and county fixed effects, where we interact the dummies for days since policy implementation with the variables of interest. This entails the following triple DiD extension of Equation 2:

$$comm_{i,j,t} = county_i + \delta_{j,t} + \delta_t G_{i,t} + \beta_{i,t} + \sum_{k=-5}^{20} \rho_k P_{i,t+k} + \sum_{k=-5}^{20} \rho_k P_{i,t+k} \times G_{i,t} + \mathbf{\Psi x_{i,t}} + u_{i,t}, \quad (5)$$

where we add, for county i, state j and day t, the group variable $G_{i,t}$ interacted with day fixed effects and with the staggered DiD dummies $P_{i,t}$, as well as state-day fixed effects $\delta_{j,t}$. We also include a control for whether the county already has a business closure policy in place. The rest of the equation remains the same. Note that the inclusion of day fixed effects interacted with the variable of interest is crucial to recovering the interpretation of the DiD estimate as the counterfactual treatment effect.[26] We also control for cumulative number of confirmed cases and deaths in each county, and double-cluster the standard errors by county and date.

Figure B.6 in Appendix thus shows how the effect of a county-level shelter-in-place policy on physical distancing differs across county subgroups. For most subgroups, we do not find evidence for significantly different responses to a shelter-in-place policy, apart from a marginally significantly stronger response for the poorest county compared to the richest county in Figure B.7 in Appendix. A remarkable exception, however, is that people in highly urbanized areas seem to respond much more strongly to shelter-in-place policies than people in heavily rural areas. This could indicate that the treatment response to such policies largely depends on enforceability – which would also explain why most of the other heterogeneity seems to matter little for treatment response even as it matters a lot for outbreak response. Moreover, these results suggest that most of the heterogeneity documented in Figure 8 is due to subgroup differences in either voluntary physical distancing or in the frequency with which shelter-in-place policies are implemented, not due to different treatment response. Similar results obtain when

[25]Note that for the rural-urban continuum index, lower values mean more urban. Also note that the decrease for rural areas does not necessarily indicate that they do not engage in physical distancing at all. It might simply indicate that, forced to stay at home, residents in such areas go out for short trips more often than otherwise.

[26]Our analysis suggests that the results obtained by Painter and Qiu (2020) are driven by the fact that they fail to incorporate these additional interactions in the regression. Thus, we argue that the presumed heterogeneity in treatment response along party lines can be largely explained by democratic and republican counties differing in voluntary physical distancing and frequency with which lock-down policies are imposed – as in Figure 8 –, rather than different treatment response to shelter-in-place policies.

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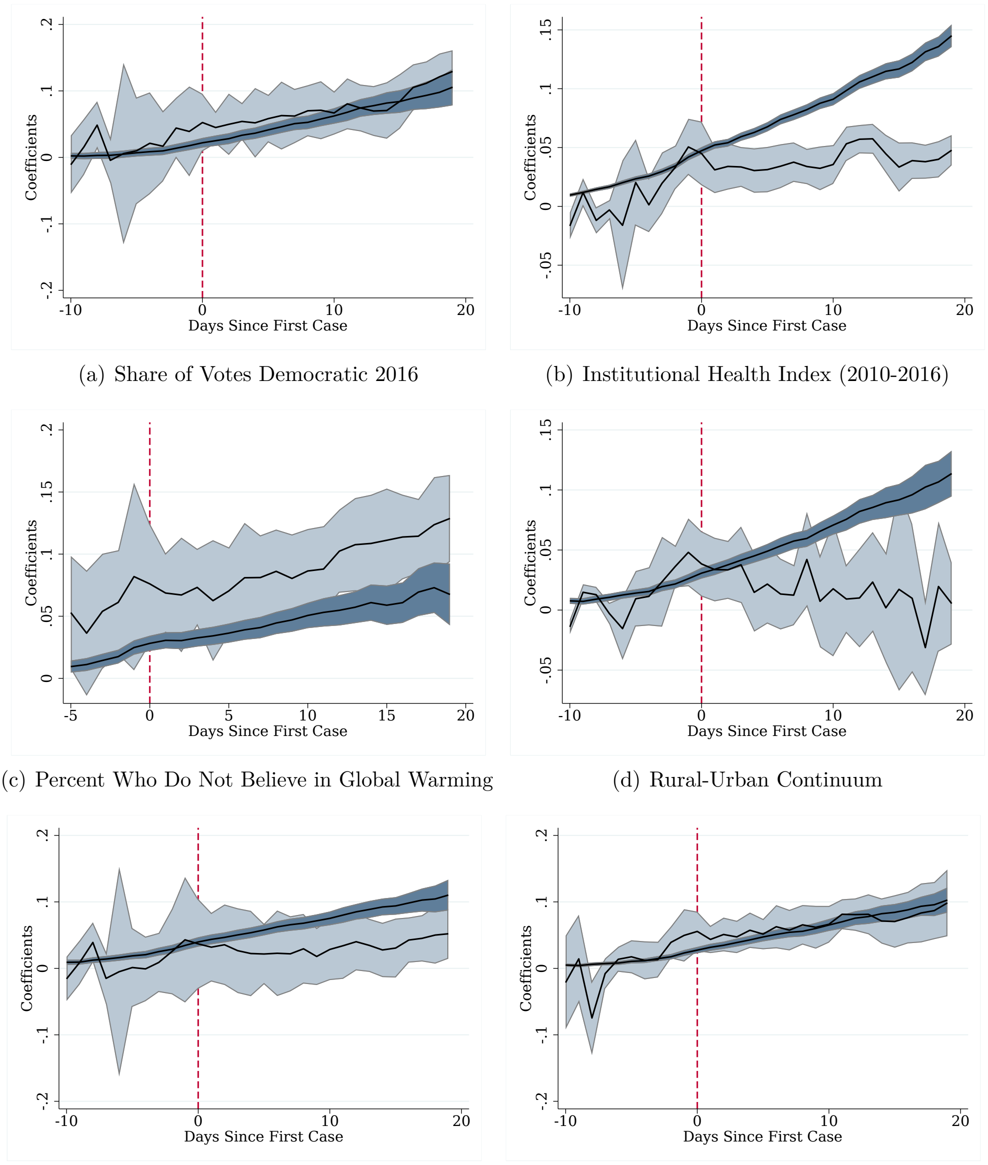
Figure 9: Physical Distancing in Counties With and Without Lockdown, by Subgroup



(a) Share of Votes Democratic 2016

(b) Institutional Health Index (2010-2016)

(c) Percent Who Do Not Believe in Global Warming

(d) Rural-Urban Continuum

(e) Median Household Income 2019Q3

(f) Percent with Bachelor's Degree

[1] Light blue: 10th percentile with shelter-in-place policy in place; dark blue: 90th percentile without shelter-in-place policy in place - for variable of interest across counties.
[2] Shaded area is 95% confidence interval. Standard errors are double-clustered by county and date. Observations: 180,295.
[3] Figure plots DiD estimate for days since 1st confirmed COVID-19 case interacted with variables of interest, in panel regression with state x day, variable of interest x day and county fixed effects.

considering state-level shelter-in-place policies, suggesting that the results of Painter and Qiu, 2020 should be interpreted with caution, as explained in Footnote [26].

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In Figure 9, we further explore the implications of the above findings by re-estimating the triple DiD with days-since-first-case dummies as the relevant time dimension, as in Equation 1. This allows us to separate the voluntary physical distancing response from the overall response, that is, the sum of voluntary and imposed distancing. We do this to compare the total increase in physical distancing of less-responsive groups to the voluntary increase of more responsive groups. That way, we come to the striking result that subgroups that take more independent action end up increasing their physical distancing in the absence of any policy by nearly as much as their counterpart subgroups do under an imposed lockdown. For example, in highly urban areas (middle right plot), people engage more intensely in voluntary physical distancing in response to the virus than people in heavily rural areas do even when there are lockdown policies in place. Similarly striking results are obtained for counties with institutions in good standing (top right) and for rich counties (bottom left). For the other variables, our findings indicate that the lockdown and voluntary response of both groups are not significantly different from each other. The reason for these findings is as above: for all subgroups at the 90th percentile, the voluntary physical distancing response is very high compared to their counterparts at the 10th percentile, however, the treatment response of both is the same. For example, counties where trust in institutions is high engage in voluntary physical distancing much more than those where such trust is low. Yet, when the government implements an additional lockdown policy, both high-trust and low-trust counties increase their physical distancing by the same additional amount. This means that lockdown policies, even when only implemented in low-trust counties, cannot close the large gap in voluntary response shown in Figure 8. These findings point towards the important conclusion that containment measures targeted at population subgroups that less easily engage in voluntary physical distancing by themselves might be more effective than indiscriminate lock-down policies. Given evidence from the epidemiological literature that the distribution of individual infectiousness in epidemics is often highly skewed around R(0), it seems likely that there are decreasing marginal returns to additional imposed physical distancing as the level of voluntary physical distancing increases (Lloyd-Smith et al., 2005). In other words, it seems likely that there are larger returns to the same increase in physical distancing for those subgroups that barely change their behavior by themselves than for those groups that already heavily engage in voluntary physical distancing. Moreover, not only should such targeted containment policies be more effective from the epidemiological point of view – they should also wreak less economic havoc than full-scale lockdowns. Thus, we conclude that containment policies targeted along socio-economic lines are likely to be more effective at containing the outbreak than total lockdowns, while also leading to less economic damage. Insofar as the groups we identify as less responsive are also typically more exposed to the effects of lockdown policies – with, for example, poor people often being less able to work from home –, this should additionally help avoid a further widening of the socio-economic chasms that drive the differences in response.

Lastly, we investigate how the effect of a county-level shelter-in-place policy differs depending on which state-wide policies are already in place. To this aim, in Figure 10, we plot the responses

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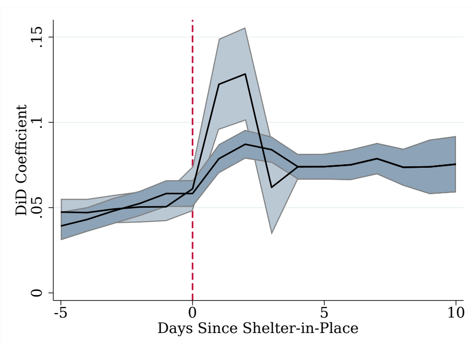
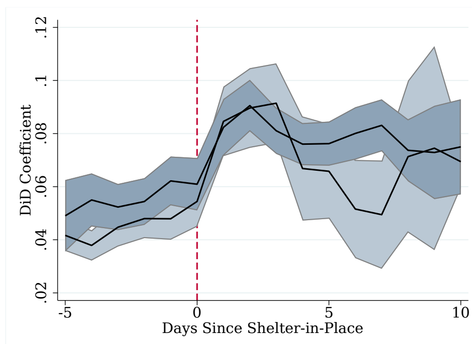
of the percentage of people staying fully home to a county-level shelter-in-place policy, for counties where a state-wide policy is already in place (dark blue) and where it is not (lighter blue). Though the confidence intervals are wide, a few patterns can be observed. First, when there is no state-wide school closure in place, the initial response of the county-level share of people staying home to a county-level shelter-in-place policy is much more pronounced, though it seems to decrease quite quickly after. When there is no state-wide business closure policy in place, there is not much difference in initial response to when there is. However, the response seems to decline quicker, possibly because without a state-wide business closure, people are tempted to defy the shelter-in-place order and go out. Finally and expectedly, when there is no state-wide shelter-in-place policy in place, implementing a county-wide stay-at-home order elicits a persistently higher response.

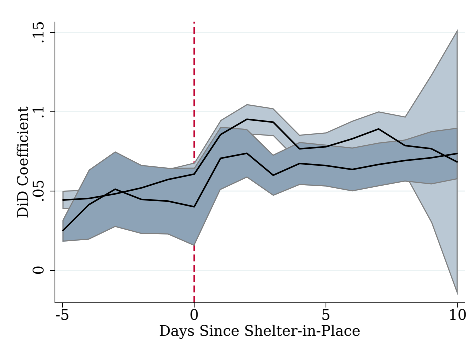
Figure 10: Interaction Between County- and State-Wide Policy, for County Shelter-in-Place



(a) State-Wide School Closure in Place



(b) State-Wide Business Closure in Place



(c) State-Wide Shelter-in-Place Order in Place

[1] Lighter blue: state-wide policy not in place; darker blue: state-wide policy in place.

[2] Shaded area is 95% confidence interval. Standard errors are double-clustered by county and date. Observations: 180,307.

[3] Figure plots DiD estimate for days since 1st confirmed COVID-19 case interacted with variables of interest, in panel regression with state-day fixed effects and county fixed effects.

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4 Conclusion

The outbreak of the COVID-19 pandemic has seen local and national governments around the world scramble to implement policies aimed at constraining social interaction so as to dampen the spread of the virus, relieve the pressure on hospital systems, and save lives. While the drastic nature of such lockdown policies all but guarantees that they reach their desired response, no credible counterfactual estimates of these policies' causal effect on people's social interactions exists so far. This paper aims to fill this gap by studying the interaction between state- and county-level lockdown policies and individuals' physical distancing behavior, using a panel dataset based on 40 million smartphone devices across the United States, combined with detailed data on state- and county-level government policies.

That way, we find that lockdown policies can bring about a counterfactual increase in the time people spend at home of up to 39%, even as our results suggest that individuals also decrease their social interactions to a more limited extent in the absence of any such policies. Moreover, we find evidence that when individuals engage more in such voluntary physical distancing, the likelihood of governments implementing restrictive measures decreases. Furthermore, we weigh in on the debate about the benefits of imposed versus voluntary physical distancing by documenting that in highly urbanized areas that are less distrustful of science, more highly educated, have higher incomes or have stronger institutions, people react more strongly to the outbreak of the virus, even in the absence of lockdown policies. Our results complement earlier epidemiological research that shows that the distribution of individual infectiousness rates in epidemics tends to be highly skewed around the basic reproductive number R(0). Together, these findings strongly indicate that less restrictive containment policies targeted along socio-economic lines are likely to be more effective at containing the outbreak than total lockdowns, while also leading to less economic damage. Lastly, we show that county-level policies tend to have a more pronounced impact when they are implemented with no state-wide policies in place, suggesting that coordination of government response at different levels can further improve outcomes.

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A Tables

Table 5: Description of Key Social Distancing Variables

Product	Variable	Description Raw Data	Aggregation
Social Distancing Metrics	**Home Distance**	Median distance traveled from the geohash-7 of the home by the devices included in the device_count during the time period (excluding any distances of 0). We first find the median for each device and then find the median for all of the devices.	Median of all CBGs in county/state.
	Home Dwell Time	Median dwell time at home geohash-7 ("home") in minutes for all devices in the device_count during the time period. For each device, we summed the observed minutes at home across the day (whether or not these were contiguous) to get the total minutes for each device. Then we calculate the median of all these devices.	Median of all CBGs in county/state.
	Share at Home	Out of the device_count, the number of devices which did not leave the geohash-7 in which their home is located during the time period.	Sum over all CBGs in county/state.
	Percentage at Home	NA (constructed variable)	Sum of Share at Home for all CBGs in county or state / sum of Total Device Count for all CBGs in county or state.
Weekly Patterns	**Traffic**	Number of visits in our panel to this POI during the date range.	Sum of total raw visit counts per day for all POIs in state/county, normalized by total number of unique devices observed in given month.

Note: Description Raw Data replicates the data description provided by SafeGraph here.

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Table 6: Summary Statistics

	N	Mean	SD	P5	P25	P50	P75	P95
SafeGraph Data:								
Traffic	2935	13.78	16.97	0.88	2.91	9.12	16.84	46.10
Median dist. from home	2907	6563.37	1434.76	4433.50	5590.00	6450.50	7404.00	8982.00
Time dwelled home	2907	672.07	114.04	470.00	617.00	677.00	730.00	861.00
% devices stayed home	2907	25.37	6.97	16.83	20.02	23.56	29.50	39.09
Share fulltime workers	2907	17.04	3.73	10.87	14.21	17.30	19.75	23.07
COVID-19 Data:								
Deaths JH	2907	3.06	22.61	0.00	0.00	0.00	0.00	10.00
Confirmed cases JH	2907	204.27	1798.36	0.00	0.00	0.00	18.00	626.00
Positive tests CTP	1145	394.18	2311.14	0.00	5.00	32.00	161.00	1328.00
Negative tests CTP	1040	2536.53	7102.81	10.00	73.00	330.00	2008.00	12432.00
Instruments:								
Max. temperature	2901	11.82	8.54	-1.10	5.60	11.10	17.80	27.20
Precipitation	2902	2.63	6.74	0.00	0.00	0.00	1.50	14.50
Inv. ventilation needed	2652	17.06	116.96	0.00	0.00	0.00	0.57	65.29
State-Level Demographics:								
Population in 1000	2907	6415.05	7272.21	702.46	1754.21	4468.40	7535.59	21299.33
Mean age	2907	39.52	1.64	36.80	38.65	39.45	40.38	42.45
Share > 65	2907	15.73	1.92	12.13	14.86	15.69	16.76	19.16
Share of asian-american	2907	5.62	7.94	1.23	2.36	3.75	5.87	11.45
Share college degree	2907	32.61	6.70	23.83	28.13	31.28	35.61	42.73
Unemployment rate	2907	2.79	0.59	2.06	2.37	2.80	3.01	3.64
Labor force participation	2907	63.52	3.82	56.22	61.25	63.70	66.49	68.93

Note: see section 2 for a detailed description of the data.

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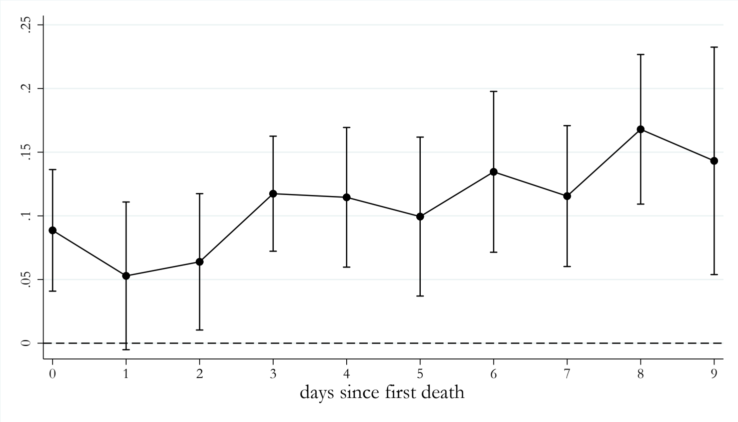
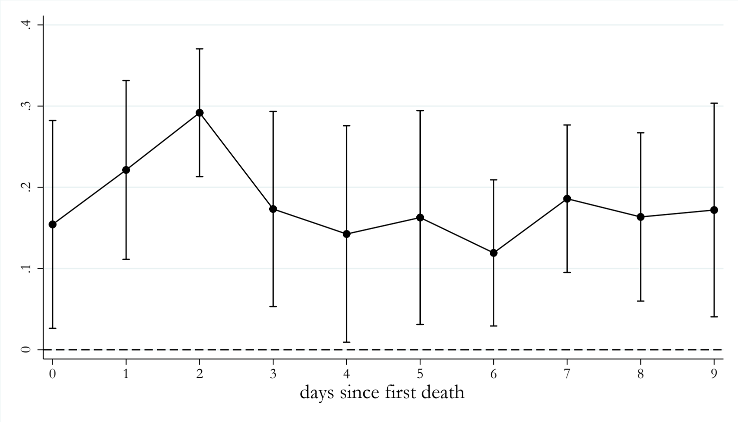
B Figures

Figure B.1: Proportional Change in Median Dwelling Time, Conditional on Safer-At-Home Policies



(a) Proportional Change if no Lockdown Enacted (Relative to no Death)



(b) Additional Change if Lockdown Enacted (Relative to no Death and no Policy Enacted

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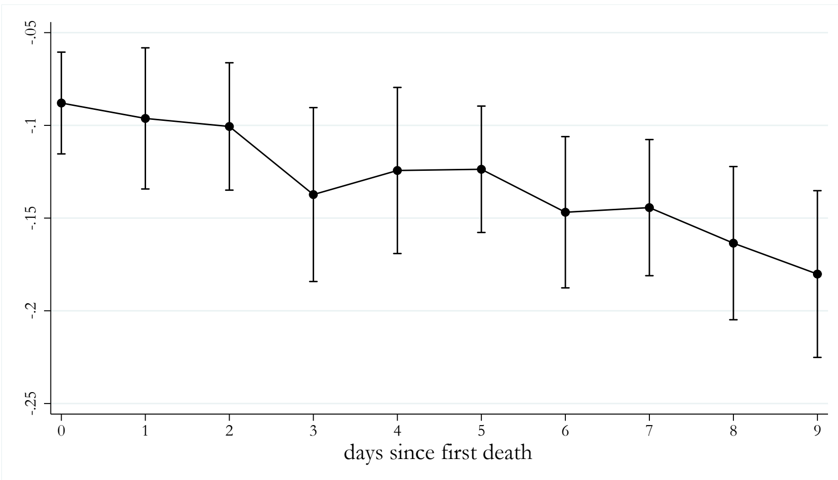
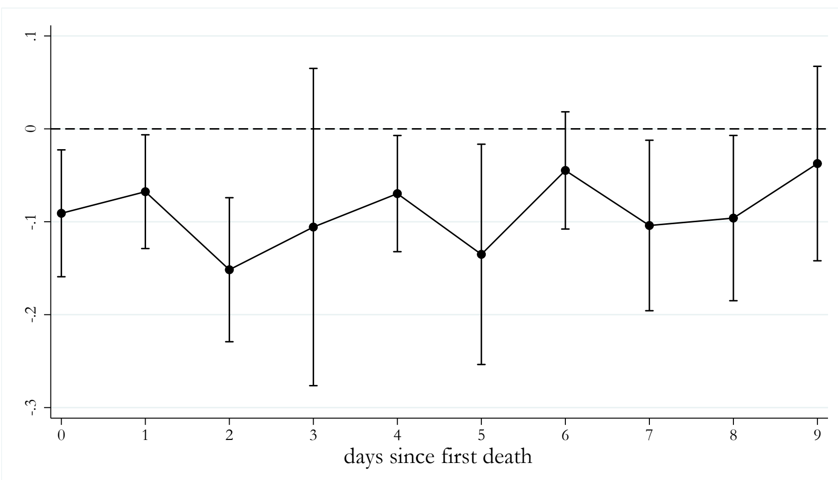
Figure B.2: ~~Proportional Change in Median Distance from Home, Conditional~~ on Safer-At-Home Policies



(a) Proportional Change if no Safer-At-Home Enacted



(b) Additional Change if Safer-At-Home Enacted

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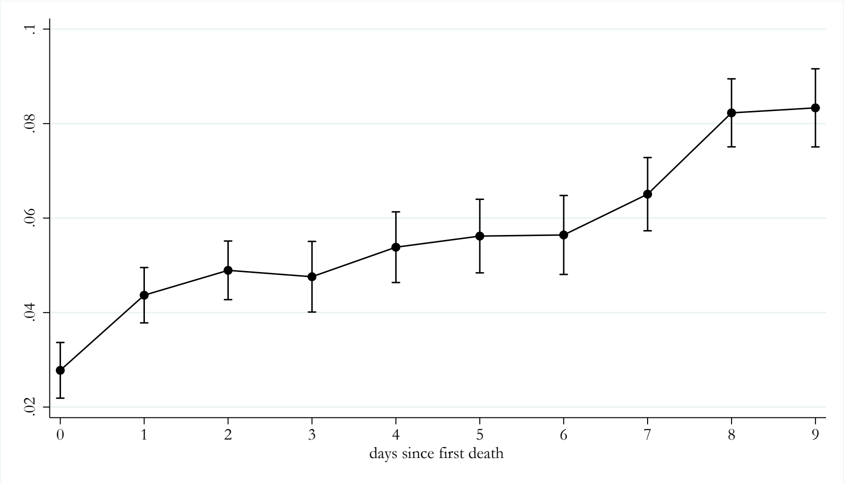
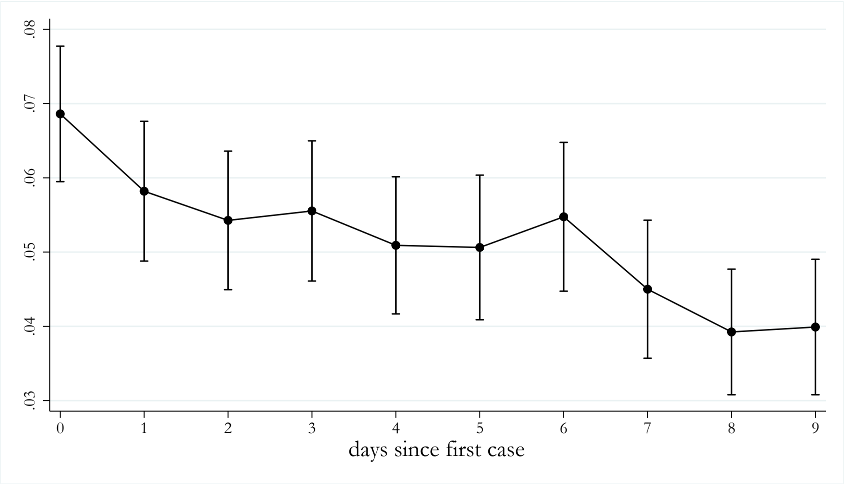
Figure B.3: Percentage Point Change in Percent Completely at Home at the County Level, Conditional on Safer-At-Home policies



(a) Percentage Point Change if no Lockdown Enacted (Relative to no Death)



(b) Additional Change if Lockdown Enacted (Relative to no Death and no Lockdown Enacted)

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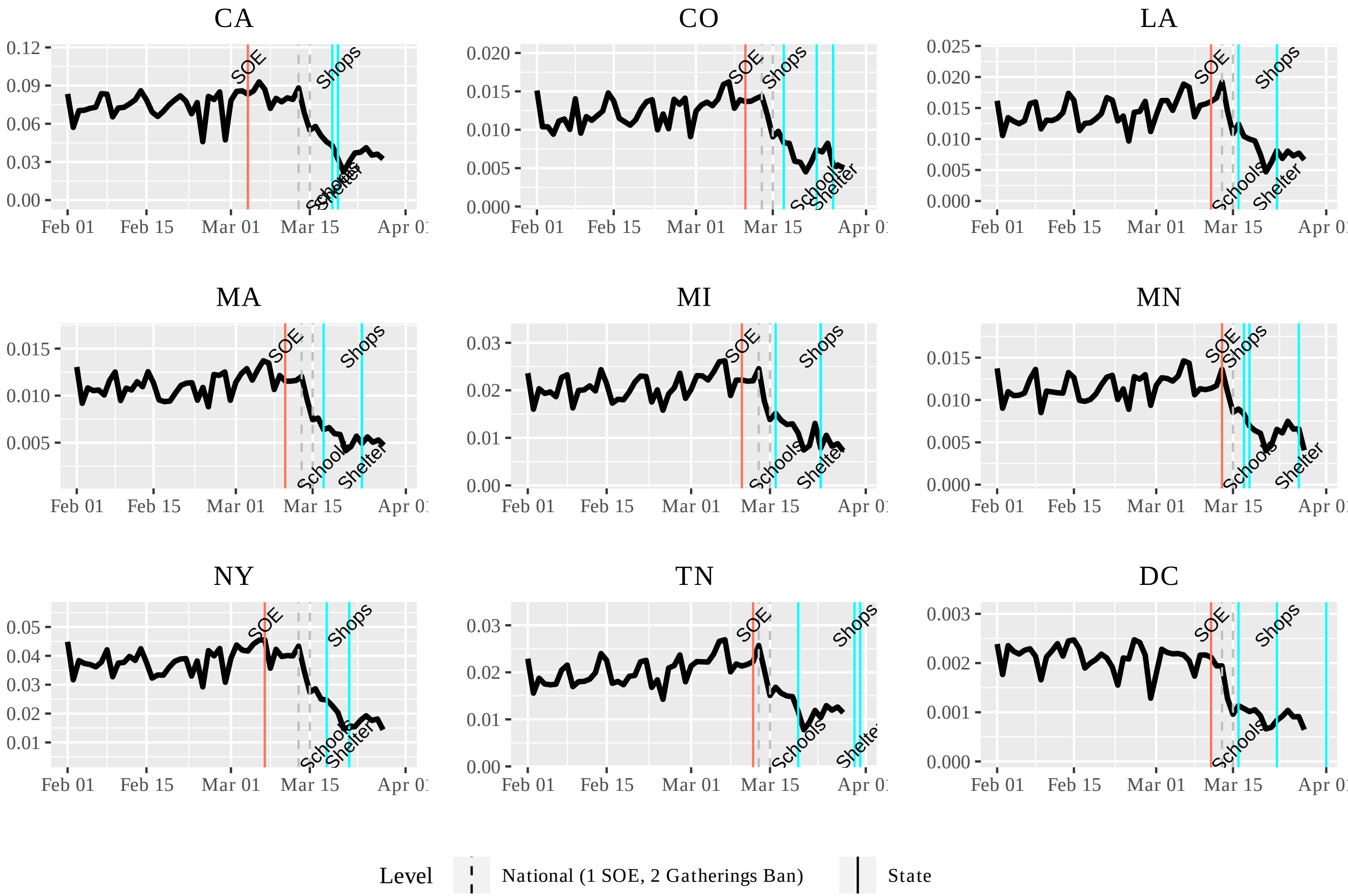
Figure B.4: Foot Traffic and Lockdown Policies in Selected States



Notes: The plots show daily foot traffic and the percentage of devices that stayed home in selected states over time. The dashed vertical lines indicate national measures (SOE, Gatherings Bans) and the solid lines represent state-level SOEs and lockdown policies.

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Figure B.5: Staggered Diff-in-Diff Estimates of the Policy Impact

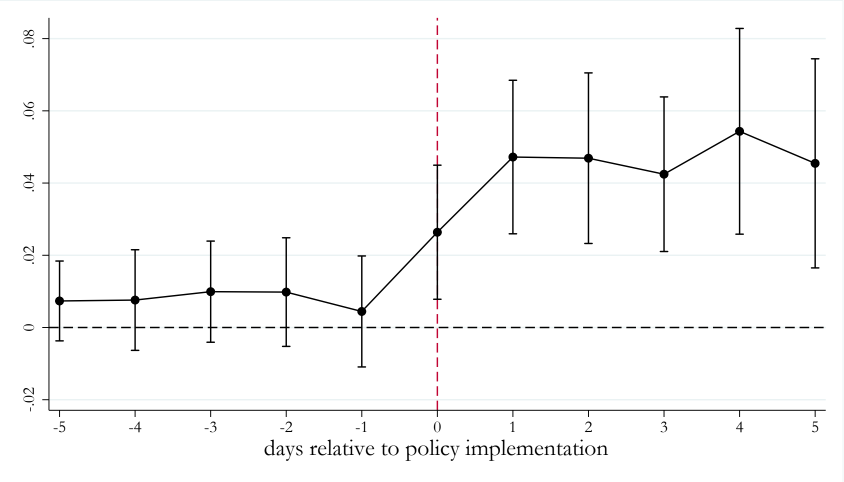

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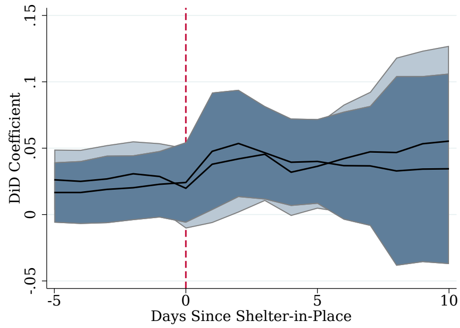
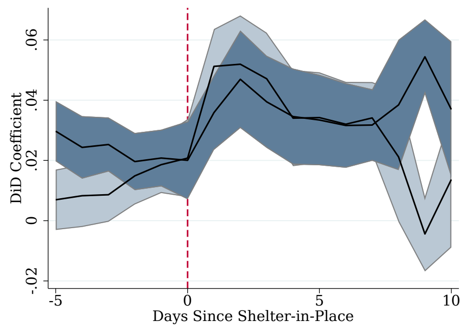
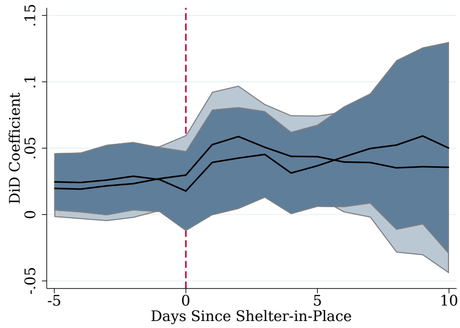
Figure B.6: Heterogeneity in Counterfactual Shelter-in-Place Response



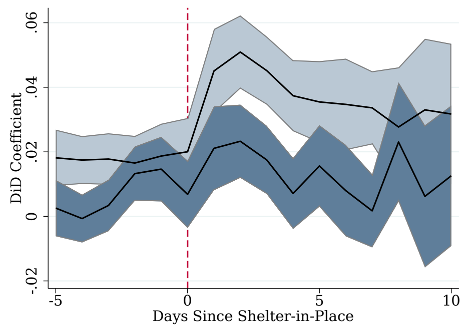
(a) Share of Votes Democratic 2016



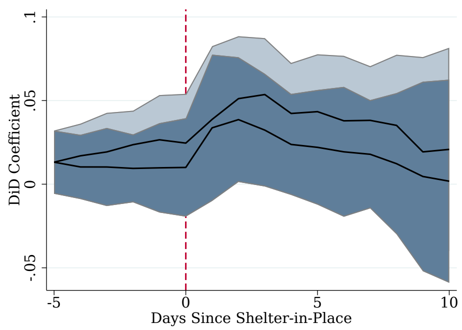
(b) Institutional Health Index (2010-2016)



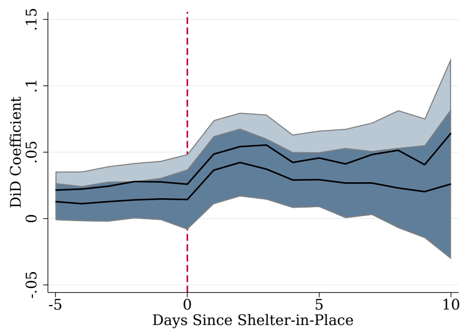
(c) Institutional Health Index



(d) Rural-Urban Continuum



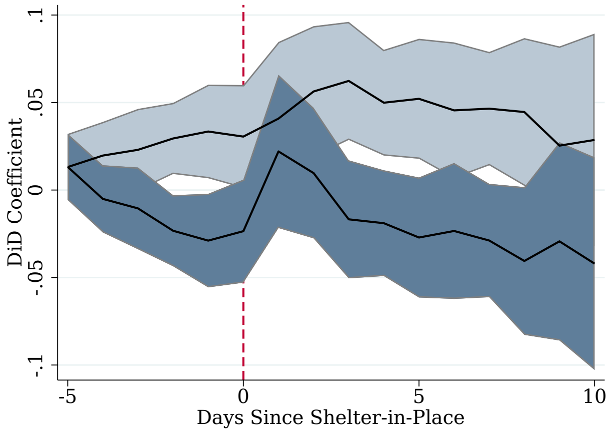
(e) Median Household Income 2019Q3



(f) Percent with Bachelor's Degree

[1] Light blue: 10th percentile; dark blue: 90th percentile - for variable of interest across counties.
[2] Shaded area is 95% confidence interval. Standard errors are double-clustered by county and date. Observations: 180,295.
[3] Figure plots DiD estimate for days since 1st confirmed COVID-19 case interacted with variables of interest, in panel regression with state x day, variable of interest x day and county fixed effects.

Figure B.7: Counterfactual Shelter-in-Place Response, for Poorest and Richest County



[1] Light blue: min; dark blue: max.
[2] Shaded area is 95% confidence interval. Standard errors are double-clustered by county and date. Observations: 180,295.
[3] Figure plots DiD estimate for days since 1st confirmed COVID-19 case interacted with variables of interest, in panel regression with state x day, variable of interest x day and county fixed effects.

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