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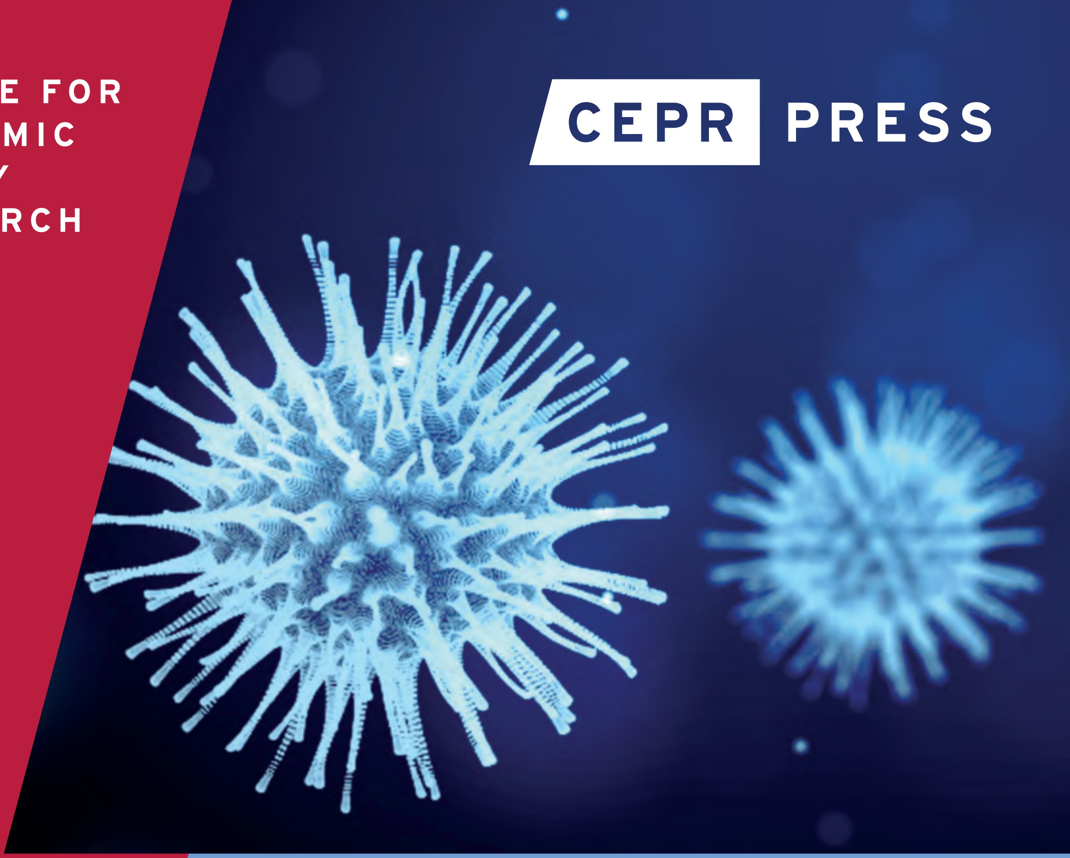

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

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Covid Economics
Vetted and Real-Time Papers

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A simple planning problem for Covid-19 lockdown[1]

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We study the optimal lockdown policy for a planner who controls the fatalities of a pandemic while minimizing the output costs of the lockdown. The policy depends on the fraction of infected and susceptible in the population, prescribing a severe lockdown beginning two weeks after the outbreak, covering 60% of the population after a month, and gradually withdrawing to 20% of the population after 3 months. The intensity of the optimal lockdown depends on the gradient of the fatality rate with respect to the infected, and the availability of antibody testing that yields a welfare gain of 2% of GDP. We also analyze a test-tracing and quarantine (TTQ) policy. We find that TTQ is, in general, complementary to a lockdown.

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1 We benefited from the comments of Andrew Atkeson, Gadi Barlevy, Mike Golosov, Fausto Gozzi, Francois Gourio, Lars Hansen, Kiminori Matsuyama, Magne Mogstad, Steve Mohr, Casey Mulligan, Tom Phelan, Filip Rozsypal, Fabiano Schivardi, Rob Shimer, Daniele Terlizzese, Fabrice Tourre, Marcelo Veracierto, Ivan Werning, and panelists and participants on the HELP! (Health and Pandemics Economics Group) seminar, the World Bank's Development Policy and Covid-19 e-seminar, the Federal Reserve Bank of Chicago Virtual Macro Seminar. The authors declare to have no conflict of interest to disclose regarding the research on this paper.

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1 Introduction and Overview

We adopt a variation of the SIR epidemiology model reviewed by Atkeson (2020) and Neumeyer (2020) to analyze the optimal control model for the COVID19 epidemic. Our aim is to contribute to the ongoing discussion on the optimal policy response to the COVID19 shock, see Barro, Ursua, and Weng (2020); Eichenbaum, Rebelo, and Trabandtz (2020); Hall, Jones, and Klenow (2020); Dewatripont et al. (2020); Piguillem and Shi (2020); Jones, Philippon, and Venkateswaran (2020) and the contributions in the volume by Baldwin and Weder (2020).

The typical approach in the epidemiology literature is to study the dynamics of the pandemic, for infected, deaths, recovered, as functions of some exogenously chosen diffusion parameters, which are in turn related to various policies, such as the partial lockdown of schools, businesses, and other measures of diffusion mitigation, and where the diffusion parameters are stratified by age and individual covariates. This is the approach followed for instance by Ferguson et al. (2020). We use a simplified version of these models to analyze how to optimally balance the fatality induced by the epidemic with the output costs of the lockdown policy.[1] The novel aspect of our analysis is to explicitly formulate and solve a control problem, where the diffusion parameter is affected by the lockdown, that is chosen to maximize a social objective while taking into account the dynamic evolution of the system.[2] A reason to write a planning problem directly is that, with social interactions, there is an externality to be corrected, as understood in much of the search literature and as carefully analyzed in Eichenbaum, Rebelo, and Trabandtz (2020) and Toxvaerd (2020). The state of the problem is two dimensional and, in spite of its simplicity, it does not have an analytic solution. By computing the optimal policy and the associated trajectories, we aim to gauge the key elements that determine the optimal *intensity* and *duration* of the lockdown.

[1]While the lockdown is not the only margin of action (other actions might involve reinforcing health treatment capacity and incentivizing the development of vaccines), in the short run this seems to be an important policy tool available and used by several countries.

[2]An optimal control problem based on a very similar epidemiological model can be found in Hansen and Troy (2011), but the objective function and the feasible policies are different.

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We solve the problem under different scenarios, that include congestion effects in the health care system, the effectiveness of the lockdown in reducing the diffusion of the virus and the possibility of testing for antibodies.

We parametrize the model using a range of estimates about the COVID19 epidemic. Since we recognize that several parameters are highly uncertain we explore a range of variations concerning the severity of the congestion effects on the fatality rate, a range of valuations for the value of lost lives, and the possibility of testing and releasing the recovered agents from lockdown. The quantitative results are useful to gauge what parameters of the problem are important in shaping the intensity and duration of the optimal lockdown policy. In our baseline parameterization, conditional on a 1% fraction of infected agents at the outbreak, the possibility of testing, and no cure for the disease, the optimal policy prescribes a lockdown starting two weeks after the outbreak, covering 60% of the population after 1 month. The lockdown is kept tight for about a full month, and is gradually withdrawn, covering 20% of the population 3 months after the initial outbreak. The output cost of the lockdown is high, equivalent to losing 8% of one year's GDP (or, equivalently, a permanent reduction of 0.4% of output). The total welfare costs is almost three times bigger due to the cost of deaths (see Panel A in Figure 1 and Table 2).

These results are based on a relatively pessimistic parameterization of the fatality rate, and on the fraction of the population that would have been infected if there was no lockdown. In the less pessimistic cases, yet in our view still realistic, obtained by assuming a lower fatality rate and/or a lower speed of spread of the virus, the optimal lockdown is shortened by more than one month. The intensity of the optimal lockdown depends critically on the gradient of the fatality rate as a function of the infected. If we consider a constant fatality rate the intensity and duration of the lockdown are significantly reduced and, in some cases, completely eliminated, even though the welfare cost of the pandemic remain high. On the other hand, the value of the statistical life we use in our benchmark case (20 times annual GDP per capita) is on the low range of the estimates in the literature. Following Hall, Jones,

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and Klenow (2020), our benchmark value takes into account that the majority of the victims of the virus have a below average life expectancy. A higher value of statistical life (say 30 times annual GDP per capita), makes the abandonment of the lockdown more gradual, taking a bit more than six months to be totally abandoned. Considering a much larger value, in the order of 80 times the annual GDP per capita, implies a very strict lockdown that lasts for about 9 months and maintains about 15% of the population in lockdown a year after.

Finally, our benchmark scenario assumes that there is an antibody test that allows those that recover to be issued an immunity card and go back to work, so that they are not subject to the lockdown. In the absence of such a test the optimal lockdown is shorter, but it involves roughly the same total number of hours lost due to the lockdown (see Figure 1 and Table 2). The most salient feature of the case where a test is not available is that the lockdown ends up sooner, more abruptly. The dynamics of the epidemiological model give the insight why this is optimal: as time goes by, the fraction of those recovered increases, and thus the lockdown becomes progressively less efficient to stop the transmission of the virus by locking down a progressively larger fraction of those that do not transmit it. The availability of such test has large welfare gains, in the order of 2% of one year's GDP.

A byproduct of the calculations is the benefit of the lockdown policy, measured as a percentage permanent GDP flow of following the optimal policy vs the case of no lockdown (see Table 2). Under our preferred values, the total welfare cost of the virus is equivalent to a loss of 30% to 40% of one year's GDP. From this loss, the part due to lockdown of workers is between 8% and 12% of one year's GDP.

Needless to say the analysis has limitations: the underlying model has no heterogeneity in fatality rates nor in diffusion rates, the lockdown policy cannot be differentiated across agent's type (e.g. young versus old, workers vs retirees). We also ignore direct health interventions that might be put in place to mitigate the consequences of the disease (e.g. building emergency hospitals).

Our objective is similar to that of Eichenbaum, Rebelo, and Trabandtz (2020). While they

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focus on a competitive equilibrium where a consumption tax is used to slow-down economic activity and the epidemic diffusion, we focus on a simple planner's problem. In our setup, the interaction of the law of motion coming of the SIR model and the lockdown policy makes the problem non-convex, which requires the use global methods. Another recent contribution addressing the optimal control problem in the presence of contagion externalities can be found in Jones, Philippon, and Venkateswaran (2020).

The outline is as follows: the next section describes the planner's problem and the epidemic model. Section 3 discusses the key model parameters. Section 4 reports the results of the optimal control problem under different scenarios. Section 4.1 quantifies the welfare costs of the lockdown policy under alternative scenarios, and compares them with the costs produced in a scenario without intervention. Section 5 discusses en extension where the policy maker has access to a technology to trace, test and quarantine infected agents. Section 6 discusses future extensions.

2 A planner model of lockdown control

We start with a modified version of the SIR model as described in Atkeson (2020). Agents are divided between those susceptible to be infected $S(t)$, those infected $I(t)$, and those recovered $R(t)$, i.e.

$$N(t) = S(t) + I(t) + R(t) \text{ for all } t \geq 0 \tag{1}$$

The "recovered" include those that have been infected, survived the disease, and are now assumed to be immune. Since we only include those that are alive $N(t)$ is changing through time. We normalize the initial population to $N(0) = 1$. The planner can lockdown a fraction $L(t) \in [0, \bar{L}]$ of the population, where $\bar{L} \leq 1$ allows us to consider that even in a disaster scenario some economic activity such as energy and basic food production will continue. We assume that the lockdown is only partially effective in eliminating the transmission of the virus. When L agents are in lockdown, then $(1 - \theta L)$ agents can transmit the virus, where

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$\theta \in (0, 1]$ is a measure of the lockdown effectiveness. If $\theta = 1$, the policy is fully effective in curbing the diffusion but, since some contacts will still happen in the population even under a full economic lockdown, we allow $\theta < 1$.

The law of motion of the susceptible agents is:

$$\dot{S}(t) = -\beta\, S(t)(1 - \theta L(t))\, I(t)(1 - \theta L(t)) \tag{2}$$

where β is the number of susceptible agents per unit of time to whom an infected agent can transmit the virus after contact. All susceptible agents that get the virus become infected. For the infected, a fraction γ recovers, thus:

$$\dot{I}(t) = \beta\, S(t)(1 - \theta L(t))\, I(t)(1 - \theta L(t)) - \gamma I(t) \tag{3}$$

Note that locking down a part of the population, while economically costly, can be very powerful in reducing the rate at which susceptible agents become infected. This is because it is the *product* of the infected and susceptible that determines the new infections per unit of time. Hence, decreasing the number of contacts of each, decreases the new infections by its *square*. In search theory Diamond and Maskin (1979, 1981) aptly named this feature "quadratic search".

A rate $0 < \phi(I) \leq \gamma$ per unit of time of those infected die. Thus, the population decreases due to death as:

$$-\dot{N}(t) = \phi(I(t))\, I(t) \tag{4}$$

While we assume that the rate γ at which infected recover is constant, the rate at which the infected die varies with the number of infected I, according to

$$\phi(I) = [\varphi + \kappa I]\, \gamma \quad . \tag{5}$$

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The term $[\varphi + \kappa I] \in (0, 1)$ is the "case fatality rate" (CFR), namely the proportion of infected persons that will die. It appears that the CFR is increasing with I, an assumption that reflects congestion effects in the health care system. The multiplication of the CFR by γ, the reciprocal of the infection expected duration, gives the fatality rate per unit of time.

We assume that each agent alive produces w units of output, when she is not in lockdown. Agents are assumed to live forever, unless they die from the infection. The planner discounts all values at the rate $r > 0$. We also assume that with probability ν per unit of time both a vaccine and a cure appear, so that all infected are cured and all susceptible become immune. The problem consists in minimizing the following (discounted at rate $r + \nu$) present value:

$$\int_0^\infty e^{-(r+\nu)t} \Big(wL\left(t\right) \Big[\tau(S(t) + I(t)) + 1 - \tau \Big] + \phi\left(I\left(t\right)\right) I\left(t\right) \cdot vsl \Big) \, dt \tag{6}$$

The flow cost for the planner of having state (S, I) at t and selecting control L has two components. The first one is $wL\left[1 - \tau + \tau(S + I)\right]$, the output lost due to the lockdown. In the case where an antibody test is available ($\tau = 1$), so that an immunity card is released to the recovered, this equals w times the lockdown rate L times the population to which it applies, i.e. the sum of susceptible and infected. In the case where the test is not available ($\tau = 0$), the cost due the lockdown is wL.

The second component of the flow cost is the product of the number of deaths per period times the shadow value assigned to each death, or the value of a statistical life (vsl). In particular, if there are I infected, the deaths per unit of times are given by $\phi(I)\, I$. The cost of each fatality is given by the assumed value of a statistical life, which is discussed below. The planner's problem is subject to the law of motion of the susceptible equation (2), the infected equation (3), the population, equation (4), and an initial condition $(N(0), I(0), S(0))$ with $I(0) > 0$ and $S(0) + I(0) \geq N(0)$. Finally, when the vaccine and cure arrives there is no more cost, and thus the continuation value is zero.

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The planner solves the following Bellman-Hamilton-Jacobi equation:

$$(r+\nu)V(S,I) = \min_{L\in[0,\bar{L}]} wL\Big[\tau(S+I)+1-\tau\Big] + I\phi(I)\cdot vsl + \\ - \left[\beta\, S\, I(1-\theta L)^2\right]\partial_S V(S,I) \;+\; \left[\beta\, S\, I(1-\theta L)^2-\gamma I\right]\partial_I V(S,I) \tag{7}$$

The domain of V is $(S,I)\in\mathbb{R}^2$ such that $S+I\leq 1$. Note that $V(S,I)$ can be interpreted as the minimum expected discounted cost of following the optimal policy in units of forgone output. We solve this problem by discretizing the model to daily intervals, using value function iteration over a dense grid for (S,I). Finally, note that the value function has analytic expressions on the boundary of its domain, where the lockdown policy is not exercised: on the $I=0$ axis we have $V(S,0)=0$, for all $S\in(0,1)$. On the $S=0$ axis we have $V(0,I)=vsl\cdot\ I\gamma\left(\frac{\varphi}{r+\nu+\gamma}+\frac{\kappa I}{r+\nu+2\gamma}\right)$ for all $I\in(0,1)$.

Discussion of modeling assumptions

1. We restrict the extent of the lockdown to $\bar{L}\leq 1$. This takes into account that some sectors cannot shut down (health, basic services, food production, etc.)

2. If $\theta=1$ the lockdown is able to completely stop the infections process, i.e. to achieve $\dot{S}=0$ (at $L=1$). If $\theta<1$ the effectiveness of the lockdown policy is partial (people keep transmitting the virus) but at a lower rate.

3. In the law of motion for S and I, given by equation (2) and equation (3), we write $\beta IS(1-\theta L)^2$, instead of $\beta IS(1-\theta L)^2/N$. This seems standard in the SIR literature, although it would be preferable to scale them by N. But since the dead are a small fraction of N we follow the literature, and thus shrink the state space.

4. Infected not in lockdown are assumed to produce as much as those susceptible or recovered not in lockdown. Conversely, agents in lockdown produce zero. Both assumptions can be easily changed by rewriting the flow values of the objective function.

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5. Agents are infinitely lived, except for the risk of dying of the virus. This simplification is acceptable given the short time horizon of the problem. We do correct for the age distribution of fatalities in our choice of the value of a statistical life.

3 Parameterization of the model

We parameterize the model using data from the World Health Organization (WHO) compiled by the Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE) while acknowledging, like the rest of the recent literature, that at this point there is considerable uncertainty about infection, recovery, and mortality rates. The data includes the total cases, including separately those that have recovered and those that have died. We define active cases as the total number of cases minus those that either recovered or died. We use daily observations of all the countries that have registered at least 100 active cases and include observations of the first 25 days after they first cross this threshold.

To calibrate β, the rate at which individuals who are infected bump into other people and shed virus onto those people, we use the daily increase in active cases and assume a value of 20 percent. The parameter γ governing the rate (per day) at which infected people either recover or die is considered a fixed parameter of the disease and is set to γ=1/18 reflecting an estimated duration of illness of 18 days as in Atkeson (2020) but also consistent with the fraction of infected agents that recovered or died according to the WHO as compiled in JHU CCSE.

We set the fatality rate $\varphi = 0.01$, which is consistent with the age-adjusted fatality rate estimated form the *Diamond Princess* cruise ship and with the lower bound mortality rate in the city of Vo' Euganeo – two cases where there has been extensive testing. We set $\kappa = 0.05$ so the fatality rate is 3 percent when 40 percent of the population is infected. There is considerable uncertainty on the fatality rate, mostly because the true rate of infected is not really known. For instance, Eran, Jay, and Sood (2020) argue that the number of infected is

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probably at least an order of magnitude larger, and thus the mortality rate much smaller.

We set the planner's discount factor to be consistent with a 5 percent annual interest rate and the per unit of time probability ν that a vaccine and a cure will appear so that it implies that it takes on average a year and a half for these medical discoveries to become available. We normalize output w=1 and adopt a baseline value of a statistical life of 20 times w. Note that in this case, a unit of output produced by each agent, w, can be interpreted as GDP per capita, let say 65,000 USD, and the shadow cost of each life lost used by the planner is 20 times annual GDP per capita, or about \$1.3 Million USD.

Our choice of the benchmark value for $vsl = 20$, and hence of the penalty deaths, is in line with Hall, Jones, and Klenow (2020). These authors use an utilitarian criterion to value the extra years of life lost among those likely to die due to the infection, obtaining a cost of about 30 times per capita annual consumption, which is very close to our benchmark.[3] The value of 20 annual per capita GDP is much lower than the typical figures for statistical value of life, which are closer to \$ 10 million, see Kniesner and Viscusi (2020), or about 150 GDP per capita. We will report results for a range of alternative values, considering vsl of 10, 30 and 80 annual GPD per capita.

Lastly, we assume that even in a disaster scenario, economic sectors such as health, government, retail, utilities, and food manufacturing will continue. These sectors combined account for 25-30% of GDP (2018). Thus, we set $\bar{L} = 0.7$.

It goes without saying that the values for several parameter are speculative. We will conduct some sensitivity analysis to illustrate their importance.

[3]Following Hall, Jones, and Klenow (2020), one can use that a year of life lost is valued as three times annual consumption. Then, one can compute the expected number of years of lives lost to those that die as a consequence of the virus, conditional on being infected. They obtain a number between 10 and 15 years, with 10 being their headline figure. Thus, $3 \times 10\,years \times$ annual consumption per capita $= 3 \times 10\,years\, \times 2/3 \times$ annual GDP per capita $= 20 \times$ annual GDP per capita.

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4 Results

We display the time path of the optimal policy starting at $I(0) = 0.01$, i.e. one percent of population infected at $t = 0$ for our benchmark parameter values.[4] In particular, we display the time path of the optimal lockdown policy $L(t)$ as function of time, the fraction of the population for which lockdown applies $L(t)[\tau(S(t) + I(t)) + 1 - \tau]$, the path of infected $I(t)$, and the total accumulated fraction of dead up to time t. Recall that $N(0) = 1$, so both infected and the stock of dead can be all interpreted as fraction of the initial population. In these graphs, the horizontal axis is time, conditional on the cure-vaccine not occurring before that period. For comparison, we also plot the path if there is no lockdown policy, i.e. for $L(t) = 0$ for all $t \geq 0$.

Benchmark case. We present the results for our benchmark case first, and then implement a sensitivity analysis. Our benchmark case favors a policy of lockdown due to the following features: *(i)* the chosen values for the parameters β and γ of the SIR model imply that a large fraction will be exposed to the virus if unchecked, $\lim S(t) \approx 0.03$ as $t \to \infty$, *(ii)* we assume that the fatality rate can increase from 1% to up to 3% of those infected when fraction of infected goes from 5% to 40%, and *(iii)* we assume that those recovered can be identified and hence they are not locked down. However our benchmark case uses a value of statistical life of 20 times annual per capita GDP, which is in line with utilitarian values of life for those likely to be affected by COVID-19, but an order of magnitude smaller than the average value of a statistical life used in other public policy evaluations. We conduct sensitivity analysis for each of the these assumptions below.

Benchmark case with testing. Panel A of Figure 1 presents the result for our benchmark parameter case with testing. The first box in the panel shows the timeline for the optimal lockdown. The lockdown starts two weeks after the epidemic outbreak. The fraction of the population in lockdown peaks at 60%, about 1 month after the outbreak, and gradually

[4] We assume that the initial fraction of the population susceptible is 97%, or $S(0) = 0.97$.

decreases to reach about 10% of the population by the 14th week of lockdown. The lockdown ends in about 4 months. The policy yields a considerable flattening of the curve of infected, as shown in the middle panel of the figure, by comparing the red (no lockdown) vs the blue line (optimal policy). In the long run, the total number of deaths is about 0.80% smaller with the optimal policy, as shown in the bottom panel of the figure.

Benchmark case without testing. Panel B of Figure 1 shows the results of the case with no test, $\tau = 0$. In this case, the lockdown applies to anybody in the population, including those that have recovered from the virus. Recall that in this case, it is less efficient to lockdown agents because the recovered are also in lockdown, which has the cost of reducing output without the benefit of reducing the transmission of the virus. In the case of no test, the lockdown declines much more sharply than in the benchmark case with testing. Interestingly, in both cases the lockdown involves similar costs in terms of forgone output, since in the absence of testing the lockdown duration is shorter but it applies to a larger fraction of people (recovered agents are also in lockdown). In spite of this similarity, we show below that welfare under the optimal policy with testing is higher, in the order of a permanent 0.1% GDP flow, which is equivalent to a one-time payment of 2% of GDP.

Details on the benchmark case with testing. Figure 2 displays the value function and the optimal policy for the benchmark parameter values. The value function is plotted in the right panel, for the relevant state space (S, I), and normalized so that $rV(S, I)/w$ is on the vertical axis. The units are permanent flow costs as a fraction of the total output before the virus. Thus, a value of 0.02, means a cost equivalent to a permanent reduction of 2% percent in the value of output (measured before the virus). On the boundary of the state space, where $S = 0$ or $I = 0$, the function $V(S, I)$ has the properties described in Section 2.

The left panel of Figure 2 plots a heat map of the optimal policy $L^*(S, I)$. Yellow indicates higher value of the lockdown rate L, and blue indicates lower values of L. Note that close to both boundaries, i.e. either $S = 0$ for $I = 0$, ie. it is optimal to have a zero lockdown rate.

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The left panel also plots two paths, using the phase diagram over the state space (S, I). These are the trajectories that the system will follow starting from the initial condition $I(0) = 0.01$ and $S(0) = 0.97$. The red path corresponds to the case of no intervention. The other path –the dashed light blue line– gives the evolution of the state under the optimal policy. It can be seen that the fraction of infected is much smaller under the lockdown policy. The two paths coincide for a while, since the initial condition lies in the region of the state space where lockdown is not optimal. Then the optimal path is controlled, and produces a much lower fraction of infected. Eventually, the path moves to the region with no lockdown, which occurs after the system has acquired herd immunity –note that at the end the trajectory I is decreasing even if there is no lockdown. This phase diagram can be used to follow any other alternative paths, such as what would happen if the optimal policy were to start after the virus has been unchecked for a longer period of time. Note that unless the susceptible have reached a very small number, starting the optimal policy later will involved immediate lockdown, i.e. the path will start in the yellow area.

Depending on parameter values and initial conditions the optimal policy may imply an early lockdown (for S, I pairs close to the $I = 0$ axis), followed by a relaxation of the policy and then by another lockdown.[5] We leave such cases for future investigations.

Lower effectiveness of lockdown. We explored the sensitivity to parameter values by changing the effectiveness of the lockdown, i.e. reducing it from $\theta = 0.5$ to $\theta = 0.3$. In the case of less effective lockdown the duration and severity are both smaller. The fraction of population peaks in approximately 20 days, but it decreases at a faster rate, reaching zero lockdown two months after the lockdown start. Instead, if the lockdown where to be more effective, say $\theta = 0.7$, the duration will be even longer.

Constant fatality rate function (no congestion of health care system). In this case the results change dramatically, in the sense that if $\kappa = 0$ under the benchmark parameters

[5]This can even be seen in the benchmark case, where there is a small isolated area of lockdown for very small positive value of I and value of S approximately between 0.4 and 0.5.

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it is essentially optimal to have a zero lockdown. This is the case where the fatality rate is constant at 1%, so there is no congestion on the health care system.

Different values of statistical life. Next we explore the consequences of a smaller implied statistical value of life, half the value of the benchmark case. Unsurprisingly, the lower value of vsl diminishes considerably the optimal lockdown level and duration, peaking at a lower value than the benchmark case, and with duration from start to finish of about 50 days. We also explored cases where the vsl is higher than our benchmark scenario. If we increase the value of statistical life to 30 times annual GDP per capita –which is in the upper end of the values consider by Hall, Jones, and Klenow (2020)[6] In this case, the lockdown starts in two weeks –a bit faster than the benchmark–, peaks in a month with about 60% of the population in lockdown, and decreases linearly and slowly, until is abandoned slightly more than six months after it stared. The fraction of population in lockdown reaches 10% only after about 4 months after the lockdown started. In this case, the more aggressive, and specially longer, lockdown policy implies that the fraction of death after the epidemic is over is reduced by 1%, about 0.20% more than in the benchmark.

Finally we consider the value of statistical life of 80 annual per capita GDP where, as expected, the optimal lockdown rate is very high and it last for a very long time. The lockdown rate starts in two weeks, and $L(t) = \bar{L}$ for about 8 months. The fraction of population in lockdown reaches 50% slightly about 3 months after the lockdown started, and it is approximately 15% a year into the lockdown, when $L(t)$ is below its allowed maximum.

Two cases with less pessimistic parameter values. In the first case the value of β is half of the benchmark value, $\beta = 0.10$, so the virus spreads a slower pace and it reaches a lower fraction of the population even if $L(t) = 0$ for all t. In the second case, the baseline mortality rate is half of that in the benchmark case, i.e. $\varphi = 0.005$. Otherwise all the

[6]This is consistent with a value of each year of extra life of 3 times annual consumption per capita, times 15 years of lost life expectancy conditional on dying after being infected.

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parameters are as in the benchmark case. In both cases the lockdown is at least one month shorter.

4.1 Size of the welfare cost under optimal policy

Table 2 summarizes the value of following the optimal policy vs. the value where there is no lockdown, for different parameter values.

Our preferred summary measure is to report $rV(S(0), I(0))/w$. This number is the total expected discounted sum of future losses, both due to the lost GDP caused by the lockdown in all future periods, as well as the values of the lost lives, where every life is evaluated using vsl. The multiplication by r in $rV(S(0), I(0))/w$, converts the expected present values into a permanent annual flow, and the division by w relates it to the output flow before the virus outbreak. We report separately the part of the flow cost $rV(S(0), I(0))/w$ that is purely due to the output cost of the shutdown.[7] The last column displays the present discounted values of the cost if $L(t) = 0$ for all t, which we label as "No Policy" in Table 2. In the three cases we express the losses in percentage.

Importantly, any of the three cost measures in Table 2 can be converted into the equivalent of one year's GDP by dividing them by r, or multiplying them by 20 given our 5% annual interest rate. For instance, dividing by r the flow measure of the cost due to the output lost gives a simple statistic measuring the severity and length of the lockdown. For instance, if this measure is 10%, then the lockdown is equivalent to lose 10% of a year's GDP, or equivalently to lockdown 10% of the population for a year.

The first three rows of Table 2 explore the different values of effectiveness of the lockdown. For the benchmark case, second row in the top panel, following the optimal policy implies a permanent loss of approximately 1.5% of output. In other words, as a consequence of the outbreak of the virus, even following the optimal policy, welfare is comparable to an equivalent measure of being 1.5% permanently poorer. We can also recapitalize this loss and

[7]The part of the cost due to output is given by $rw \int_0^\infty e^{-(r+\nu)t} \left[1 - \tau + \tau L(t)(S(t) + I(t))\right] dt$.

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express it as fraction of one year's GDP, obtaining 28%. From the 1.5% total permanent loss, 0.4% is output loss due to the lockdown, or equivalent to 8% of one year's GDP. For the same parameters, if there is no lockdown (No Policy), the loss is equivalent to a permanent decrease in output of 1.9%.

The second panel corresponds to the case of different values of a statistical life. Recall that the benchmark case assumes a value of a statistical of life (vsl) of 20 annual GDP per capita. We also consider cases of 10, 30, and 80 annual GDP per capita. For a vsl of 30 annual GDP per capita, the part due to output loss is a permanent flow of 0.6% or equivalent to 12% of one year's GDP.

The third panel corresponds to the case where the case fatality rate $\phi(I)$ is constant at $\varphi = 0.01$, or equivalently $\kappa = 0$. In this case, the optimal policy has no lockdown, so the loses of the optimal policy and the case of no policy are the same, and also much smaller, since the death rate does not spike up. This highlights the importance of the assumption implied in our benchmark case that ϕ is increasing, which captures the extra fatalities due to the congestion in the heath care system caused by a large number of infected.

The fourth panel corresponds to the case of no antibody test ($\tau = 0$). For this case, we present different values of a statistical life. Each row expresses vsl as a multiple of the annual GDP per capita and otherwise the same parameters as in the benchmark case. Comparing the benchmark case –i.e. the second row of the top panel– with the same case without test –i.e. the second row of the last panel– we find the value of the test. In particular, the expected discounted cost under the optimal policy is, expressed as a permanent flow, 0.1% (10 basis points) higher without test than with test, i.e. 1.6% vs 1.5%, or in terms of a one time value approximately 2% of a year's GDP. For a smaller value of vsl, we find that the difference is smaller than 0.1%. Instead, as vsl increases to multiples of annual GDP per capita of 30 and 80, the difference measuring the value of the test as a permanent flow of GDP loses is 0.20% and 0.80% respectively. For our preferred parameter values (i.e. vsl between 20 and 30 times annual GDP per capita), the value of the test is equivalent to between 2% and 4%

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of one year's GDP.

The last panel of the table contains two cases in which the outbreak is less serious, as discussed above. In these two cases, the losses are considerably smaller.

5 Extension: the Tracing-Testing-Quarantine policy

In this section, we add a second policy to the planner problem: tracing-testing-quarantine (TTQ). In this case, the planner will chose two controls as a function of the state: the rate of tracing-testing-quarantining as well as the lockdown rate. The goal is to understand whether this policy is complementary or substitutable with the lockdown policy and to explore the parts of the state space in which each policy used. We first describe the set-up adding TTQ, and then we show that in a special, yet interesting case, we can analyze the two policies in a comparable two state planning problem. The two state system has computational advantages and, more importantly, it facilitates the interpretation and comparison with the previous case when only the lockdown policy is used. We parameterize the cost of tracing-testing as a function of the number of people that will be put in quarantine and also in terms of the composition of the pool of infected-recovered to which the testing-tracing applies. This allows us to consider degrees of effectiveness of the available technology, going from the (ineffective) extreme in which it is equivalent to random testing to one in which the cost does not depend on the prevalence of infected among the pool to be traced. We use to examples to illustrate the use of TTQ vs Lockdown, as we vary the effectiveness of tracing.

Setup with Testing-Tracing-Quarantine (TTQ). To analyze TTQ we introduce, Q the stock of infected that are in quarantine. Q is the stock of those that have been identified (traced), tested as infected, and subsequently quarantined, and have not yet recovered or died. Each period the planner decides to trace a flow of agents at a rate T, at a tracing and testing cost $c(T; S, I, Q)$ per period. The remaining law of motions for the total number of infected I and susceptible S are changed accordingly. The state is the triplet (S, I, Q) with

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a law of motion:

$$\dot{S}_t = -\beta S_t(I_t - Q_t)(1 - \theta L_t)^2 \tag{8}$$

$$\dot{I}_t = \beta S_t(I_t - Q_t)(1 - \theta L_t)^2 - \gamma I_t \tag{9}$$

$$\dot{Q}_t = T_t - \gamma Q_t \tag{10}$$

Those quarantined do not contribute to the transmission of the virus, hence the term $(I_t - Q_t)$ in the law of motion for S and I. Tracing and testing a flow T_t of agents adds to the stock of those in quarantine. Those in quarantine recover at the same speed as those infected. The remaining notation, such as the "epi" parameters β, γ, the lockdown control L_t, and the parameter on effectiveness of lockdown θ are as in our baseline model.

The function $c(T; S, I, Q)$ gives the cost of tracing-testing T agents, which are put in quarantine when the state is (S, I, Q). This cost does not include the forgone output of the quarantine. We allow the cost function c to depend the flow of those traced-tested-quarantined, T, as well as on the composition of the state (S, I, Q). We assume that the function $c(T; S, I, Q)$ is increasing and convex in T, for fixed (S, I, Q), and that $c(0; S, I, Q) = 0$. Below, we elaborate more on the parameterization and interpretation of the cost function c and the presence of the state (S, I, Q) on it.

Given a state (S_0, I_0, Q_0) the planner minimizes:

$$\begin{aligned}\mathcal{V}(S_0, I_0, Q_0) = \min_{\{L_t, T_t\}} \int_0^\infty e^{-(r+\nu)t} \Big\{ & wL_t \Big[\tau(S_t + I_t - Q_t) + (1-\tau)(1-Q_t)\Big] \\ & + wQ_t + c(T_t; S_i, I_t, Q_t) + vsl\, \phi(I_t) I_t \Big\}\, dt \end{aligned} \tag{11}$$

subject to the laws of motion equation (8), equation (9) and equation (10) above for each $t \geq 0$. Note that those in quarantine do not work, so that there is the extra cost wQ_t in the period return function. Note also that the lockdown L_t applies to the remaining agents, which itself depends on whether there is an antibody test or not –in our notation whether the parameter $\tau = 1$ if there a test, or $\tau = 0$ otherwise. The parameter w, the value of statistical life vsl, the fatality rate function ϕ, and the total discount rate $r + \nu$ are as in our baseline case.

Two comments about the boundaries of the state space. First, if $Q_t = I_t$, i.e $X_0 = 0$, then $\dot{S}_t = 0$ and $\dot{I}_t - \dot{Q}_t = -T_t$. In this case, it will be optimal to set $L_t = 0$ and $T_t = 0$, and hence $I_r - Q_r = I_t - Q_t$, and $S_r = S_t$ for all the future $r \geq t$. Second, note that with a positive but finite value of $T_r = \hat{T} > 0$ applied for a long enough time, then $X(t) = 0$ in finite time $t < \infty$.

State Space Reduction. In this subsection, we describe the special case in which we can write the problem in equation (11) as a two dimensional state problem. We also describe the parameterization of the cost $c(\cdot)$ of tracing and testing.

To reduce the state space define X as the stock of those infected, not in quarantine:

$$X = I - Q \tag{12}$$

so that $\dot{X}_t = \dot{I}_t - \dot{Q}_t$, thus we can write:

$$\dot{S}_t = -\beta S_t X_t (1 - \theta L)^2 \tag{13}$$

$$\dot{X}_t = \beta S_t X_t (1 - \theta L)^2 - T_t - \gamma X_t \tag{14}$$

The initial conditions of interest are $X(0) = I(0)$ and $S(0) = 1 - X(0)$, since there is quarantine. Notice that $S + X \leq 1$ and that $T \in (0, X)$.

To eliminate $\{Q_t\}$ from the state, we rewrite the objective function. The expected discounted cost of output forgone for those in quarantine, denoted by $\mathbb{C}(\{Q\})$, can be written, using integration by parts and the law of motion of Q, as follows:

$$\mathbb{C}(\{Q\}) \equiv \int_0^\infty e^{-(r+\nu)t} Q_t dt = \frac{Q_0}{r + \nu + \gamma} + \int_0^\infty \frac{e^{-(r+\nu)t}}{r + \nu + \gamma} T_t dt$$

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which is equivalent to "booking" the expected discounted cost every time someone is traced and put in quarantine. The advantage of this formulation is that we can keep track of the forgone cost of output due to the quarantine using the contemporaneous control T_t.

The introduction of X as a state variable, and the use of the current control T to represent $\mathbb{C}(\{Q\})$ allow us to eliminate one state variable in the law of motion of the state. However, this is not yet enough to write the problem as a two-state variable problem, since the return function still requires to have (S, X, Q) or alternatively the original (S, I, Q). To see this note that the period cost is given by:

$$wL\Big[\tau(S+X) + (1-\tau)(1-Q)\Big] + \frac{wT}{r+\nu+\gamma} + c(T; S, I, Q) + vsl\,\phi(X+Q)\,(X+Q)$$

We will add two assumptions, which will allow to eliminate Q as part of the state, which we discuss in three steps:

1. The first term in the flow cost contains the forgone output cost of lockdown if there is no test, i.e. the term $wL(1-Q)$ if $\tau = 0$. This term can be dispensed of by focusing on the case with an antibody test, i.e. the case with $\tau = 1$. We will assume this from now on.

2. The second term where we have a Q is the specification of the tracing-testing cost $c(\cdot)$. We discuss the proposed formulation, and how it dispensed from the use of Q. The cost of finding a number of people T that are infected and aren't currently in quarantine, i.e. a member of the population X, should depend on the size of X in the population that is being trace-tested. If we assume that $\tau = 1$, that population is of size $S + X$. In one extreme, if testing is random, the number of people that have to be tested to identify T is $T(S + X)/X$. Simply put, it is harder to find someone infected if there are very few infected in the population and we search at random. If, instead, there is a smart tracing technology, the cost can scale at a lower rate relative to the composition

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of the pool. This motivates the following functional form:

$$c(T,S,X) = \eta\left(T\left(\frac{S+X}{X}\right)^{1-\zeta}\right) \tag{15}$$

where η is a weakly increasing, positive, and convex function, and where $\zeta \in [0,1]$ indexes how smart the tracing is. If $\zeta = 0$ then there is no tracing, and it is just random sampling. If $\zeta = 1$ then tracing is very powerful, the fraction in the population is immaterial, and the cost depends only on the number to be traced. Summarizing, the cost function $\eta(z)$ depends on the number of "tasks" that have to be carried out to identify T infected, and we parameterize the number of tasks as $z = T\left((S+X)/X\right)^{1-\zeta}$, where each "task" is a combination of tracing and testing.

3. The third term where Q shows up is the number of deaths per unit of time $\phi(X+Q)\,(X+Q) = \phi(I)\,I$, which depends on the total number of infected $I = Q+X$, regardless of whether they are in quarantine or not. This can be dispensed with if we consider the case in which the fatality rate function $\phi(\cdot)$ is constant, i.e. $\kappa = 0$, so that $\phi(X+Q) = \varphi\gamma X + \varphi\gamma Q$, where φ and γ are constant parameters.

Combining these assumptions, i.e. $\tau = 1$ and $\kappa = 0$, and again using integration by parts and the law of motion of Q to rewrite $vsl\,\varphi\gamma\int_0^\infty e^{-(r+\nu)t}Q_t dt$, we obtain the following per period flow cost:

$$wL\,(S+X) + T\frac{w + vsl\,\varphi\gamma}{r+\nu+\gamma} + \eta\left(T\left(\frac{S+X}{X}\right)^{1-\zeta}\right) + vsl\,\varphi\gamma X$$

Two-state-problem. If we consider the case of $\tau = 1$, i.e. the presence of an antibody test, so the first term involving Q drops out of the period cost, and $\kappa = 0$, so that Q drops out of the term involving the fatalities per unit of time, we can formulate the problem with only two state variables, but with two controls, L and T.

$$(r+\nu)v(S,X) = \min_{L\in[0,\bar{L}],T\in[0,\bar{T}]} wL\Big[S+X\Big] + T\frac{w+vsl\,\varphi\gamma}{r+\nu+\gamma} + \eta\left(T\left(\frac{S+X}{X}\right)^{1-\zeta}\right) + vsl\,\varphi\gamma X$$
$$+ \left[\beta\, S\, X\,(1-\theta L)^2\right]\left[\partial_X v(S,X) - \partial_S v(S,X)\right]$$
$$- \left[\gamma X + T\right]\partial_X v(S,X) \tag{16}$$

In the formulation in equation (16), we have also imposed a maximum flow of tracing-testing capacity per period of $\bar{T}$. We summarize the previous argument in the next proposition:

Proposition 1. Assume that there is an antibody test, so $\tau = 1$, and that the fatality rate function $\phi(I) = \varphi\,\gamma$ is constant, i.e. $\kappa = 0$. Let (S,I,Q) be the initial conditions for the original three state variable problem defined in equation (11), with a minimized value $\mathcal{V}(S,I,Q)$ and associated optimal policies $\mathcal{L}(S,I,Q), \mathcal{T}(S,I,Q)$. Let (S,X) be the initial conditions for the modified two state variable defined in equation (16), with a minimized value $v(S,X)$ and associated optimal policy $L(S,X), T(S,X)$. Then, for all $(S,I,Q) \in \mathbb{R}^3_+$ with $S+I+Q \leq 1$, and $I \geq Q$, we have:

$$\mathcal{V}(S,I,Q) = v(S,I-Q) + Q\frac{w+vsl\,\varphi\gamma}{r+\gamma+\nu} \tag{17}$$
$$\mathcal{L}(S,I,Q) = L(S,I-Q) \text{ and } \mathcal{T}(S,I,Q) = T(S,I-Q) \tag{18}$$

We note that the minimization problem in the right hand side of equation (16) is a convex problem in T. Instead, the minimization problem with respect to L, as in the problem without TTQ, is convex at the point where $\partial_X v(S,X) \geq \partial_S v(S,X)$.[8] It is instructive to compare the first order conditions for the two optimal policies. To simplify the exposition here, we

[8]In our computations we found this condition to hold in all the state space.

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will assume that they hold at an interior solution. Furthermore, we will use a quadratic cost $\eta(z) = z^2\alpha/2$. In this case the optimal L and T satisfy:

$$L = \frac{1}{\theta}\left[1 - \frac{w}{\theta\beta\, S\, \left(\frac{X}{S+X}\right)[\partial_X v(S,X) - \partial_S v(S,X)]}\right] \tag{19}$$

$$T = \frac{1}{\alpha}\left(\frac{X}{S+X}\right)^{2(1-\zeta)}\left[\partial_X v(S,X) - \frac{w + vsl\,\varphi\gamma}{r+\nu+\gamma}\right] \tag{20}$$

Both policies are aimed at reducing the stock infected X, so they depend on $\partial_X v(S,X)$. For $\zeta \leq 1/2$, so that the tracing-testing is not substantially better than randomly sampling the population, the expressions for the optimal L and T depend on a similar way on $\partial_X v(S,X)$ as well as on the ratio $X/(S+X)$, especially so for small values of X and larges values of S. This suggest that the two policies are complementary when ζ is low. Instead, with $\zeta = 1$, these expressions suggest that tracing will be used for low X and high S, but lockdown will not be used for those levels.

Numerical Examples. We display the heat map of policies L and T and the value function for the same parameter values used in Table 1, setting $\tau = 1$ and $\kappa = 0$ as required by our previous proposition. We set the upper bound on tracing-testing flow to $\bar{T} = 1$, i.e. testing at a speed such that the entire population will be tested in a year, and we set the testing-tracing cost to be quadratic, i.e. $\eta(z) = z^2\alpha/2$, with $\alpha = 0.02$. With this specification, if $z = T((S+X)/X)^{1-\zeta} = 1$, the cost will be $\alpha/2 = 0.01$. We consider the two extreme values of the effectiveness of tracing $\zeta \in \{0,1\}$. For instance, if $\zeta = 1$, then $z = 1$ means that with "perfect" tracing it takes one task to test-track one infected agent. Instead, with $\zeta = 0$, tracing one infected agent requires running $((S+X)/X)$ tasks.

Figure 3 shows the optimal policy and value function obtained from the baseline parameterization under two alternative assumptions about the efficiency of tracing. The upper panel assumes random tracing ($\zeta = 0$), i.e. to find infected individuals the population has to be tested at random. This makes testing very expensive, especially when there is a small

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number of infected, as shown by equation (15) which diverges as $X \to 0$. As a result, the policy makes no use of testing, nor of the lockdown. This is illustrated by the red path highlighted in the phase diagram of the upper panel of the figure. Recall that, as explained above, the model assumes a constant fatality rate ($\kappa = 0$), so that lockdown was not chosen even in the absence of the TTQ policy. Therefore, the overall welfare cost of this economy is the same one that was recorded in the absence of the TTQ policy following an outbreak with a 1% of infected agents. This cost is about 0.9% of annual GDP (see the third panel of Table 2).

Instead, when tracing is perfectly efficient ($\zeta = 1$), the policy changes substantially, as can be seen from the lower panel of the figure. Tracing, testing and quarantine even a tiny fraction of the population becomes substantially cheaper now, since they can be immediately identified as opposed to be searched at random. Since those agents can be easily discovered, it is optimal for the policy maker to trace them an quarantine them. The resulting plan, following an outbreak with a 1% of infected agents, yields a cost that is about 0.2 of annual GDP, a value that is about 4 times smaller than the cost of the benchmark case without the TTQ policy (the optimal path is hardly visible in the figure as the optimal policy squashes the fraction of infected to zero very rapidly).

Finally, we have tried larger values of a statistical life, such as vsl 40 or 80 times annual GDP, and $\zeta \in \{0, 1\}$. In these cases, we have found that in a larger and substantively overlapping region of the state space both policies are used. The subset of the state space differs depending on the values of vsl and ζ, but the fact that they overlap confirms the complementarity that is apparent from our analysis of the first order conditions above in equation (19) and equation (20).

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6 Future work

There are several extensions of interest. Our benchmark analysis with linear costs to social activity implies a gradual lockdown. Allowing for non-linear output costs will affect the implementation of the lockdown and shorten its duration, possibly giving rise to periodic lockdowns. We also overlooked the fact that a long lockdown could have "scarring" effects on the economy that could delay its restart (e.g. it could trigger a cascade of bankruptcies, with long unemployment spells affecting the workers' skills). Second, the quadratic search effects we assumed are a natural starting point under the SIR framework. Alternative matching technologies delivering different speed of transmission seem worth exploring. It would also be interesting to explore the optimal lockdown policy in a setup where social distancing is endogenous, since behavioral changes often taken place before governments enact the lockdown. Third, the considerable uncertainty surrounding key parameters of the SIR model suggests that a robust control approach is valuable. Lastly, it might be interesting to bring geographic elements and population migration into the picture. We believe all these are important topics for future research that can be analyzed within our setup.

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7 Figures and Tables

Table 1: Parameter Values for Benchmark Case

Parameter	Value	Definition/Reason
β	0.20×365	Annual increase of active cases if unchecked
γ	$1/18 \times 365$	Annual rate of infected recovery (includes those that die)
φ	0.01	Case fatality rate of 1%
κ	0.05	Implies a 3 percent case fatality rate with 40 percent infected
r	0.05	Annual interest rate 5 percent
ν	0.667	Prob. rate vaccine + cure (exp. duration 1.5 years)
$\bar{L}$	0.70	1 - GPD share health, retail, government, utilities, and food mfg.
θ	0.50	Effectiveness of lockdown
vsl	20	Value of Statistical Life $20 \times$ w (i.e. $vsl \approx \$1.3$M)

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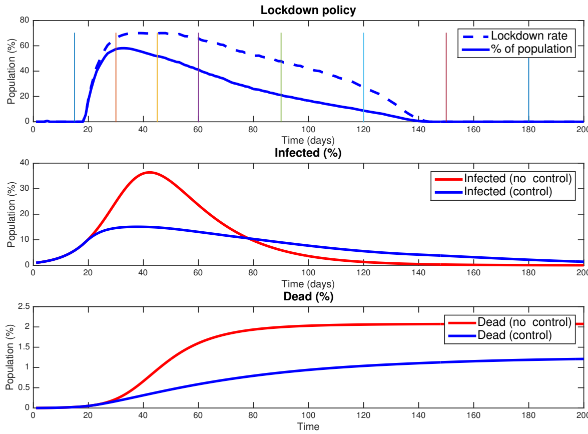
Figure 1: **Time paths under baseline parameters**

Panel A – Case w / testing ($\tau = 1$)



Panel B – Case w/o testing ($\tau = 0$)

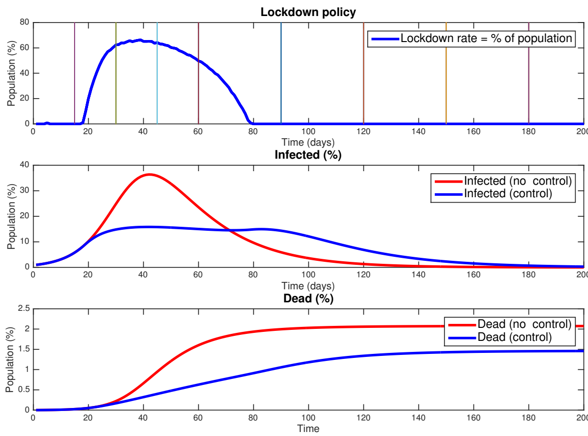
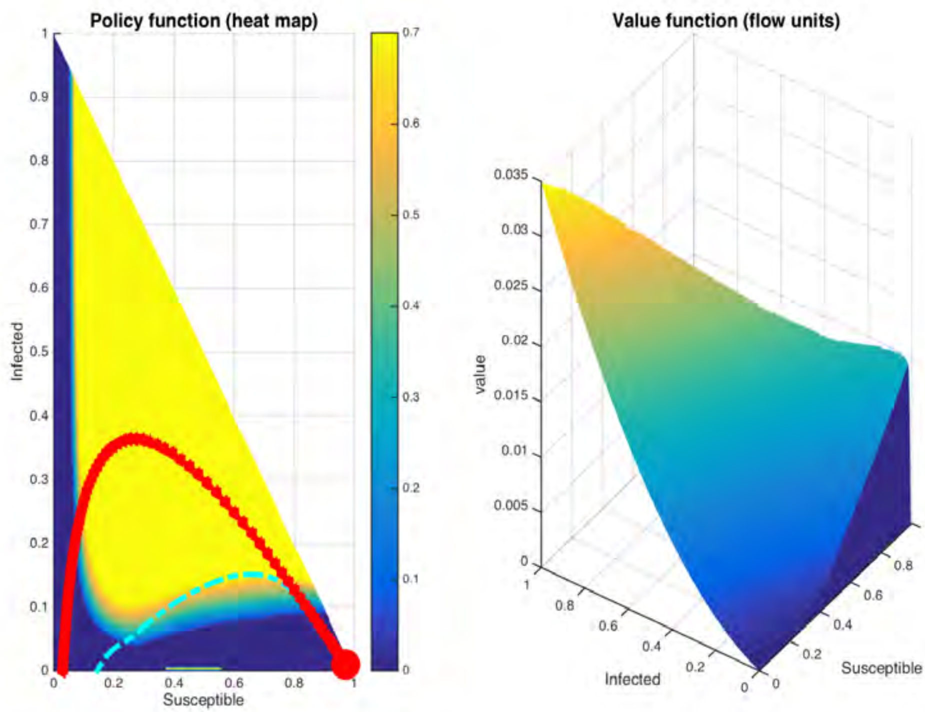


Figure Note: This figure uses the benchmark parameter values of Table 1. Panel A considers the case where a test is available. Panel B considers the case where the test is not available. The red lines describe the uncontrolled system, where no Lockdown is exercised. The blue lines correspond to the optimal control case. The initial condition is $I(0) = 0.01$ and $S(0) = 0.97$.

Figure 2: Value Function and Optimal Policy, benchmark case



Note: The figure on the left shows the optimal policy for the benchmark parameter values. The blue area indicates lower values of lockdown and the yellow color higher values. The figure on the left depicts the value function. The units for the value function are permanent flow cost as a fraction of the total output before the epidemic.

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Table 2: Welfare Losses $\left(\frac{rV(S,I)}{w}\right)$ with Optimal Policy vs. without Intervention

Case	Parameters	Optimal Policy		No Policy
		Welfare Loss	Output Loss	Welfare Loss
		Benchmark Case		
Low effectiveness	θ=0.3	1.7 %	0.3 %	1.9%
Medium effectiveness	θ=0.5	1.5 %	0.4 %	1.9%
High effectiveness	θ =0.7	1.4 %	0.4 %	1.9 %
		Alternative Values of Statistical Life		
vsl = 10× GDP per capita		0.9 %	0.2 %	0.9 %
vsl = 30× GDP per capita		2.0 %	0.6 %	2.8 %
vsl = 80× GDP per capita		3.7 %	1.4 %	7.5 %
		Constant fatality rate κ=0		
Low effectiveness	θ=0.3	0.9 %	0.0 %	0.9 %
Medium effectiveness	θ=0.5	0.9 %	0.0 %	0.9 %
High effectiveness	θ=0.7	0.9 %	0.0 %	0.9 %
		No testing of the recovered $\tau = 0$		
vsl = 10× GDP per capita		0.9 %	0.1 %	0.9 %
vsl = 20× GDP per capita		1.6 %	0.4 %	1.9 %
vsl = 30× GDP per capita		2.2 %	0.6 %	2.8 %
vsl = 80× GDP per capita		4.5 %	2.5 %	7.5 %
		Less pessimistic parameter values		
Lower speed of spread of the virus	$\beta = 0.1$	0.8 %	0.1 %	0.8 %
Lower fatality rate	$\varphi = 0.005$	1.1 %	0.4 %	1.5 %

Note: Welfare losses are measured by the permanent percent reduction in per capita GDP induced by the policy (or its absence) under various parameterizations. Output losses is the welfare cost component due to the reduced level of economic activity (i.e. excluding fatalities). The benchmark parameter values are from Table 1. Multiplying any of the numbers in the last three columns by $1/r = 20$, converts the losses from permanent flow to a one time payment as a fraction of a year GDP. The initial condition for all scenarios is $I(0) = 0.01$ and $S(0) = 0.97$.

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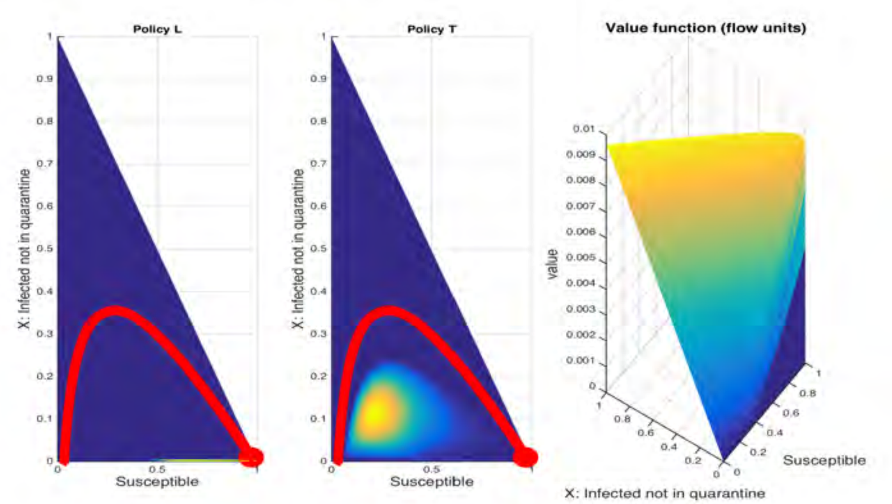
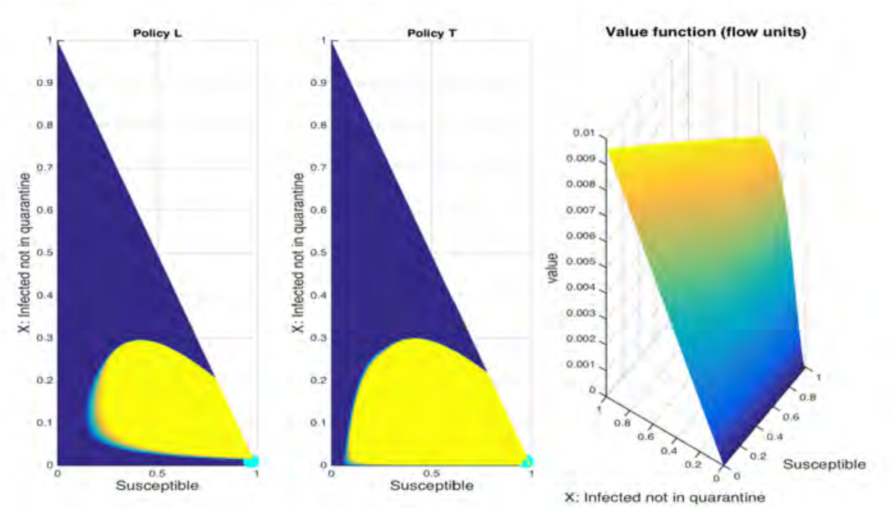
Figure 3: Value Function and Optimal Policy with Testing-Tracing-Quarantine

Random tracing



Perfect tracing



Note: The figure uses the benchmark parameter values. The upper panel assumes random tracing, namely $\zeta = 0$. The lower panel assumed perfect tracing, namely $\zeta = 1$

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Economic policy incentives to preserve lives and livelihoods[1]

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The Covid-19 pandemic has motivated a myriad of studies and proposals on how economic policy should respond to this colossal shock. But participants in this debate seldom recognize that the health shock is not entirely exogenous. Its magnitude and dynamics themselves depend on economic policies, and the explicit or implicit incentives those policies provide. To illuminate the feedback loops between medical and economic factors we develop a minimal economic model of pandemics. In the model, as in reality, individual decisions to comply (or not) with virus-related public health directives depend on economic variables and incentives, which themselves respond to current economic policy and expectations of future policies. The analysis yields several practical lessons: because policies affect the speed of virus transmission via incentives, public health measures and economic policies can complement each other, reducing the cost of attaining desired social goals; expectations of expansionary macroeconomic policies during the recovery phase can help reduce the speed of infection, and hence the size of the health shock; the credibility of announced policies is key to rule out both self-fulfilling pessimistic expectations and time inconsistency problems. The analysis also yields a critique of the current use of SIR models for policy evaluation, in the spirit of Lucas (1976).

1 Work on this paper was carried out while Roberto Chang served as BP Centennial Professor at the London School of Economics and Political Science. We acknowledge with thanks very useful conversations on the subject of this paper with several LSE colleagues, with Ricardo Hausmann from the Harvard Kennedy School, and with Norman Loayza from the World Bank. All errors are our own.

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1. Introduction

Imagine you are a middle-aged person living in a middle-class neighborhood in one of the world´s great cities. It has been a month since the government confined you and your family to your flat, and you are getting anxious. You are not one of those privileged professionals who can do all of your work online. Instead, you run the kind of small business that requires face-to-face contact, all day long. The government postponed some of your tax payments and the bank gave you a bigger credit line. But nonetheless your cash reserves are running low. As is the patience of your employees, who send ever more frequent messages asking when they will able to go back to work. They understand taking public transport to get to their jobs is risky, but staying home with the prospect of much-reduced incomes is looking riskier still. Your business could afford to remain closed for another month if you were certain the economy would spring back to normal at the end of that period, but nowadays … who can be certain about anything?

Much has been written since Covid-19 hit about the stark choices governments face between preserving lives and preserving livelihoods. Much less has been said about the equally stark choices regular citizens face. Yet in the end, what citizens do could be at least as important as what governments do in determining how, when and at what cost we overcome the pandemic.

If the those regular citizens live not in prosperous New York, London or Milan, but in Manila, Sao Paulo or Lagos, the choices they face will be particularly unappealing. Initial income levels matter. Going for two or three months with reduced or no paycheck may be feasible for well-off families in rich countries, but not for households in developing countries whose incomes hover barely above the survival line. In the developing world the prevalence of informal jobs in informal firms further hinders the policy response, since governments may be unable to identify and get emergency financial aid to the workers and firms that need it. In the absence of past tax returns and accounting statement, banks may not be able to lend in order to tide people over until the crisis ends.

And where governments have been inept, corrupt, or both, citizens may ignore their entreaties to stay locked down –or to return to work when the time comes. Even worse: because people´s willingness to forego income today hinges crucially on their confidence they will enjoy restored incomes in the future, trust in government policies, and the credibility of government announcements of an eventual recovery, are absolutely crucial for fighting the pandemic. But in countries where governments have seldom delivered on past promises, why should citizens believe them now?

To make sense of all of these complex and possibly conflicting factors, we need an *economic* theory of pandemics. And what the world has at its disposal today, for the most part, are *epidemiological* theories of pandemics. The difference is not just academic. *Epidemiological* theories are backward-looking: people´s past choices determine how many cases of infection there are today. By contrast, *economic* theories are forward-looking: people´s choices today – including the decision to engage or not in risky behavior that could result in infection— depend crucially on what they expect the future will bring.

An economic theory of pandemics is also necessary for the proper design of what government should and should not do during a pandemic. That is because economic policies can not only alleviate the economic and social effects of disease, but also change the severity of the pandemic itself. They can do so by changing the incentives that people face when making choices that, explicitly or implicitly, determine their risk of infection.

If this is so, then the analysis of alternative policies should take into account their possible incentive effects and the resulting impact on the dynamics of disease. Badly designed economic policies can be at odds with lockdowns, social distancing and other public health measures. But, our analysis shows, thoughtful economic and public health policies can also reinforce each other in reducing the impact of the pandemic.

To illuminate the feedback loops between medical and economic factors, we develop a minimal economic model of pandemics. In the model, epidemiological dynamics are similar to those in the standard SIR (susceptible-infected-recovered population) models. But, in contrast with those models, here contagion dynamics are affected by economic choices about whether to work or stay at home, today and in the future. In spite of its simplicity, the model yields interesting and sometimes unexpected results.

Unsurprisingly, the decentralized equilibrium of our economy is inefficient, because an externality is at work: when deciding whether or not to stay at home, people do not take into account the impact of their choice in the relative numbers of healthy and infected people “out there” in the workplace, and therefore on the overall speed of disease transmission.

Less obviously, the externality means that people can behave in a manner that is too risk-averse relative to the social optimum. If many infected people are at work already, and there isn´t enough testing to identify them and compel them to stay home, then having one more person go to work could in fact reduce the share of infected people in the workforce, and therefore cut back on the risk of infection. Since people do not internalize this effect, they choose to stay away from work even in circumstances when this is not socially desirable.

Multiple expectational equilibria can also occur. If one person expects others to behave in such a way as to reduce the risk of infection, then it can pay off to ignore lockdown provisions and go to work. An equilibrium follows in which no one stays home. Conversely, the expectation that others will stay home can make it attractive to stay home, and society ends up in a full —and fully voluntary— lockdown. These equilibria can be Pareto ranked. We show the economy need not land in the outcome a benevolent social planner would have chosen. Depending on parameter values, full lockdown and no lockdown at all can be equilibrium outcomes, even when neither is optimal.

Using this model we then turn to the effects of alternative economic and public health policies. We show that several economic policies can make a difference not only for economic payoffs but also for health outcomes. One such policy is paying people to stay home during the infection period.

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Such a transfer can induce more people to stay home, reducing contagion. But, we show, not just any payment will do. The transfer has to be large enough to induce expectations that other people will also stay at home. If too small, the transfer by itself will not succeed in eliminating the equilibrium in which everyone goes to work. Yet the transfer policy can work if complemented by fines on people who break a government-mandated lockdown. This illustrates how economic and public health policies can complement one another. An implication is that economic policies that provide appropriate incentives can reduce the costs of lockdowns — something government will like to hear, since the productivity and fiscal costs of generalized lockdowns are huge.

Strikingly, expectations of policies to be enacted after the initial contagion phase is over can matter for the extent of contagion itself. Any policy that causes people to expect higher future wages or, more generally, higher economic returns to being healthy —and therefore able to work— can induce individuals to stay home during the contagion phase. This is a novel reason to support expansionary policies to be implemented once the pandemic has peaked: if people come to expect them, they will have more reason to avoid infection today.

The danger, on the other hand, is that if people are pessimistic about the future they will behave today in ways that increase the risk of infection —and as a result make that pessimism self-fulfilling. Another danger is time inconsistency: after the pandemic has peaked the policymaker may find it that the cost of honoring the promise of wage subsidies or fiscal expansion is too high, and may therefore renege on the earlier announcement. This suggests that only governments with credible leadership and a history of respecting promises will be able to generate the kind of expectations of future policy that can help contain the pandemic today.

Finally, we also show large-scale testing to be a promising policy. But the conclusion comes with a twist: because testing reduces the risk of going to work, governments will have to pay people more to persuade them to stay home. So testing may have an indirect fiscal cost, unacknowledged so far.

The paper is structured as follows. Section 2 sets up our basic economic model of pandemics. Section 3 discusses the individual decision of whether to stay at home or working, and hence of how much exposure to infection risk is tolerable. Section 4 characterizes the general equilibrium of the model, while Section 5 contains a discussion of welfare aspects.

We develop our policy analysis in sections 6 and 7. Section 8 speculates on possible extensions, offers conjectures, and suggests additional implications. In that section we also relate our analysis to other existing work. Section 9 concludes.

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2. A model of epidemics and economic incentives

Consider a simple model of an economy that lasts two periods, $t = 0, 1$. One can think of period 0 as the initial contagion stage and of period 1 as the recovery phase.
There is a continuum of agents. Population is constant and its size normalized to one. There are two locations we call “home” and “work”. Each individual who goes to work in period t produces a quantity w_t of a single final good, so total output in this economy depends on the number of people who work outside their homes. Normally everyone would go to work, but these are not normal times.

At the beginning of time a fraction $1 - h_0$ of the population is infected with a virus. The rest are healthy. Assume further that a fraction q of the whole population is impossible to reach or test. As a result, in period 0 people in that group always go to out to work. Being drawn randomly from the whole population, qh_0 are healthy and $q(1 - h_0)$ are infected.

The remaining $1 - q$ people are available for testing.[1] Assume for simplicity that all are tested. Naturally, $(1 - q)h_0$ are revealed to be healthy and $(1 - q)(1 - h_0)$ are revealed to be infected. Those who learn they are ill are compelled to stay home and remain isolated. But each healthy person must decide whether to stay home or go to work. Call these people “decision-makers”.

A decision-maker’s choice is not trivial. If she stays home she has given earnings e_0, also in units of the good. She earns w_0 if she goes to work, but can contract the virus if she meets an infected person. As with all infected agents, the decision-maker must stay home at t = 1 if she gets the virus. In addition to being unable able to work, infected people suffer a utility loss χ. This is meant to capture the direct pain and suffering associated with illness.

The key aspect of this model is that the evolution of contagion is determined by people’s choices, which are health choices but also economic choices. To see this, let p denote the fraction of decision-makers who choose to go to work, and let be ϕ the probability that a healthy individual who goes to work does not get infected with the virus. It follows that the number of healthy people in the final period is

$$h_1 = h_0 - (1 - \phi)[qh_0 + p(1 - q)h_0]$$

The previous expression is just like the key equation in the famous SIR model of infectious transmission (Kermack and McKendrick, 1927), except that here ϕ depends on p. This apparently minor difference turns out to be crucial, since p (and therefore ϕ) are *endogenous*: they depend on the choices of decision-makers and reflect expectations about economic policy.

[1] Here and in the remainder of the paper we refer to antigen testing —that is, testing to detect if a person is currently infected. There is also antibody testing, which detects whether a person has developed immunity to the disease.

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Period 1 is very simple. Health status becomes public information at the end of period 0 and infection lasts until the end of period 1. So in that period $1 - h_1$ people are ill and must stay home, in which case they earn some amount e_1. The remaining h_1 people are healthy and, assuming $w_1 > e_1$, they choose to work and earn w_1.
How do people become infected? Healthy individuals can only catch the virus if they go to work in period 0. There is no contagion at home, reflecting the assumption that sick people are isolated.

In the workplace, the basic assumptions of the SIR model apply. When at work a person can be the victim of contagion by randomly meeting an already-infected co-worker. It follows that the probability that a healthy person at work is still healthy in the final period is simply equal to the percentage of the working population that is healthy. That is,

$$\phi = \frac{qh_0 + (1-q)ph_0}{q + (1-q)ph_0} < 1$$

The probability that a healthy agent who goes to work gets infected is then $1 - \phi$.[2]

With this definition the transition equation can be written as

$$h_1 = h_0 - \phi q(1 - h_0)$$

This is a little model of a huge phenomenon. Yet the model clearly illustrates a crucial interaction that has been virtually ignored in the literature: the dynamics of contagion depend, at least in part, on people's choices; and those choices depend on economic considerations —not only about current conditions, but also about future economic policies and outcomes.

3. Individual decisions

Consider the choice of a decision-maker in period 0. Staying home means that she receives earnings e_0. In addition, since there is no contagion at home, she will be able to work in period 1 and earn the reward w_1. Assume, for simplicity, that agents have linear utility and there is no discounting. Then the value to the decision-maker of staying at home is $e_0 + w_1$.

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[2] A more general formulation would allow each individual at work randomly to meet $(1 + \rho)$ others also at work. In turn, a healthy person at work would get infected with some probability κ if she met an infected worker. To alleviate notation, we shall impose $\rho = 0$ and $\kappa = 1$ in the subsequent discussion, although it will be clear that more general cases are easy to analyze.

Alternatively, the decision-maker can go to work in period 0. But then she runs the risk of infection and being unable to work in period 1. Recalling that the probability of infection at work is $(1-\phi)$, and that infection also causes a utility loss χ, the value of going to work in period 0 is $w_0 + \phi w_1 + (1-\phi)(e_1-\chi)$.

Hence a decision-maker will go work today if $w_0 + \phi w_1 + (1-\phi)(e_1-\chi)$ is greater than $e_0 + w_1$ or, equivalently, if

$$w_0 - e_0 > (1-\phi)(w_1 - e_1 + \chi)$$

She will stay home if the opposite is true.

This inequality is crucial and establishes how individual agents choose their exposure to contagion depending on economic variables. Indeed, the inequality compares the current gain from going to work to the expected loss, the latter given by the probability of infection times the sum of two elements: foregone income and disutility in the case of infection.

A decision-maker's choice depends on a "double relative": today's value of working relative to staying at home, and tomorrow's overall welfare relative to today´s. Both intra-temporal and intertemporal considerations matter. This will be particularly important for our policy analysis.

Observe also that the decision-maker's choice depends on $(1-\phi)$, the probability of infection at work. But, as we saw, that probability depends on how many decision-makers go to work. The final outcome is then determined by the equilibrium choices of all decision-makers.

4. Equilibria

An equilibrium is defined in the usual way. Given the linearity of the model, it is natural to start by asking whether there are equilibria with either $p = 0$ or $p = 1$.

Consider $p = 0$ first. In that case, $\phi = h_0$, reflecting the fact that if no decision-maker goes to work the probability of meeting a healthy agent in a random meeting is just equal to the frequency of the healthy in the initial working population. For this to be an equilibrium, a typical decision-maker must find it optimal to stay at home, which requires

$$w_0 - e_0 < (1-\phi)(w_1 - e_1 + \chi)$$

or, with $\phi = h_0$,

$$\frac{w_0 - e_0}{w_1 - e_1 + \chi} < 1 - h_0$$

Since the term on the RHS is always less than 1, an equilibrium in which all decision-makers stay at home exists in this model under some parameter conditions.

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What are those conditions? Observe first that the LHS is smaller, and the preceding inequality less restrictive, if χ is larger. This is only natural: if working outside the home can result in infection, decision-makers will choose to stay home if χ is sufficiently large.

Other factors are economic. The inequality is more likely to be satisfied if the relative cost of staying home today is small compared to the relative cost of staying home tomorrow. This is why the ratio on the LHS of the inequality increases with $w_0 - e_0$ and falls with $w_1 - e_1$.

Finally, the inequality is less restrictive if h_0 is small. In that case, the probability meeting an infected person at is large.

In an equilibrium with $p = 0$, the final number of infections is minimal. The transition equation for the share of healthy people becomes:

$$h_1 = h_0 - q h_0 (1 - h_0)$$

Note that this equation again has the SIR form, but now with $\phi = h_0$.[3]

While infections are lowest in an equilibrium with $p = 0$, the implications for production are ambiguous. In the first period the number of people at work is as small as it can be, so total output is minimized in that period. On the other hand, the number of available workers and, hence, total output in the second period are both maximized. We elaborate on the policy implications of this tradeoff in a later section.

Can there be an equilibrium with $p = 1$? Analogous reasoning leads to the conclusion that the answer is yes if

$$\frac{w_0 - e_0}{w_1 - e_1 + \chi} > 1 - \frac{h_0}{h_0 + q(1 - h_0)}$$

The intuition is analogous as that of the case $p = 0$. But there is a key difference. In an equilibrium with $p = 1$ each decision-maker's perception of the probability of infection if she goes to work is different than in an equilibrium with $p = 0$. This is because of the "contagion technology": the proportions of healthy versus and workers depend on how many decision-makers go to work.

The period-1 shares numbers of infected and healthy people are again given by equations of the SIR type. The healthy evolve according to $h_1 = h_0 - \phi q(1 - h_0)$, but in this case

[3] In this equilibrium, advocates of the SIR model would claim that the model would have been "right" if only they had been able to pin down the correct ϕ from past information. This is reminiscent of Lucas (1983), and also consistent with the current debate of shifting U.S. predictions for the impact of Coronavirus. See sections 8 and 9 for further discussion.

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$$\phi = \frac{h_0}{h_0 + q(1 - h_0)} < 1$$

which is bigger than the ϕ in the $p = 0$ equilibrium. This underscores the fact that the dynamics of contagion depend on economic factors. One of the important economic determinants is people's expectations about the future, which play no role in SIR-type models.

In fact, multiple self-fulfilling expectational equilibria can exist in this model. Given the analysis above, equilibria with $p = 0$ and $p = 1$ are feasible provided that

$$(1 - h_0)\left(\frac{q}{q + h_0(1 - q)}\right) < \frac{w_0 - e_0}{w_1 - e_1 + \chi} < (1 - h_0)$$

The intuition is as follows. More people get infected with the virus if more decision-makers go to work instead of staying home. But if more decision-makers go to work and infection rates increase, the relative rewards of working relative to staying home change in favor of the former, inducing more decision-makers to work, even after taking into account the higher risk of getting sick. Conversely, if more people stay home, infection rates fall, and future economic conditions change so as to induce decision-makers to remain home. So there is strategic complementarity across decision-makers´ actions, and that can produce multiple equilibria.

We do not want to overemphasize here the possibility of those multiple expectational equilibria. But we do wish to underscore the crucial role of expectations in determining the dynamics of contagion. The speed of contagion is not only a public health issue: it is an economic issue as well.

The main and key implication so far is that there is a two way interaction between public health outcomes (and, as we will see, policies) and economic variables, including policies. That the interaction goes both ways turns out to be crucial to think about policy. But so far in the discussion the link has only been recognized in one direction: economists have largely taken the dynamics of the epidemics as an exogenous shock, and tried to tweak the policy response to attenuate social costs. Our analysis reveals that feedback in the other direction can also matter: economic policies influence the severity of the pandemic itself.

We expand on the policy analysis shortly. But before it is necessary to take a stand on what is socially desirable in this situation. We now turn to that issue.

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5. Welfare implications

Suppose that the social welfare function is nothing but the weighted average of individual welfare levels, with the weights provided by the shares of the population at work and at home. Therefore,

$$W = [q + p(1-q)h_0]w_0 + [(1-q) - p(1-q)h_0]e_0 + h_1 w_1 + (1-h_1)(e_1 - \chi)$$

Clearly, social welfare is a function of p, the share of people who go to work. Ask next which is the setting of p a benevolent planner would choose in order to maximize social welfare. Appendix 1 shows that the sign of the derivative of W with respect to p is the sign of

$$(w_0 - e_0) - (w_1 + \chi - e_1)(1-\phi)^2$$

So if $(w_1 + \chi - e_1)$ is sufficiently large relative to $(w_0 - e_0)$, then social welfare is always decreasing in p. This is because having more people go to work has two effects that point in the same direction: it increases the human cost of infection and also cuts back on the number of people healthy who can go to work in the future, when $(w_1 - e_1)$, the gain from working relatively to staying at home, is large. In this case, there is no tradeoff between protecting lives and protecting livelihoods: keeping at home everyone who can be compelled to do so is clearly the better policy.

Conversely, if $(w_1 + \chi - e_1)$ is small relative to $(w_0 - e_0)$, then staying at home has benefits but also costs, because it means foregoing the relatively large reward from working in period 0. In this case there is indeed a tension between protecting lives and protecting livelihoods.

Appendix 1 also shows that the second derivative of W with respect to p is always positive, meaning the social welfare function is convex, not concave, in the share of people to go to work. So there is no interior optimum. The choice for the benevolent planner is simply between $p = 0$ (everyone stays home) or $p = 1$ (everyone who can goes to work).

Which one is better? Appendix 2 shows that $p = 0$ is preferred if

$$\frac{w_0 - e_0}{w_1 - e_1 + \chi} < \gamma(1 - h_0)$$

where

$$\gamma = \frac{q(1-h_0)}{h_0 + q(1-h_0)} < 1$$

By contrast, under decentralized decision-making the condition was

$$\frac{w_0 - e_0}{w_1 - e_1 + \chi} < 1 - h_0$$

Two conclusions strike the eye. The first is that the condition for the planner is not the same as for the individual. That is not surprising, given that there is an obvious externality: in deciding to go or not to work, individuals do not take into account the impact their own decisions have on the aggregate infection risk.

The second conclusion is more surprising: because the coefficient γ is smaller than one, the condition for $p = 0$ to be optimal is more stringent for the planner than for the individual! Put differently, $(w_1 + \chi - e_1)$ has to be larger relative to $(w_0 - e_0)$ in the case of the planner. So individuals are more "conservative" (more inclined to stay home) than is socially optimal.

Why is that so? Because the proportion of infected people is smaller among decision-makers than among people "out there" in the workplace, and what decision-makers fail to internalize is that if they go to work, they actually help reduce —not enhance— the risk of contagion at work.

The practical implication is that society could end up locked down even in situations in which that is not socially desirable to do so. That may seem far-fetched but isn´t. Think of the UK, which initially tried to adopt a soft lockdown like the one Sweden has adopted, but soon gave up because of political pressure to "do more". Or think of Chile, where mayors are constantly pressuring the national government to impose a more stringent lockdown, in more regions of the country, than the government thinks is necessary or desirable.

The point may also be relevant when the time comes to lift lockdown policies. So far the focus has been on persuading people to stay home. But eventually governments will also have to persuade people to go back to work. The analysis here suggests that the second task may turn out to be anything but easy or straightforward.

We have postulated that the social welfare function is the weighted average of the ex post utility of the individual agents in the economy, which turns out to coincide with the expected welfare *ex ante* (that is, prior to the contagion period) of the representative individual. One can argue, however, that social welfare can be different from expected individual welfare for a number of reasons. So the social cost of infection could larger than the individual cost. One way to capture this possibility is to replace the parameter χ in the previous social function W by some $\hat{\chi} > \chi$, with the gap $\hat{\chi} - \chi$ capturing the discrepancy between the social and individual cost of infection.

With this change the analysis in this section remains the same except for one observation: if the social cost $\hat{\chi}$ is high enough, the social optimum entails minimizing the extent of contagion — that is, setting $p = 0$ no matter what. In the current debate it is often claimed that policy should aim to minimize the number of infections regardless of economic costs. Assuming a sufficiently large $\hat{\chi}$ is one way to formalize and justify that belief.

6. Policies during the contagion phase

Our model is extremely simple, but precisely because of that simplicity it helps identify and understand the implications of alternative policies —both of public health policies such as lockdowns and economic policies such as taxes and transfers.

Government policies require resources, which in turn have an alternative social value. To say something about desirable policies, one must take this alternative social value of resources into account. We do that in the following way.

Suppose the government that can impose taxes, make transfers and enact laws. Assume it can also provide a public good, which is purchased at the end of period 1 and has social utility value proportional to the amount spent. One can think of the public good as infrastructure, or international reserves, or the assets held in a sovereign wealth fund. Regardless of the precise interpretation, suppose that if the government invests i in the public good, all agents receive a utility bonus αi, where α is a positive constant. The assumption that the marginal value of the public good is constant keeps the analysis that follows manageable.

As for public finance, assume that at $t = 0$ the government has an initial endowment $f > 0$. Aside from transfers to households, the government has no other expenditures. It can borrow or lend at a zero interest rate (this is consistent with equilibrium because our assumptions ensure that private agents would in fact be willing to borrow and lend at a zero rate).

Imagine that in the absence of the virus the government would have imposed no taxes nor made any transfers. In that case, the size of the public good provided would be given by the size of the initial government reserve, so $i = f$. Utility for each person would be $w_0 + w_1 + \alpha f$.

Now consider what happens when the virus hits. As a benchmark, suppose that

$$\frac{w_0}{w_1 + \chi} > 1 - h_0$$

We showed earlier that under these parameter values the only equilibrium in the absence of government action is $p = 1$ and therefore the highest possible rate of infection. In that case the virus causes expected utility to fall to

$$[q(1 - h_0) + h_0]w_0 + h_1 w_1 - \chi(1 - h_1) + \alpha f$$

with

$$h_1 = h_0 - \frac{q h_0(1 - h_0)}{q + (1 - q)h_0}$$

The absence of government action implies two kinds of losses: fewer agents work in both periods and in the end there are $(1 - h_1)$ infections, which inflict a direct utility loss $\chi(1 - h_1)$.

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Now suppose instead that in response to the virus the government gives a transfer to people who stay at home in period 0. This means that the government makes e_0 positive instead of zero. What is the impact? With a positive e_0, one might guess that expected utility would become

$$[q(1-h_0)+h_0]w_0+(1-q)(1-h_0)e_0+h_1w_1-\chi(1-h_1)+\alpha[f-(1-q)(1-h_0)e_0]$$

with h_1 defined as in the previous equation. This is a natural conjecture. With $p=1$, a group of people of size $(1-q)(1-h_0)$ would receive the transfer, which would have to be financed with an equivalent-size reduction in public good provision.

Would this policy be welfare-improving? The expression above reveals it would be if and only if α, the marginal value of the public good, is less than one. When $\alpha>1$ a positive e_0 would not be justifiable, no matter how much direct pain and suffering the virus causes. Remarkably, this conclusion would follow independently of the values of w_0, w_1 and χ.

The preceding analysis takes the dynamics of infection as "shock" to be confronted by economic policy. That is precisely what makes it wrong. It fails to acknowledge that e_0 alters economic incentives for people to stay home and, in so doing, it can cut the severity of the infection shock.

In particular, suppose that e_0 is chosen so that

$$(1-h_0)\left(\frac{q}{q+h_0(1-q)}\right)>\frac{w_0-e_0}{w_1+\chi}$$

Then, in equilibrium, p must fall to zero: no decision-makers go to work and expected utility is

$$qw_0+(1-q)e_0+h_1w_1-\chi(1-h_1)+\alpha[f-(1-q)e_0],$$

where, in this case,

$$h_1=h_0-qh_0(1-h_0)$$

This last equation indicates that the number of infections falls to its lowest possible level.

Therefore, the correct analysis differs from the previous "incorrect" one by taking into account the changes that e_0 induces on individual choices. It recognizes that a large enough e_0 causes decision-makers to stay home. Total output changes: it falls in period 0 because fewer people go to work, and increases in period 1, because more people are healthy then. Last but certainly not least, the increase in h_1 has the direct beneficial effect of reducing pain and suffering.

The total fiscal cost of transfers would be $(1-q)h_0e_0$, with a direct utility impact of $(1-\alpha)(1-q)h_0e_0$. If $\alpha<1$ there is no tradeoff. But if $\alpha>1$ the policy has a direct utility cost, which has to be weighed against the indirect utility benefit caused by the change in behavior. The rewards for work w_0 and w_1 and the direct cost of infection χ are important to evaluate overall welfare effects. Indeed, for a large enough χ, it would be optimal to set a positive e_0.

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The general point is that economic policies can have incentive effects on the individual decision problems about how much infection risk to take, which can induce agents to change their choices in a way that alters the dynamics of infection. Designing economic policy to deal with a pandemic must take this possibility into account, for it can alter the relative evaluation of alternative policies. At the same time, the potential change in behavior can provide opportunities to reduce the human cost of the crisis if measures are properly tailored.

Consider, for example, the impact of cash transfers. In our model, a general cash transfer in period 0 is simply a gift of some size, say τ, to all agents. A moment's thought reveals that the transfer's impact on expected utility is just $(1-\alpha)\tau$, the difference between the consumption value of the transfer to agents minus the value of the cost of the transfer (the reduction of the size of the public good i). What about the impact on equilibrium infection rates? There is none, since a general cash transfer does not have any incentive effects: it increases the payoff of deciders by τ regardless of whether they work or stay home.

In contrast, a policy of giving transfers to individuals that stay home in the initial period does have incentive effects, as we saw before. This is the traditional argument for targeted cash transfers, except that here "targeted" acquires a particular meaning: transfers are more effective if allocated to people who stay home, because in addition to compensating for lost income they reduce the relative reward of work and hence the risk of infection and the spread of the virus.

The same argument applies to expanded unemployment insurance benefits. If viewed simply as a way of propping up household consumption, the policy is imperfect in that it only reaches people who already had jobs. Our model reminds us that increased unemployment insurance benefits have an additional effect: they can induce workers to stay home. In fact, e_0 could be interpreted as unemployment insurance.

So far we have asked how government can induce people to stay home by means of economic incentives. But "lockdown" policies can also be non-voluntary. Suppose that the government enforces a lockdown by imposing a penalty π on anyone found working during the contagion period. We can thing of π as a fine, jail time, or perhaps social sanction like public shame. In all these interpretations π, if paid in equilibrium, involves a deadweight loss.

A small π would not induce the low-infection equilibrium, but it is obvious that a large enough π would induce decision-makers to stay home, resulting in the low-infection equilibrium. If this equilibrium is preferred to the high-infection one, the lockdown has a beneficial effect.

But it can also result in a deadweight loss. If you interpret q in our model as the fraction of the population that must work during the contagion period (for instance, those workers perform essential functions), then the social deadweight loss of the lockdown is at least $q\pi$. In fact, it could be larger. If incentives to work are strong enough, then as many as $q+(1-q)ph_0$ could choose to pay the fine, in which case the deadweight loss would be $[q+(1-q)ph_0]\pi$.

This suggests that lockdowns enforced by fines can be a very blunt way to slow the spread of the virus. But it also reveals a more subtle point: economic policies can make a lockdown more effective. To see this, suppose that the penalty π is too small in the sense that equilibrium would remain at $p = 1$. Clearly a sufficiently large increase in the period-1 transfer e_0 would ensure that equilibrium shifts to $p = 0$. Hence the transfer would render the otherwise counterproductive lockdown effective at reducing infection. And the reverse also holds: a transfer e_0 can be too small by itself to ensure the low infection equilibrium, but can attain that equilibrium if a lockdown policy is added. In other words, economic policy and health policy can be *complements*.

7. Contagion and expectations of policies during the recovery

People's choices in period 0, and hence the dynamics of infections, depend not only by policies on that same period. They also depend on expectations about policies and economic outcomes in period 1. This is so because decision-makers face an intertemporal trade-off: working today, and earning more income than if staying home, puts them at risk of infection and not being able to work tomorrow. Hence their choice depends on policies that affect the relative reward to work tomorrow, and on w_1, the expected size of that reward.

For instance, consider a transfer of size τ to people who work in period 1. If the transfer is large enough, in the sense that

$$(1 - h_0)\left(\frac{q}{q + h_0(1 - q)}\right) > \frac{w_0}{w_1 + \tau + \chi},$$

then the high-contagion, $p = 1$ equilibrium disappears and the only feasible outcome is the one with $p = 0$. Intuitively, expectations of a high reward to work in the final period increase the expected cost of infection, inducing the individual decision-maker to stay home.

We can think of the period 1 reward to work as resulting from expansionary macroeconomic policy in the recovery phase. For example, one could append to our simple economy a macroeconomic model. The government would have the ability to increase w_1 by means of a fiscal expansion presumably financed by borrowing, implying a final fall in the size of the public good i. In such a situation, a fiscal expansion would work exactly as the τ transfer just described.

If the low-infection equilibrium is socially preferred to the high-infection equilibrium, then there is a new argument in favor of expansionary policies during the recovery phase: such policies might be desirable not only because of their impact on output and wages during the infection phase, but also because they affect incentives and help lower the rate of infection, increasing the size of the workforce available during the recovery.

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This argument is quite intuitive. People will be willing to be "locked down" and to forego income in the short run if they expect the initial sacrifice will have a payoff in terms of both reduced infection rates *and* higher chances for well-paid employment once the crisis begins to abate. But if people come to expect the economy will be in sorry shape and their own incomes will be low in the future, then it is quite possible they will feel compelled to go out and try to increase their earnings today. That, of course, will increase the rate of infection, lower h_0 and reduce aggregate income tomorrow, thus ensuring the economy will indeed be in bad shape!

This line of reasoning suggests a second avenue for strategic complementarities and possible multiple equilibria in this model. So far we have treated w_1, the wage in the recovery phase, as exogenous and independent of the number of people who are healthy and able to work in period 1. But it could well that there are some economic activities that have fixed costs of operation, so that they need minimum numbers of workers and/or customers to restart. In that case the average wage could be increasing in h_1, the share of healthy people in period 1.

The rest of the story is easy to tell. If people expect a high monetary reward from being healthy and being able to work in the future, then they will be more likely to stay home and reduce the chance of infection today, enlarging the workforce tomorrow and making a buoyant economy possible. At the same time, the pickup in economic activity would increase government tax revenues, making it more feasible for the government to undertake expansionary policies and deliver another round of growth vitamins.

The lesson, then, is that people´s willingness to behave cautiously during the emergency depends crucially on expectations of what will happen to the economy and what government policies will be during the recovery phase. But before we get too excited at the prospect of self-confirming cycles of optimism and infection abatement, one warning: promises of future expansion may be time-inconsistent, and therefore less than fully credible.

This is clear in the case of $\alpha > 1$. Then, when the recovery phase arrives the government will have an incentive to reduce the size of any transfer τ it may have previously promised: each unit saved in transfers would allow for a unit increase in the size of the public good, implying a net utility gain of $(\alpha - 1)$. Since at that point the final number of infected people has already been determined, a benevolent government would deliver smaller transfers than announced earlier. As we know full well from the literature on time inconsistency, government promises during the initial contagion phase would then be likely to be ignored, unless the government has some way to commit not to break those promises during the recovery phase.

So we conclude that policies expected for the recovery phase can have a significant influence on individual choices during the initial crisis phase and, consequently, on the dynamics of contagion and the spread of the virus. At the same time, for those policies to have an impact they have to be announced in advance and be credible. This suggests that only governments with enough credibility, built via durable institutions or a history of honoring promises, can take advantage of this policy option and use it to diminish contagion.

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8. Extensions and relation to existing work

How general are our results? At some level, they are very general: they come from marrying the standard account of infection transmission with a minimal model of economic behavior that responds to incentives. And they follow from a very simple but intuitive principle: if economic policies can affect those incentives, then they can affect the transmission of disease. So our approach to policy should apply in any model where the dynamics of infection depend, at least to some degree, on individual economic choices.

While our main messages do not depend on the particulars of the model (which is why we endeavored to convey them in the simplest model we could think of), it is worth thinking about the role of different features of the model and how some of our more specific results may depend on them.

Many of our assumptions, such as the linearity of preferences or a fixed output per worker, should not be too hard to relax and are unlikely to change anything substantial in the analysis.

More fruitful is to examine the implications of changing the technology of infection, which is the more novel part of our model. We started by assuming that a share q of the population cannot be reached or tested, while the rest of the population can be. As a result, so-called decision-makers are drawn from a set of people who know they have been infected. When those decision-makers choose to go to work, they enlarge the share of healthy people in the workforce. That is why ϕ, the probability of being infected at work, is increasing in p, the share of decision-makers who do work.

That specification is special in several ways. It implies that the share of decision-makers who are infected is less than the share of infected people "out there" in the workplace (or the street, the store, the public bus or the subway cart). That seems like a reasonable description of society in the early stages of spread of the virus, when many people are yet to be reached by authorities, informed of what is going on, and tested. But it also means that sending more decision-makers to work during the contagion period changes the proportions of healthy people versus infected ones in favor of the former. And while all decision-makers know themselves to be healthy, they do not internalize the impact of their individual choices on the aggregate probability of infection. This combination of features explains why there may be strategic complementarities, allowing for multiple equilibria and for the peculiar nature of externality effects.

We can ask, then, what happens if the parameter q falls. This is a particularly interesting question because a lower q is tantamount to an increase in the scale of testing, which Paul Romer and others have forcefully advocated.[4] Leaving aside issues of feasibility and scalability of large-scale testing, what are the effects of that policy?

[4] See, for example, Romer and Garber (2020).

For any given p, in the model the effect of q on the probability that a decision-maker stays healthy is given by:

$$\frac{\partial\phi}{\partial q} = -\frac{h_0\, p(1-h_0)}{[q+(1-q)ph_0\,]^2} < 0$$

So more testing means fewer chances of being infected and stronger incentives to go to work.

Assume that the government attempts to induce decision-makers to stay home by giving them a transfer during the contagion period. Recall that the transfer would be always (that is, regardless of expectations) effective at attaining such objective only if

$$(1-h_0)\left(\frac{q}{q+h_0(1-q)}\right) > \frac{w_0-e_0}{w_1+\chi}$$

Clearly, the LHS is an increasing function of q.

Therefore, in the presence of more testing, the transfer necessary to keep people home is larger! This may seem surprising but is not: if it is now less risky to go to work, people will demand a larger compensation to stay home.

So large-scale testing is not without wrinkles. Or, to put it differently, to the direct logistical costs of testing millions of people every few days one should add the higher indirect cost of compensating them, once they have been tested, to make sure they do not go to work.

An extension would need to place the extent of testing at the center of our model. For instance, different shares could be tested within the q-population that must always go to work and the $(1-q)$ population that can choose whether to do so. That could reverse the nature of the externality at work, and cause equilibrium behavior to be excessively risk-taking.

Observe also that we have assumed that, after testing, individuals not only learn if they are infected or not, but also forced to stay home if they turn out to be sick. In the parlance of Romer and others, we have assumed a “testing-cum-isolation” policy. But one could also ask what would happen if there is random testing but no isolation requirement. This may be a realistic alternative.

In our model analyzing a testing-without-isolation policy would require asking what would happen if infected individuals had the choice of working or staying at home in the initial period. Presumably the answer would depend on assumptions about how the rewards from working are affected by sickness —in a plausible case, w_t would be lower for infected people. This extension may be worth pursuing, but falls outside the main focus of our paper.

Likewise, we have assumed that individuals are *ex ante* identical. A straightforward extension of our model could allow for *ex ante* health heterogeneity. We assumed so far that at work a healthy person gets infected with probability one if she meets an infected coworker. Instead one could

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assume that the probability is given by some idiosyncratic parameter θ, where θ has a non-degenerate distribution in the population. This would capture the fact that people have different degrees of susceptibility to contagion, perhaps because of age.

An educated conjecture is that appropriate assumptions about the distribution of θ would introduce enough smoothness into the model so that equilibria other than the extreme $p = 0$ and $p = 1$ would appear. An interior equilibrium, with $0 < p < 1$, would have the appealing property that only *ex-ante* healthier decision-makers (that is, those with θ greater than a certain threshold, if higher θ corresponds to lower probability of infection) would work.

Guessing other consequences of this extension is more hazardous. It is not obvious, for instance, that multiple equilibria would disappear; on the contrary, equilibria could become even more abundant. These questions offer promising avenues for future research.

Clearly many other extensions are imaginable, and one could endlessly conjure alternative formulations and their implications. To a large extent this is the case because the literature on the economics of pandemics is in its very early infancy. So rather than speculating further on variations of the model, it seems more fruitful at this point to clarify how our paper contributes to the related literature.

Our paper is most closely related to the very recent papers on macroeconomic policy responses to the Covid-19 crisis. Prominent examples are Fornaro and Wolf (2020), Faria e Castro (2020), and Jorda, Singh and Taylor (2020). These and other papers attempt to characterize the dynamics of the economy under alternative macroeconomic policies in an infinite-horizon setting. But they all take the dynamics of the Covid-19 pandemic as exogenously given.

Fornaro and Wolf (2020) argue that the pandemic can be seen as an adverse shock to productivity growth, while in Faria e Castro (2020) pandemics are tantamount to preference shocks. By contrast, our model has only two periods and is much less ambitious in terms of dynamics, but it does characterize the dependence of contagion on individual economic decisions. And, to the extent that individual decisions depend on current and future policy, the evolution of the pandemic can be influenced by policy. In this sense, modeling the impact of Covid-19 as exogenously given shocks potentially leads to invalid policy analyses. But the quantitative significance of this shortcoming remains, of course, an empirical issue.

Two recent papers include a channel for policy to influence virus dynamics though its impact on the decisions of individuals: Eichenbaum, Rebelo and Trabandt (2020); Jones, Phillipon, and Venkateswaran (2020).[5] They all develop dynamic models where a virus hits the economy and contagion follows SIR-type dynamics. Moreover, SIR equations are assumed to depend on consumption and hours worked. As in our analysis, individual agents understand that their consumption and labor supply choices have implications for their exposure to contagion.

[5] See also Kaplan, Moll and Violante (2020).

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But there are several differences between those papers and ours. The main focus of Eichenbaum et al. and Jones et al. is on describing and quantifying dynamic implications, while our goal is to clarify and explore the channels through which policy can affect behavior and therefore the transmission of infection.

Perhaps most consequential for policy are differences in the specific way economic activity affects contagion. Eichenbaum et al. and Jones et al. both assume that contagion increases with the levels of aggregate consumption and production. They do not provide a microeconomic justification for that assumption, but simply take it as a reduced form.

In contrast, our paper provides an explicit environment where SIR-type dynamics emerge endogenously. This difference turns out to matter. For example, in Eichenbaum et al. and Jones et al., increasing consumption taxes during the contagion phase of a pandemic reduces infections, which is an argument in favor of such a policy. In our model, consumption taxes have no impact on individual choice and therefore no effects on contagion dynamics.

The gravity of the Covid-19 epidemic has motivated a myriad of policy proposals. An influential collection is Baldwin and Weder di Mauro (2020). Loayza and Pennings (2020) provide a useful policy overview, with emphasis on developing countries. Gourinchas (2020) discusses the need to coordinate economic responses and health policy, but he does not provide a formal analysis.

Macroeconomics *aficionados* will recognize a close connection between our analysis and the influential Lucas (1976) critique of econometric policy evaluation. For a given set of economic and health policies, any equilibrium of our model implies that infection dynamics are similar to those of the SIR model, whose parameters are a function of "deeper" underlying aspects of the environment, including policies. An implication is that the SIR parameters must change if policies change. That is not simply a theoretical curiosity. Rather, it is critical for policy analysis.

Lucas argued that macroeconomic policy based on reduced form econometric equations, especially the Phillips Curve, was unsound, because the parameters of those equations would shift as people changed behavior in response to policy. Strikingly, he showed that this would be the case even if the predictive power of the econometric equations, estimated from data from previous episodes, was strong: the equations would become unstable and the parameters change in undefined ways when new policies were implemented. Substitute "reduced form econometric equations" for "SIR equations" and the Lucas Critique applies with force to the current situation. This is one key takeaway from our paper.

9. Final remarks

The success or failure of public policies to fight the pandemic will depend on whether those policies induce socially-desirable patterns of behavior among ordinary citizens. And how people choose to behave in turn depends on a myriad of factors, including not only expectations of future policies, but also expectations of how other people will respond to those policies.

This paper provides a minimal model to understand the feedback loops involving economics, public health and expectations. One lesson is that is easy for things to go frightfully wrong. If people come to be pessimistic —for instance, about the extent of contagion or the future health of the economy— they can react in ways that will make that pessimism self-fulfilling.

But another lesson is that there are policies that can potentially avoid those pitfalls. This paper has studied and characterized some of those policies in a minimal setting. Doing so in a richer environment, where the quantitative aspects of those policies can be explored more fully, is clearly a priority for future research.

We claim that economic policy can change the dynamics of contagion via its impact on incentives. How important is that link likely to be in practice? Several aspects of the current crisis suggest it can be quite important indeed.

Look at the massive change in recent projections of Covid-19 deaths in the United States. As recently as the end of March, the Trump administration was publicly projecting virus-related deaths between 100,000 and 240,000 by the end of the U.S. Summer. Less than two weeks later, the official estimate came down to just 60,000. This much-lower number is comparable to the usual number of deaths caused by influenza every year.

What explains the astonishingly large and sudden change in the official estimates? According to health officials and commentary by public health experts, the previous dire predictions assumed low compliance rates with lockdown and social distancing measures. That assumption turned out to be wrong: compliance by the U.S. population has been much better than expected, and that accounts for the bulk of the change in death estimates.[6]

This is, of course, encouraging news. The main point, however, is that whether or not people adhere to instructions to stay at home is crucial for the number of deaths from the virus. It is less obvious that those individual decisions are likely to influenced by economic factors and policy incentives. In fighting the pandemic, policymakers and economists will be well served by remembering that fact and its implications.

[6] This is an ongoing debate that has been widely reported by the press. See, for example, “US Coronavirus Predictions Have Shifted. Here is Why”, CNN.com, April 9 2020.

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Appendix 1

Welfare is

$$W = [q + p(1-q)h_0]w_0 + [(1-q) - p(1-q)h_0]e_0 + h_1 w_1 + (1-h_1)(e_1 - \chi)$$

Using the transition equation GDP can be written as

$$W = e_0 + e_1 + [q + p(1-q)h_0](w_0 - e_0) + [h_0 - \phi q(1-h_0)](w_1 + \chi - e_1) - (1-h_0)\chi$$

It follows that

$$\frac{\partial W}{\partial p} = (1-q)h_0(w_0 - e_0) - q(1-h_0)(w_1 + \chi - e_1)\frac{\partial \phi}{\partial p}$$

which, substituting in the value of $\frac{\partial \phi}{\partial p}$, becomes

$$\frac{\partial W}{\partial p} = (1-q)h_0[(w_0 - e_0) - (w_1 + \chi - e_1)(1-\phi)^2]$$

So W can be either increasing or decreasing in p.

Notice also that

$$\frac{\partial^2 W}{\partial p^2} = 2(1-q)h_0(w_1 + \chi - e_1)(1-\phi)\frac{\partial \phi}{\partial p}$$

$$\frac{\partial^2 W}{\partial p^2} = \frac{2(w_1 + \chi - e_1)(1-q)^2 {h_0}^2 (1-\phi)^3}{q(1-h_0)} > 0$$

So if $(w_1 + \chi - e_1)$ is sufficiently large relative to $(w_0 - e_0)$, W is a U-shaped function of p, with a minimum at

$$\phi = 1 - \left(\frac{w_0 - e_0}{w_1 + \chi - e_1}\right)^{\frac{1}{2}}$$

Finally, note that welfare if $p = 0$ is

$$W(p=0) = e_0 + e_1 + q(w_0 - e_0) + h_0[1 - q(1-h_0)](w_1 + \chi - e_1) - (1-h_0)\chi$$

and, if $p = 1$, it is

$$W(p=1) = e_0 + e_1 + [q + (1-q)h_0](w_0 - e_0) + h_0\left[\frac{h_0}{h_0 + q(1-h_0)}\right](w_1 + \chi - e_1) - (1-h_0)\chi$$

Appendix 2

From the above, it follows that

$$W(p=0) - W(p=1) = (1-q)h_0 \left\{ (1-h_0) \left[\frac{q(1-h_0)}{h_0 + q(1-h_0)} \right] (w_1 + \chi - e_1) - (w_0 - e_0) \right\}$$

So from the point of view of the planner it is best to set $p = 0$ and keep everyone home if

$$\frac{w_0 - e_0}{w_1 - e_1 + \chi} < \gamma(1-h_0)$$

where

$$\gamma = \frac{q(1-h_0)}{h_0 + q(1-h_0)} < 1$$

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Where are the missing emergencies? Lockdown and health risk during the pandemic[1]

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Health care practitioners around the globe have observed that the COVID-19 crisis has been associated with an unprecedented decrease in non-COVID-19 visits to emergency departments. We corroborate this observation using administrative daily data from Chile and study the potential causes for this decrease. To that end, we merge regional emergency visits with Google mobility data and show that the crisis-induced changes in mobility patterns explain a significant portion of the overall drop in nonrespiratory emergency room visits, especially for visits related to trauma and poisoning. Our results reveal that an important reason for the dramatic drop in non-COVID-19 utilization of emergency care is the lower incidence of emergencies. This result suggests that lockdown measures may have the unexpected benefit for public health of freeing up healthcare resources to confront the pandemic.

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1 Introduction

Emergency care utilization around the globe has plummeted after the onset of the COVID-19 pandemic (Garcia et al., 2020; Rodríguez-Leora et al., 2020).[1] The leading explanation offered by health care practitioners for this phenomenon is that many patients, some with potentially serious conditions, have stopped going to the emergency department (ED) due to fear of contracting the novel SARS-CoV-2 virus at the hospital.[2] However, another cause of the drop in emergencies is that individuals were confined to their homes and stopped working, commuting, or exercising outdoors. The large decline in these activities brought about by the pandemic could have lead to a decrease in accidents and other health emergencies related to these activities. Therefore, part of the drop in emergency care utilization could have been due to the decrease in risky behavior and the subsequent decrease in the need of emergency care.

Disentangling these two explanations is important because they each contain different implications for population health in the short and medium run and also for our understanding of the role played by the policies surrounding the pandemic. On the one hand, if most of the decrease was due to a lower willingness to visit the ED—for instance, due to fear of contracting the virus—the pandemic could have dire consequences on population health well beyond the direct health effects of the SARS-CoV-2 virus due to worsening conditions of the untreated patients. On the other hand, if most of the decrease in ED visits was due

[1]For instance, according to NHS England figures, in March 2020, the number of people attending Accidents and Emergency departments in English hospitals was down 29 percent from the same month the previous year – about 1.5 million in March 2020, compared to nearly 2.2 million in March 2019. Emergency admissions were also down, falling by 23 percent on last March, to nearly 428,000 ("Coronavirus: A&E visits drop sharply as calls to 111 double," Philippa Roxby, BBC News, April 9, 2020)

[2]See, for example, reports in New York: "Amid the Coronavirus Crisis, Heart and Stroke Patients Go Missing, Gina Kolata, The New York Times, April 25, 2020; New Haven: "Hospital admissions for strokes appear to have plummeted, a doctor says, a possible sign people are afraid to seek critical help," Kevin Sheth, The Washington Post, April 9, 2020; Michigan: "ER visits drop amid COVID-19 outbreak; doctors fear patients avoiding hospitals during pandemic," Jim Kasuba, News-Herald, April 14, 2020; Vancouver: "ER doctors worry people with serious health concerns are avoiding the hospital," Randy Shore, Vancouver Sun, April 22, 2020; England: "Fears that seriously ill people are avoiding A&E as numbers drop," Sarah Marsh, The Guardian, March 27, 2020; Chile: "Qué pasa con las urgencias? Atenciones bajaron 51% desde la llegada del covid-19," Max Chavez, El Mercurio, April 20, 2020.

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to a lower incidence of accidents and health conditions that required an emergency visit, the negative consequences associated with lower utilization would be muted. Importantly, this cause would indicate an overlooked benefit of lockdowns for public health, as they free up healthcare resources to confront the pandemic. Moreover, by assessing the relative importance of each explanation we can also uncover what specific factors contributed to a much lower use of emergency care after the onset of the pandemic relative to "normal times."

In this paper, we shed light on the causes of the drop in emergency care visits by quantifying the fraction of the drop that can be explained using data on high-frequency (daily) mobility in Chile. Mobility data is an observable proxy for social and economic activity that is, in principle, related to the incidence of some types of emergencies. Therefore, the extent to which the decrease in mobility can explain the decrease in emergency care provides a lower bound for the share of the reduction in emergency care utilization that can be explained by lower social and economic activity as opposed to changes in willingness to visit the ED.

We start by documenting large declines in ED visits in Chile that occurred following the adoption of initial measures aimed to increase social distance. Similar to what has been reported elsewhere, we observe substantial decreases across several subgroups of ED cases. During the period of analysis, total non-respiratory ED visits declined by 49 percent. This decline includes a 25 percent reduction in visits related to heart attacks and a 54 percent decline in visits related to trauma and poisoning.

To examine the relationship between ED visits and mobility, we combine daily data on emergency room utilization with daily mobility patterns recently released by Google. Based on the daily variation in mobility before the adoption of social distance measures (the "pre-COVID-19 period"), we estimate a simple and parsimonious model that relates daily mobility patterns with ED visits in the *pre-COVID-19 period.* Then, we compare the actual visits to those predicted by the model under the mobility patterns observed during the pandemic. In other words, we "train" our data during the *pre-COVID-19 period* to investigate the extent to which the decline in ED visits during the pandemic can be predicted with the observed

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changes in mobility.

We find that a simple linear model relating emergency visits to the six mobility measures provided by Google allows us to predict 42 percent of the decline in non-respiratory visits after the onset of the pandemic. We further investigate the ability of the model to predict the decline in two selected subgroups of ED non-respiratory cases, trauma and poisoning, and heart attacks, for which we can predict 95 percent and 90 percent of the respective drop using our OLS specification. However, the mobility variables only poorly explain the levels of heart attack visits, and the ability of our model to predict their drop is highly dependent on the specification. Using a flexible lasso, higher polynomials, and interactions of the mobility variables with regional effects, we are able to predict 60 percent of the overall drop in non-respiratory cases and all of the drop in trauma and poisoning, but none of the drop in heart attacks.

The Chilean context is well-suited for this analysis for three important reasons: First, detailed ED data is available daily at the hospital level, which allows us to construct a high-frequency panel at the regional and type-of-emergency levels that we combine with the mobility data. Second, during the period of our analysis the spread of the virus was well contained in the country so hospitals operated well below their capacity during the pandemic. Excess capacity of hospitals and ED rooms helps us rule out unmet demand due to supply-side factors. Finally, the drop in ED visits in Chile is comparable in magnitude to the decrease reported elsewhere, which suggests that our results are informative to other countries as well.

Our paper contributes to a growing body of empirical research analyzing the impacts of the lockdown measures implemented to confront the COVID-19 pandemic. This literature has been mostly focused on analyzing its impact on the spread of the disease (Fang et al., 2020; Juranek and Zoutman, 2020; Qiu et al., 2020).[3] Alexander and Karger (2020) study the effect of the lockdown on consumption. Our paper provides novel insights by showing

[3]Farboodi et al. (2020) show that individual's optimizing behavior generated social distance before shelter-in-place restrictions came into effect.

that lockdowns generate positive public-health externalities by reducing the demand for emergency room services.[4]

In addition to providing insights specific to pandemics like the COVID-19 crisis, our paper also connects to broader questions in health economics and health care policy. First, our paper contributes to the debate regarding the productivity of health care spending. The large drop in ED visits brought about by the pandemic and the lockdown measures could suggest that a large fraction of pre-COVID-19 emergency-room visits were only marginally beneficial to patients. In fact, several studies have argued that many ED cases are actually non-urgent and thus could be handled in less expensive, regular physician visits without any deterioration in the patient's condition.[5] Our findings suggest that the lower incidence of conditions due to lower exposure to risk played an important role in this decrease bounding the role played by behavioral responses related to the decision to go to the ED.

Second, this paper is also related to the literature on countercyclical health, which suggests that the economic downturns can improve health by decreasing working hours and changing individual's allocation of time and health behavior (see, e.g., Ruhm, 2000, 2005a,b, 2007; Evans and Moore, 2012), by their effect on traffic (He, 2016; Rodríguez-López et al., 2016), or due to countercyclical quality of health care (Stevens et al., 2015). Our results show that lower social and economic activities, as measured by mobility patterns, decrease the incidence of health conditions that lead to emergency room visits.

The paper is organized as follows: Section 2 presents a brief summary of the unfolding of the pandemic in Chile. Section 3 introduces the data. Section 4 documents the decrease in ED visits in Chile. Section 5 presents our main empirical strategy and the results. Section 6 concludes.

[4] Adda (2016) provides a comprehensive analysis of the economic costs of infections and a cost-benefit analysis of social distancing interventions.

[5] The OECD reports that between 12 and 56 percent of ED visits in OECD countries are non-urgent (James et al., 2017) and these represented $38 billion per year (Delaune and Everett, 2008) in the U.S. One potential explanation is that patient preferences for seeking emergency care are high because of the access to a wide array of medical services is accessible 24 hours a day, 7 days a week (Durand et al. (2012)). An important caveat is that there is a not a clear consensus of what an urgent visit is. See Durand et al. (2011) for a review of the classification methods used in the health literature and their implications.

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2 The COVID-19 crisis in Chile

The confirmation of the first case of COVID-19 in Chile occurred on March 3, 2020. On March 15 the government announced the first set of measures restricting mobility. All these measures started on March 16, and mainly contemplated a nationwide closing of schools and educational establishments, restaurants, and movie theatres, as well as forbidding events with more than 50 people. Further measures adopted were a national night curfew between 10 PM and 5 AM starting on March 22, and localized lockdowns in specific municipalities starting on March 26.[6] On March 23, when there were were 93 total positive cases, the first death related to COVID-19 was identified.

Figure 1 shows the evolution of COVID-19 cases and deaths over time. By April 14 the total number of cases and deaths were 7,525 and 82, respectively. [7] We include a dashed vertical line on March, 13 which we use to mark the onset of the crisis in Chile. On March 13 (two days before the nationwide lockdown measures) the national cumulative number of cases was only 33, and there were no COVID-19-related deaths reported. However, cases and deaths started to increase rapidly afterwards.

[6]Lockdowns were implemented selectively. Due to their initial higher contagion rate seven municipalities of the Santiago metropolitan area were under a total lockdown that lasted fifteen days. People under lockdown were required to obtain a special permit to move from one location to another. Later, thirteen additional municipalities across the country were under temporary lockdown at some point between March 30 and April 23.

[7]These figures are fairly low (both in absolute terms and in a per-capita basis) compared to the spread of the pandemic in other OECD countries.

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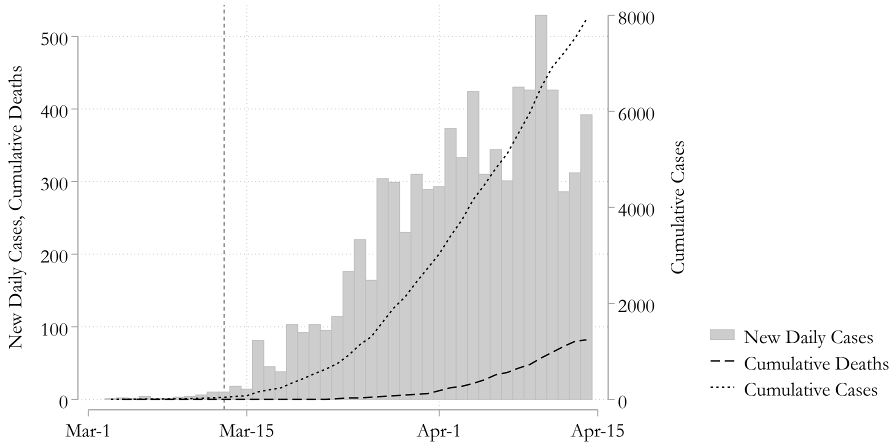
Figure 1: Number of COVID-19 cases in Chile



Note: The graph shows the number of new daily cases, the number of cumulative cases, and the number of deaths of COVID-19 in Chile. Dashed vertical line is plotted on March, 13 and indicates the last weekday before the first of set of mobility restricting measured were adopted. Data from Department of Epidemiology, Ministry of Health, Government of Chile; via `https://github.com/maibennett` and Our World in Data `https://ourworldindata.org/coronavirus`.

3 Data

Our main empirical analysis combines daily administrative data on ED admissions with daily data from the Google Community Mobility Reports. Table 1 summarizes the data we use in this paper.

3.1 The Google Community Mobility Reports

The Google Community Mobility Reports use mobile geo-locations to compute an index of the time spent by users in six different categories of places: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential. The report shows how visits and length of stay at different places differ with respect to a baseline. The baseline is

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the median value, for the corresponding day of the week, during the 5-week period between January 3 to February 6, 2020. The mobility data is available from February 15, 2020. In this paper, we use data up to April 11, 2020. The data were released by Google in an effort to inform the debate around COVID-19. The data is available at the daily-level for all 16 Chilean regions.[8] In the Appendix we show plots of the time series of each mobility index in the six categories of places for our period of analysis. Beginning on March 13, there is a sharp decrease on time spent in most categories, except for residential. These plots reflect nationwide compliance with government measures that aimed to increase social distance among the population. For comparison, we also show how the mobility indexes compared to those in the U.S. We find that the mobility in Chile decreased in most categories much more than in the U.S., especially in retail and recreation, and in grocery and pharmacy.

3.2 Emergency Visits

The data for emergency visits comes from daily public reports by the Chilean Ministry of Health. The data shows the number of ED visits in each hospital in Chile, split by categories of related diagnoses.[9] In 2020 and before the COVID-19 crisis, the average day-region had 2,795 ED visits. In this paper we focus on non-respiratory visits, which accounted for 84 percent of the total visits in the period of analysis.[10] Within the non-respiratory visits, we show results for two sub-categories of interest: trauma and poisoning, that correspond to 16 percent of cases, and heart attacks (or acute myocardial infarction, AMI) which account for 0.1 percent of cases. Trauma and poisoning cases are interesting because they constitute in our dataset the largest well-defined cause of ED visits and because we expect this category to be strongly related to mobility patterns. We also focus on AMI due to the several recent media reports highlighting the drop in this category, and the report of recent cases where

[8]Regions are the main sub-national administrative units.

[9]The cases are classified using the ICD classification method. Each category in the data corresponds to related ICD codes.

[10]We exclude all respiratory causes from our analysis that contain acute bronchitis (J20-J21), influenza (J09-J11), pneumonia (J12-J18), and other respiratory causes (J22; J30-J39, J47, J60-J98).

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Table 1: Descriptive statistics by period of analysis

	Before March 13	Post March 13
Panel A: ED visits		
Total Non-respiratory:	2,328.82	1,183.35
	(177.67)	(342.48)
Heart Attacks	2.77	2.08
	(1.57)	(1.61)
Trauma or Poisoning	378.22	175.86
	(45.93)	(57.68)
Panel B: Mobility Index		
Residential	0.68	19.57
	(1.70)	(6.68)
Workplaces	4.36	-34.63
	(9.36)	(17.31)
Retail and Recreation	1.13	-56.57
	(7.48)	(18.34)
Grocery and Pharmacy	3.67	-32.98
	(6.57)	(19.20)
Parks	-5.99	-58.60
	(17.81)	(12.90)
Transit Stations	0.74	-54.12
	(8.52)	(17.46)

Notes: Panel A shows average daily number of emergency daily visits by region in each category. Panel B shows average Google Community Mobility Report indexes by region in the different categories. Both panels show summary statistics before and after March 13. Standard deviations are reported in parenthesis.

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individuals have suffered an AMI and have not sought timely ED care. In addition, AMIs are likely among the most severe well-defined cause that individuals go to the ED for. However, AMIs constitute only a very small fraction of the ED visits in Chile.

4 The Decrease in Emergency Visits

As in many other countries, there was a sharp drop in emergency visits in Chile after the beginning of the pandemic, in mid-March 2020. Figure 2 shows the total number of all non-respiratory ED visits in Chile for 2019 and 2020. These visits decreased on average from 37,592 before the pandemic to 19,109 after the beginning of the pandemic, which represents a drop of 49 percent.

To quantify the drop in ED visits we estimate a difference-in-differences model. For each diagnosis k, we estimate the regression equation

$$Y_{dkr} = \beta \text{COVID-19}_k + \mu_{dow,k} + \nu_{mk} + \tau_{yk} + \alpha_{rk} + \epsilon_{dkr} \tag{1}$$

where d is the day counted after January 1, y is year, m is month of the year and r is region.

We present the results in Table 2. We find a statistically significant drop in the three categories. The beginning of the COVID-19 pandemic led to a decrease of 1,290 non-respiratory emergency visits, of which 240 and 0.76 were due to trauma and poisoning and AMI, respectively. These figures represent 52, 61, and 25 percent of the average number of regional daily visits in the pre-pandemic period for three categories, respectively.[11]

5 Empirical Analysis

The goal of the empirical analysis is to quantify the share of the decline in emergency room visits that can be explained by changes in risk exposure to accidents or non-COVID-19

[11] For AMI, in which the mean is close to zero, a Poisson model with a similar specification results in an estimate of -0.285 and standard error of 0.065.

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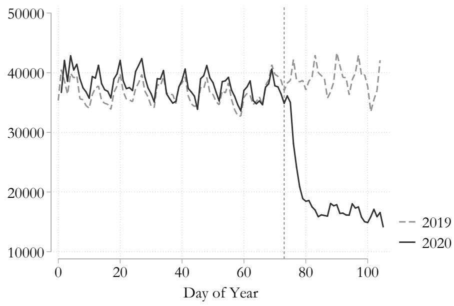
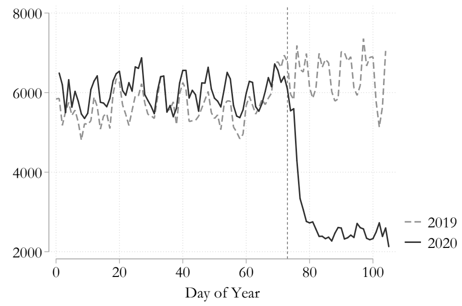
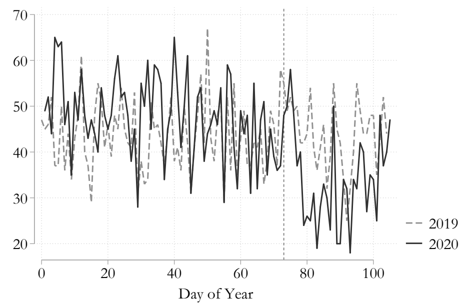
Figure 2: Emergency Room Visits in Chile in 2019 and 2020



(a) All Non-Respiratory



(b) Trauma and Poisoning



(c) Acute Myocardial Infarction

Note: The graph shows total emergency visits in Chile for the days after the first Wednesday of the year for the years 2019 and 2020 (January 2 and January 1, respectively) in different categories. The vertical line indicates March 13, 2020, which indicates the date when COVID-19 started spreading.

Table 2: Effect of the pandemic on emergency visits - by category

	(1) All Non-Respiratory	(2) Trauma and Poisoning	(3) Acute Myocardial Infarction
COVID-19 Spread	-1290.15**	-240.01**	-0.76**
	(456.65)	(85.85)	(0.27)
N	3150	3150	3150
R-Squared	0.19	0.20	0.01
Mean Dep. Variable	2,506.19	396.61	3.02

Note: The table shows the effect of the pandemic spread on total emergency room visits in Chile between January 1 and April 14, where we use 2019 as the control group for 2020. The estimation includes day of the week, month of the year, year, and regional fixed effects. The mean dependent variable includes only observations before March 13 in 2019 and 2020. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

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diseases, as proxied by an observable set of indicators. If most of the decline in visits is predicted by changes in these observables, the decrease in ED visits attributed to a decline in individuals' willingness to visit the ED would be small. In this case, the decline would be mostly attributed to a lower incidence of conditions that warrant a visit to the ED. Alternatively, if the drop in ED visits cannot be explained by these observables, the drop in the ED would be explained by unobservable factors that include, among others, changes in attitudes towards visiting the ED because of the fear of contracting the SARS-CoV-2 virus at the hospital.

Our approach consists of using the pre-COVID-19 period to infer the relationship between mobility (as a proxy for social and economic activities and risk exposure) and the various types of ED visits. We then use the empirical relationship between those two variables in the pre-COVID period to predict the number of emergency room visits in the period after the onset of the COVID crisis. That is, we use the data before March 13 as our 'training' dataset, from which we estimate the parameters relating mobility with emergency visits, and use those estimates to construct the emergency visits predicted by the model under the post-COVID-19 mobility patterns.

Figure 3 provides a simple explanation of our approach. The figure plots the Z-score of the mobility to transit stations measure against the Z-score of the trauma and poisoning visits in the capital city (Santiago). Z-scores for the entire sample period are based on the means and standard deviations in the pre-COVID period. Therefore, the magnitude in both axis corresponds to the deviation of a particular measurement with respect to the pre-COVID mean as fraction of the pre-COVID standard deviation.

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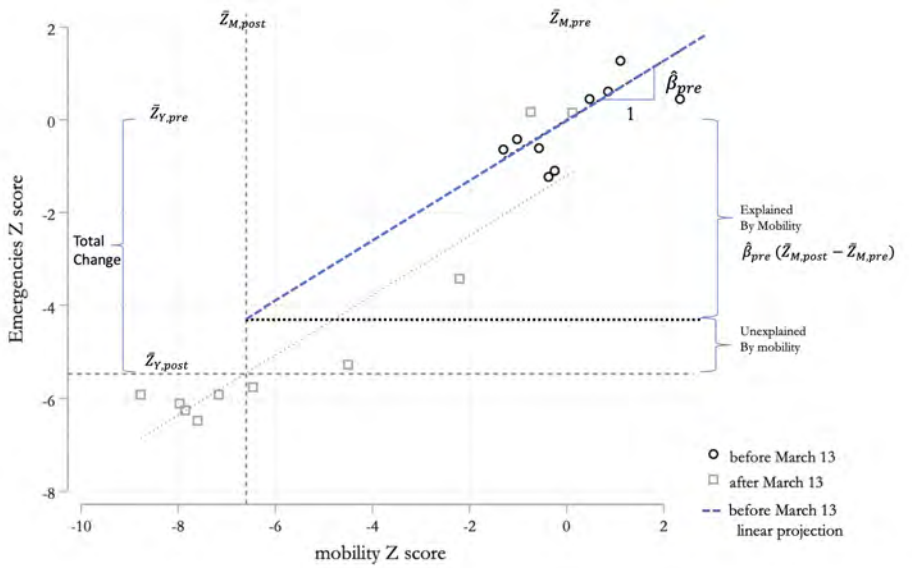
Figure 3: Normalized Mobility and Normalized Trauma and Poisoning in Santiago



Note: The figure shows a binned scatter plot of the normalized (Z-score) transit stations mobility and normalized (Z-score) trauma and poisoning emergency visits in the Metropolitan region (Santiago and its surroundings). The normalizations use the corresponding pre-March 13 mean and variances in Santiago. The straight lines represent the linear fit for each period.

In the case of a simple univariate model for ED visits, our empirical strategy would consist of (i) estimating the slope $\hat{\beta}_{pre}$ using the pre-COVID period, and (ii) using $\hat{\beta}_{pre}$ to project the linear relationship up to the mean mobility in the post-COVID period $\bar{Z}_{M,post}$. The share of total change in average visits $\bar{Z}_{Y,post} - \bar{Z}_{Y,pre}$ that is explained by the change in mobility corresponds to $\hat{\beta}_{pre}(\bar{Z}_{M,post} - \bar{Z}_{M,pre})$. As we discuss in more detail in Section 5.4, this decomposition is akin to the 'three-fold' Blinder-Oaxaca decomposition of gender wage gaps used in the labor economics literature.[12]

Our main empirical strategy uses the insight described in Figure 3, but allows for a

[12] In principle we could also perform a decomposition of the pre/post-March 13 differences using the 2019 data. However, the analysis would require assumptions on mobility patterns and their impact on emergencies in 2019 (which we do not observe).

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flexible relationship between ED visits and the six different mobility indices included in the Google Mobility Reports.

5.1 Model Specification

We posit a simple linear model for non-respiratory and trauma and poisoning visits in day d, for diagnosis k and region r:

$$Y_{dkr} = f_{kr}(\mathbf{M}_{dr}) + \mu_{dow(d),k} + \epsilon_{dkr} \tag{2}$$

where f_{kr} is a type- and region-specific function, $\mathbf{M}_{dr} \in R^6$ is a vector containing the daily measures of the Google Mobility Report in the six categories of places, and $\mu_{dow(d),k}$ are type-specific dummy for the day of week (Monday, Tuesday, etc.).

In our first specification we use a parsimonious linear model for f_{kr}: $f^a_{kr} = \alpha_{kr} + \sum_{j=1}^{6} \beta_{kj} M_{drj} + \mu_{dow(d),k} + \epsilon_{dkr}$. We estimate the coefficients of this first specification via OLS. In our second specification we allow f_{kr} to contain the squared terms of the mobility indexes and a full set of interaction terms between the region and the mobility indices as well. The specification thus becomes: $f^b_{kr} = \alpha_{kr} + \sum_{j=1}^{6} \beta_{krj} M_{drj} + \sum_{j=1}^{6} \beta_{kj} M^2_{drj} + \mu_{dow(d),k} + \epsilon_{dkr}$. We estimate this model via lasso. In addition, to account for the low incidence of heart attacks we estimate Poisson (count) models with similar specifications for AMI visits that we either estimate via maximum likelihood or by lasso.[13]

As noted above, we estimate the model using the 2020 data for the *pre-COVID-19 period only*. Then, we compute the predicted values, $\widehat{Y}_{dkr}$, for the entire sample: the pre-COVID-19 period (in-sample prediction); and post-COVID-19 period (out-of-sample prediction). Finally, we compute the country-level predicted totals as the sum of the regional predictions $\widehat{Y}_{dk} \equiv \sum_r \widehat{Y}_{dkr}$.

[13] We estimate lasso using the implementation of Friedman et al.'s (2010) coordinate descent algorithm. We use Townsend (2018) for the linear models and the R glmnet package for the Poisson models. Also, in reality we implement elastic net, which is a generalization of lasso, but the elastic-net penalty found by the algorithm is the same as lasso's for the linear models.

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5.2 Pre-COVID-19 relationship between ED and mobility

We estimate Equation (2) in the pre-pandemic period. We find that the mobility data is strongly correlated in the pre-COVID-19 period with non-respiratory and trauma and poisoning emergencies, but not with AMI visits. The F statistic (and its corresponding p-value) for the joint test that the six coefficients of the mobility variables equal zero in the pre-COVID-19 (training) sample ($\beta_{k1} = \beta_{k2} = ... = \beta_{k6} = 0$) are $F = 11.37(0.00)$, $F = 7.67(0.00)$, $F = 2.50(0.02)$ for the non-respiratory, the trauma and poisoning, and the heart attacks visits, respectively. We show the estimation results in the Appendix.

5.3 Post-COVID predictions

We present the predicted ED visits for our selected subgroups of ED cases in Figure 4. Each panel in the figure presents (i) the actual time series, (ii) the prediction from a model that only includes day-of-week and region fixed effects, and omits the mobility data; (iii) the OLS (or Poisson) prediction, and (iv) the lasso prediction.

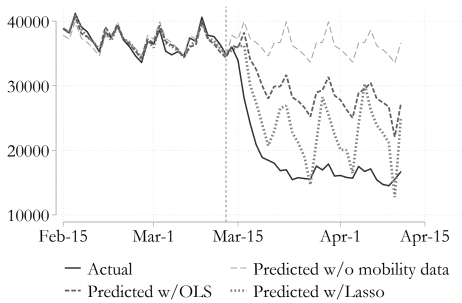
We find that the mobility patterns explain a large fraction of the decrease in the emergency visits for all non-respiratory visits, and trauma and poisoning emergencies among them, cases where the mobility is highly correlated with emergencies in the pre-COVID-19 period. For the case of AMI visits, the models do a worse job predicting the number of visits. We think this is natural because AMIs are less dependent than the other types of ED visits we study on the mobility indexes.[14] We provide numbers for the share of the explained drop in the next subsection.

5.4 Decomposition

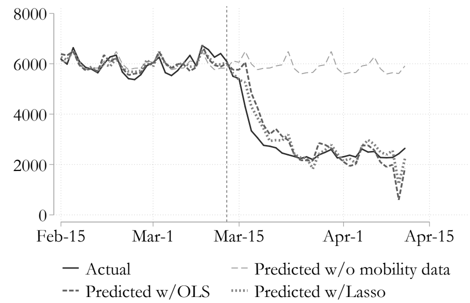
We formalize the graphical analysis with a decomposition of the differences in emergencies across periods using the Oaxaca-Blinder method. This method, derived by Blinder (1973)

[14]The lasso predictions are somewhat sensitive to the seed choice. In the Appendix we show lasso results with different initial seeds.

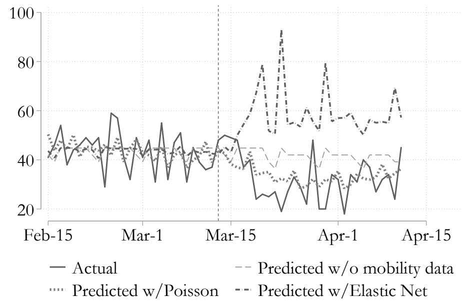
Figure 4: Actual and Predicted Emergencies by Type



(a) All Non-Respiratory



(b) Trauma or Poisoning



(c) Acute Myocardial Infraction

Note: The vertical line represents divides the period that was used for prediction and the actual prediction using Google's Community Mobility Reports and regional fixed effects. Lasso and Elastic Net predictions are equivalent for all non-respiratory and trauma or poisoning categories.

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and Oaxaca (1973) is traditionally applied in labor economics to study the wage gap across groups (e.g., males vs. females) by decomposing the gap into the part that can be explained by observable characteristics (e.g., differences in 'endowments,' such as education in the gender wage gap literature) and the part of the gap that cannot be explained by observables. We apply the same logic to decompose differences in average visits across the two groups of observations defined by the calendar time: the group of post-March 13 days and the group of pre-March 13 days. The goal of the decomposition is to quantify the part of the difference in average visits across the two groups that can be explained by the model, particularly by

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the mobility variables.

To simplify the notation, we rewrite the general model for average visits in each period as:

$$
\begin{aligned}
E[Y_{pre}] &= \bar{X}'_{pre}\beta_{pre} \\
E[Y_{post}] &= \bar{X}'_{post}\beta_{post}
\end{aligned}
$$

A "three-fold" decomposition of the gap $E[Y_{pre}] - E[Y_{post}]$ can be written as:

$$
E[Y_{post}] - E[Y_{pre}] = (\bar{X}_{post} - \bar{X}_{pre})'\beta_{pre} + \bar{X}'_{pre}(\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre}) \quad (3)
$$

The first part of this decomposition, $(\bar{X}_{post} - \bar{X}_{pre})'\beta_{pre}$, corresponds to the difference in average visits across periods that can be explained by observables. This component corresponds to the part of the gap that can be explained by extrapolating the pre-COVID-19 relationship (β_{pre}) from the pre-COVID-19 average mobility $\bar{X}_{pre}$ onto the post-COVID-19 average mobility ($\bar{X}_{post}$) (see Figure 3). Consequently, the sum of the second term and the third term $\bar{X}'_{pre}(\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre})$ corresponds to the part of the gap that we cannot explain by observables.

Diving each side of Equation (3) by $E[Y_{pre}]$ can re-write the equation as

$$
\underbrace{\frac{E[Y_{post}] - E[Y_{pre}]}{E[Y_{pre}]}}_{\text{Difference \%}} = \underbrace{\frac{(\bar{X}_{post} - \bar{X}_{pre})'\beta_{pre}}{E[Y_{pre}]}}_{\text{Explained by Observables \%}} + \underbrace{\frac{\bar{X}'_{pre}(\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre})}{E[Y_{pre}]}}_{\text{Unexplained by Observables \%}}, \quad (4)
$$

which results in the share of the explained and unexplained gap in percentage terms.

Table 3 shows the result of this decomposition, where each panel corresponds to a different type of ED visit. Panel (a) shows that total non-respiratory visits dropped by 18,327 visits

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per day, a 49.2 percent decrease after the onset of the crisis. Our OLS model predicts a drop of 7,682. Thus, a simple linear model of the Google mobility indexes predict 41.9 percent of the drop in the non-respiratory ED visits. Moreover, the lasso regression is able to explain 60 percent of the overall drop. Panel (b) repeats the decomposition for trauma and poisoning. We find that both the OLS regression and the lasso regression can explain more than 95 percent of the decrease. Finally, Panel (c) shows that the simple Poisson regression can explain 90 percent of the decrease in AMI. However, we think the AMI result is not very plausible due both to the contradicting lasso prediction of an increase in 148 percent in AMI visits and the low OLS F statistic.

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Table 3: Decomposition of the Drop in Emergency Visits

	1	2	3
	Observed	**Predicted**	
		OLS	Lasso
Panel (a)	Total Non-respiratory		
Before March 13 (A1)	37,051	37,051	37,051
After March 13 (A2)	18,580	29,370	24,288
Difference, in levels (A1-A2)	-18,471	-7,682	-12,764
Difference (%) (A1-A2)	-49.9%	-20.7%	-34.4%
Difference Explained by Model (%)	-	41.6%	69.1%
Panel (b)	Trauma and poisoning		
Before March 13 (A1)	6,010	6,010	6,010
After March 13 (A2)	2,754	2,932	2,920
Difference, in levels (A1-A2)	-3,256	-3,079	-3,090
Difference (%) (A1-A2)	-54.2%	-51.2%	-51.4%
Difference Explained by Model (%)	-	94.5%	100.4%
Panel (c)	Acute myocardial infarction		
Before March 13 (A1)	44	44	44
After March 13 (A2)	32	34	58
Difference, in levels (A1-A2)	-11	-10	15
Difference (%) (A1-A2)	-26%	-23%	33%
Difference Explained by Model (%)	-	86%	-148%

Note: The table shows the result of a Oaxaca-Blinder decomposition of the drop in visits into a part that is explained by the mobility indexes and a part that is not.

6 Summary and Conclusion

Worldwide, the overall utilization of emergency care has decreased dramatically during the COVID-19 pandemic. In this paper, we leverage high-frequency data from Chile to show that observed changes in population's mobility can explain roughly half of that decrease.

Our results call into question the idea that most of the decrease in ED visits can be attributed to a widespread fear of attending the ED. By using a simple model we quantify the portion of the decrease in ED visits that is due to a change in mobility. The portion of the decrease that is left unexplained by our model includes all other determinants of the observed drop in ED visits not captured by the mobility measures, such as a decrease in the willingness to visit the ED due to fear of contracting the virus at the hospital. Therefore, our findings provide an upper bound to the role that individuals' behavioral responses in the decision of whether to go to the ED has played in decreased ED utilization, which are potentially welfare-decreasing. Moreover, our results suggest that lockdown measures may have had an unexpected positive effect by freeing up healthcare resources to confront the pandemic.

Although our results suggest at least 40 to 60 percent of the decrease in emergency room visits is simply due to a lower need of emergency care, we cannot reject that some portion of the decrease is due to fear of contracting the virus while visiting the hospital. Even a small share of fear-induced drop in emergency-care utilization for serious conditions may signify large welfare losses overall. In particular, the mobility data used in this paper does not fit well the incidence of heart attacks, and therefore we cannot rule out that an important fraction of the reduction in emergencies for heart attacks is due to patients with heart attacks having a lower willingness to visit the hospital. Moreover, a complete assessment of the lower ED utilization brought about by the pandemic would require data on health outcomes.

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Appendix

A1 Google Mobility Report

The Google Mobility Report shows how visits and length of stay at different places change compared to a baseline. The baseline is the median value, for the corresponding day of the week, during the 5- week period Jan 3–Feb 6, 2020. The data was publicly available as of April 2020 in `https://www.google.com/covid19/mobility/`.

These changes are calculated using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps. Mobility trends are split in the following categories:

1. Retail and recreation: Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
2. Grocery and pharmacy: Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.
3. Parks: Mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens.
4. Transit Stations: Mobility trends for places like public transport hubs such as subway, bus, and train stations.
5. Work: Mobility trends for places of work.
6. Residential: Mobility trends for places of residence.

More details on how mobility index are calculated can be found in `https://www.google.com/covid19/mobility/data_documentation.html?hl=en#about-this-data`.

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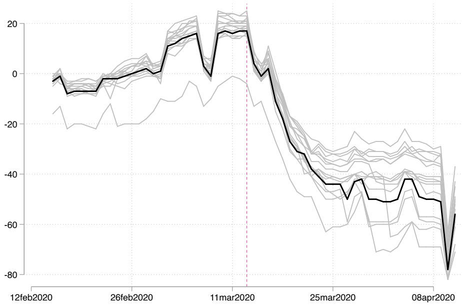
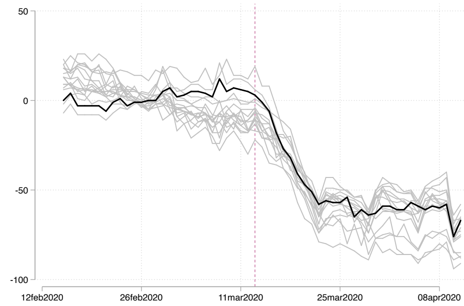
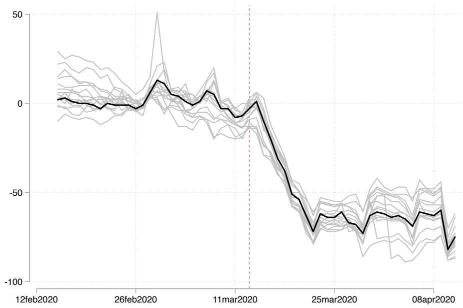
Figure A1: Mobility evolution across Chilean regions



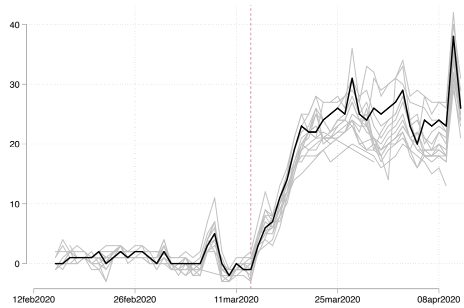
(a) Workplaces



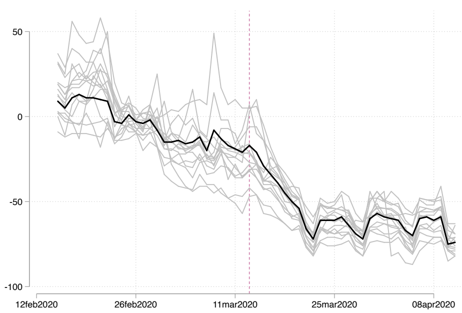
(b) Transit Stations



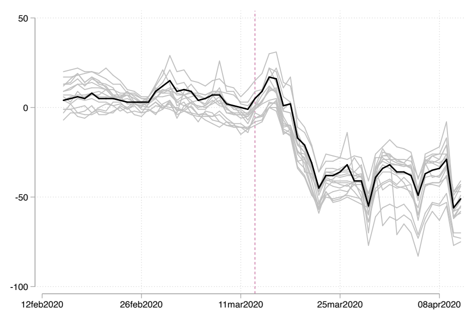
(c) Retail and Recreation



(d) Residential



(e) Parks



(f) Grocery and Pharmacy

Note: The figure presents the different mobility indexes for the Chilean regions. Each panel shows how visits and length of stay at different places changed compared to a baseline period. This baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The gray lines indicate different regions, and the black line show the national average. The vertical line indicates March 13, which denote the beginning of the COVID-19 pandemic in Chile.

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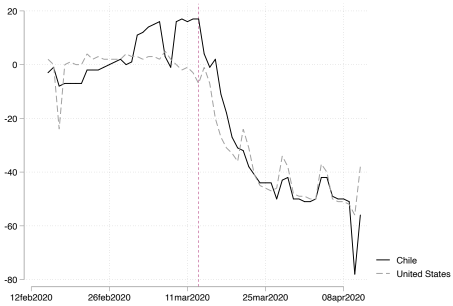
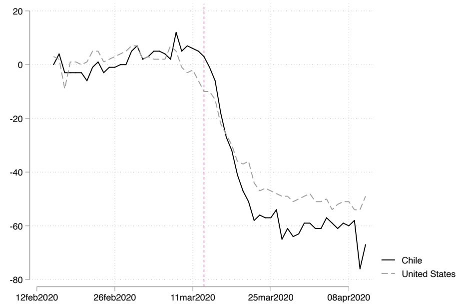
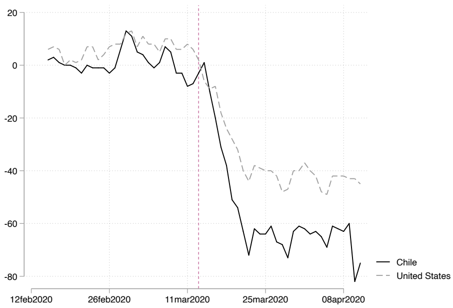
Figure A2: Mobility evolution in Chile and the United States



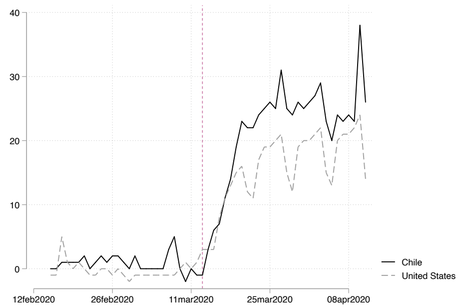
(a) Workplaces



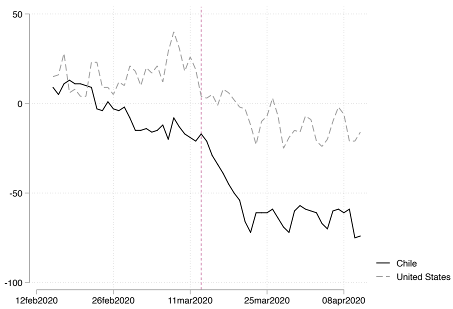
(b) Transit Stations



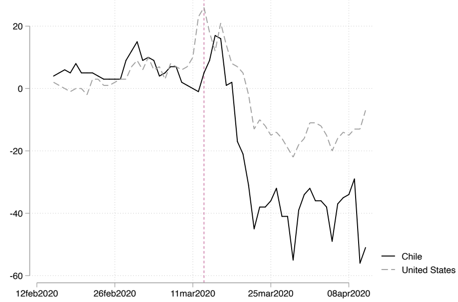
(c) Retail and Recreation



(d) Residential



(e) Parks



(f) Grocery and Pharmacy

Note: The figure presents national mobility indexes for Chile and the United States. Each panel shows how visits and length of stay at different places changed compared to a baseline period. This baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The gray lines indicate different regions, and the black line show the national average. The vertical line indicates March 13, which denote the beginning of the COVID-19 pandemic in Chile.

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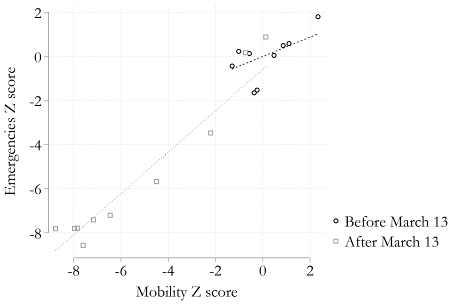
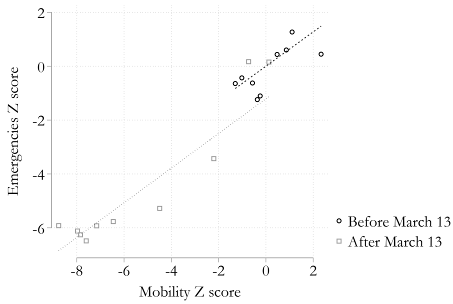
A2 Normalized Mobility and Emergency Visits

We present more examples of binned scatterplots relating (normalized) emergency visits with (normalized) mobility measures. We show the case of all non-respiratory conditions and trauma and poisoning for the Metropolitana and the Biobío region, which gather 50 percent of the country's inhabitants.

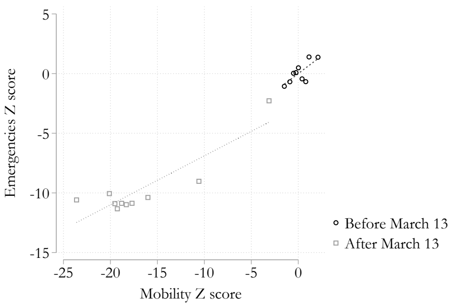
Figure A3: Normalized Mobility and ED visits



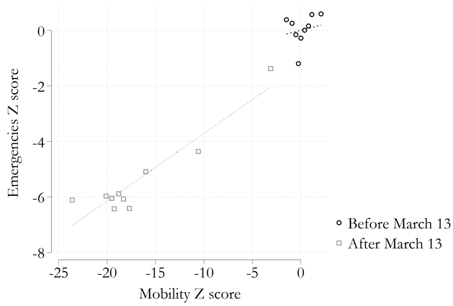
(a) Non-Respiratory - Metropolitana



(b) Trauma or Poisoning - Metropolitana



(c) Non-Respiratory - Biobío



(d) Trauma or Poisoning - Biobío

Note: The Figure presents binned scatterplots of transit station mobility and emergency visits in the Metropolitana and Biobío regions of Chile. The dotted lines show a linear fit for observations before and after March 13, the date of the beginning of the COVID-19 pandemic.

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A3 OLS estimates

Table A1 shows the results of estimating Equation 2 by OLS.

Table A1: OLS estimates

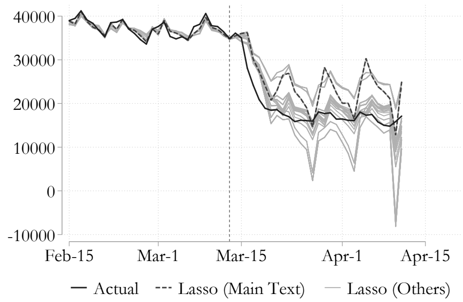
	All non-respiratory		Trauma and Poisoning		Acute Myocardial Infraction	
Residential	115.60	-0.85	15.57	2.56	-0.02	-0.10
	(104.77)	(14.73)	(16.87)	(2.75)	(0.09)	(0.07)
Workplaces	11.80	5.91	2.52	3.45***	-0.04*	-0.04**
	(29.88)	(4.68)	(4.99)	(0.86)	(0.02)	(0.02)
Retail & Recreation	-184.72***	-3.83	-31.08***	-1.49**	-0.16***	-0.01
	(32.57)	(2.51)	(5.60)	(0.58)	(0.03)	(0.02)
Grocery & Pharmacy	186.91***	2.50	34.58***	1.10	0.14***	0.01
	(45.94)	(4.29)	(7.87)	(0.86)	(0.04)	(0.02)
Parks	3.39	5.49**	1.81	1.02***	-0.04***	-0.02***
	(16.44)	(2.33)	(2.75)	(0.39)	(0.01)	(0.01)
Transit Stations	56.35***	1.32	4.89**	2.05***	0.11***	0.03*
	(13.81)	(2.20)	(2.31)	(0.63)	(0.02)	(0.02)
Region F.E.	N	Y	N	Y	N	Y
Day-of-week FE	N	Y	N	Y	N	Y
F-stat.	12.13	11.37	8.48	7.67	12.56	2.50
p-value	0.00	0.00	0.00	0.00	0.00	0.02
R^2	0.12	0.99	0.12	0.99	0.13	0.68
R^2adj	0.11	0.99	0.11	0.99	0.12	0.66

Notes: The table shows the results of a OLS estimation of Equation (2) in the pre-pandemic period. For comparison purposes, the table shows the results of running an OLS model for AMI visits even if in the main analysis we estimate a Poisson model for this category. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

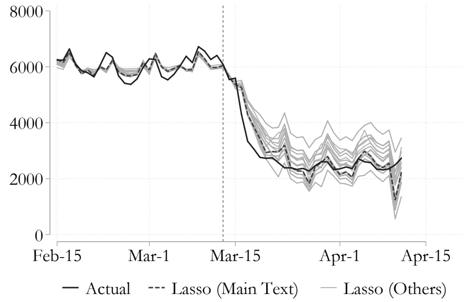
A4 Robustness of the Lasso Regressions

Figure A4 shows plots for different seeds of the same lasso specification and the sample sample as in the main text. These plots are meant to show only the instability in variable selection in the pre-COVID period for each emergency type and not the standard errors of lasso.

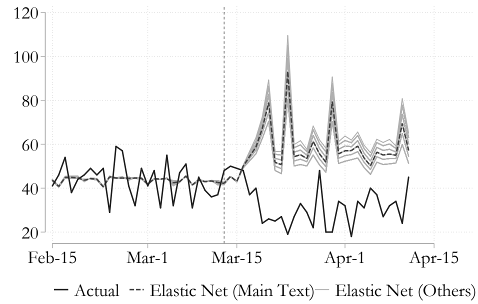
Figure A4: Lasso predictions—Actual and Predicted Emergencies by Type



(a) All Non-Respiratory



(b) Trauma or Poisoning



(c) Acute myocardial infarction

Notes: The vertical line represents the period that was used for prediction and the actual prediction using Google's Community Mobility Reports and regional fixed effects. Lasso and Elastic Net predictions are equivalent for all non-respiratory and trauma or poisoning categories.

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Health vs. wealth? Public health policies and the economy during Covid-19[1]

Peter Zhixian Lin[2] and Christopher M. Meissner[3]

Date submitted: 28 April 2020; **Date accepted:** 28 April 2020

We study the impact of non-pharmaceutical policy interventions (NPIs) like "stay-at-home" orders on the spread of infectious disease. NPIs are associated with slower growth of Covid-19 cases. NPIs "spillover" into other jurisdictions. NPIs are not associated with significantly worse economic outcomes measured by job losses. Job losses have been no higher in US states that implemented "stay-at-home" during the Covid-19 pandemic than in states that did not have "stay-at-home". All of these results demonstrate that the Covid-19 pandemic is a common economic and public health shock. The tradeoff between the economy and public health today depends strongly on what is happening elsewhere. This underscores the importance of coordinated economic and public health responses.

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1 We thank Haoze "Anson" Li and Jingxuan Ma for research assistance. We thank Jonathan Dingel for clarifying some data issues. Matthias Blum, Barry Eichengreen, Gregori Galofré-Vilà, Peter Sandholt Jensen, Peter Lindert, Alan M. Taylor and seminar participants at UC Davis provided helpful early feedback.

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1. Introduction

We study the health and economic impacts of non-pharmaceutical public health interventions (NPIs) to mitigate the spread of Covid-19. Since emerging in December 2019, Covid-19 has spread to nearly all countries in the world. Every state and territory in the USA has reported at least one case to date. Theoretical and empirical literature in epidemiology and public health has argued that NPIs can be important in decreasing peak mortality and cumulative mortality (Hatchett et. al, 2007; Markel et. al, 2007; Bootsma and Ferguson, 2007 and Barro, 2020).[1] Countries, states, and cities recently imposed a number of NPIs to enhance social distancing with the aim of mitigating the spread of Covid-19. Have these had benefits for public health but at the cost of the economy?

The economic consequences of public health policies during global pandemics is challenging. Global pandemics are rare events (Barro et. al. 2020; Jordà et. al, 2020 and Correia et. al). New insights combining economic and epidemiological modeling is emerging with new theoretical predictions. The key tradeoff is between public health and the economy (Gourinchas, 2020). Aggressive NPIs benefit public health and help manage the pandemic with limited medical capacity. NPIs may however damage the economy and create high levels of unemployment. But, even without policy, people pay attention to news and events elsewhere reacting with spontaneous social distancing (Eichenbaum et. al. 2020; Baldwin, 2020; Krueger et. al, 2020). There may also be important economic spillovers to NPIs (Beck and Wagner, 2020).

A pandemic can impact an economy in many ways: reductions in people's willingness to work, dislocations in consumption patterns and lower consumption, added stress on the financial system, and greater uncertainty leading to lower investment. These are respectively referred to as (labor) supply shocks, demand shocks, financial shocks and uncertainty shocks. Connected economies and epidemiological communities also move in synch. Even a healthy economy, or an economy that has not mandated a shutdown, may feel the impact of external events. With the exception of the 1918 influenza, recent pandemics have neither had as large of a global impact, nor has there been as much real time data available to empirically assess the economic and public health impact of NPIs. We study outcomes during the Covid-19 pandemic.

We have three main results. First, our analysis shows NPIs may have been effective in slowing the growth rate of confirmed cases of Covid-19 but not in decreasing the growth rate of cumulative mortality. Second, we find evidence of spillovers. NPIs may have impacts on other jurisdictions. Finally, there is little evidence that NPIs are associated with larger declines in local economic activity than in places without NPIs.

[1] Hatchett et. al. (2007) find NPIS reduce "peak mortality" but mostly statistically insignificant impacts on cumulative mortality of NPIs in their sample of 17 cities. Barro (2020) finds the same in a broader sample of US cities.

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The reason we fail to find evidence consistent with a macro-health/economy tradeoff is that epidemiological and economic shocks have been common to the US and indeed to the world. Our results parallel those of a recent contribution which shows that US cities that applied more intensive NPIs in 1918-19 did not suffer greater economic mis-fortune than other cities without such policies (Correia et. al, 2020). Moreover, economic policies may have un-even impacts on certain economic sectors and types of jobs. We find states with a larger share of employment in jobs that can be done at home have lost fewer jobs after stay-at-home.

We also address the issue of spillovers in NPI policy and public health: do local policies have effects on other jurisdictions and territories? We find they do, at least within the United States. This is not true across borders. In light of this, delaying implementation of NPIs may have little extra economic benefit when significant trade partners have already implemented such policies and when information and disease travels rapidly. This new evidence can account for the lack of a tradeoff between health and the economy.

A relevant comparison to the Covid-19 pandemic is the 1918 influenza pandemic. A significant strand of the literature has developed unique data from this historical pandemic in the United States. In 1918 and 1919, NPIs significantly lowered peak mortality rates. Some weaker evidence shows that these may have reduced total cumulative mortality in US cities.[1] The recent Covid-19 pandemic and associated implementation of NPIs allows us to gauge whether such policies have been effective for public health and if there are economic costs to these policies.

2. Methods

2.1 Data collection

For public health data in US states, we rely on confirmed cases and deaths of Covid-19 reported by the *New York Times* on a daily basis. These data are based on reports from state and local health agencies. Confirmed cases and deaths across countries are from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University representing a compilation of data reported by the WHO and various countries' public health authorities. We use country and US state-level data beginning in January 2020 up to April 2020. We have data for over 70 countries and 50 US States + the District of Columbia.

Data on NPIs at the country level come from the Oxford Covid-19 Government Response Tracker (Hale et. al. 2020). These data cover seven policy responses: School closures, workplace closures, cancellation of public events, closure of public transport, public information campaigns, restrictions on internal movement, and international travel bans. This source reports data from over 100 countries. Data on "stay-at-home" orders for US states is from the official orders or announcements made by public health authorities at each state.

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Real-time data that helps understand the macro economy is relatively scarce and has only become available in recent decades. Recent research uses real time data from private financial (fin-tech) companies to track consumer spending as well as movement based on privately collected GPS signals from mobile phones. Such data is subject to measurement error, reports for limited and small samples, and cannot be considered as fully indicative of the macroeconomic situation (Baker et. al. 2020).

We use initial claims for unemployment insurance published by the US Department of Labor (i.e., initial jobless claims) at the state level on a weekly basis. Each state's data are as of the end of the week (i.e., Saturday). We use data which are not seasonally adjusted and which are subject to revision. Initial jobless claims represent a consistent and reliable indicator of the US labor market at the local level, are of reasonable quality, and are often used as a leading indicator for macroeconomic forecasts. These data exclude the self-employed. We also supplement the economic data with information on the employment shares in selected industries we believe may be hardest hit in the recent months such as oil and gas extraction, retail, food processing/restaurants, wholesale and arts, recreation and leisure. We also use information on the share of jobs in a state that can be carried out by telecommuting (Dingel and Neiman, 2020).

2.2 Data Analysis

Our main dependent variables are the daily growth rates of the (natural) logarithm of cumulative confirmed cases or deaths of Covid-19. We acknowledge considerable debate about measurement error due to variable testing rates across localities. Potential for measurement error also exists for the mortality data. There have been cases of deaths at home from those not admitted to nor tested in hospitals. Using excess mortality is an option but systematic data is not readily available nor directly comparable.

We also use the logarithm of initial jobless claims at the state-level as a dependent variable. Data are not seasonally adjusted since such adjustments apply to all cross-sectional units (i.e., states) and are captured in period/day intercepts. Initial jobless claims are subject to revision. Our data end with information on the week ending 4 April. The latest revisions apply to weeks before and including the week ending 28 March, 2020.

Country-level NPIs are reported on a scale of 0/1/2. A value of 0 is for "no measure in place". A value of 1 indicates the NPI is recommended, and a value of 2 is the most stringent. We re-code data to take the values of 0 and 1. Here 0 represents both 0 and 1 in the raw data, and 1 is a raw value of 2 the most stringent NPI possible.

State-level NPIs are for so-called "stay-at-home orders". Such rules vary in their particular prescriptions. They typically mandate that people refrain from meeting in groups, limit physical social interaction to within households, and that people frequent only essential businesses. In person work is allowed only for "essential" businesses.

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Throughout our paper, we assume that NPIs and their timing are exogenous and uncorrelated with unobservables especially expectations about the future path of mortality and the expected path of economic and social variables of interest. We also allow for leads of NPIs to deal with the issue of reverse causality from mortality to NPIs.

We allow for policy spillovers by measuring the level of policies in all other states. In our international sample, we look at policies of other countries that share a border. Each policy in another state (or country) is divided by the centroid-to-centroid distance. For robustness we also population weighted each other state's distance weighted policy. States with closer proximity to the observation have a bigger potential spillover since we assume economic and social interactions are roughly linear in the log of physical distance with an elasticity of -1. The measure for state i of all other states' NPI policies is $S_{i,-i} = \sum_{j \neq i} \frac{1(\text{Stay−at−Home}_j=1)}{\text{distance}_{ij}}$. We also introduce the sum of policies in the states which share a border with state i, $S'_{i,-i} = \sum_n 1(\text{Stay-at-Home}_\text{n} = 1)$ where n indexes states in the set N of i's neighboring states. Similarly, we can control for the confirmed cases of other states with distance weighting and in neighboring states. For countries we focus on policies only in bordering countries.

In all models we include controls for calendar weeks, state-level fixed effects and event-time trends (linear, quadratic and cubic terms were tested). The event is defined either as the number of days elapsed between the current date and the date a state reached the first death or first confirmed case of Covid-19. We also cluster standard errors of estimated coefficients at the state level.

2. Results

3.1 Policies and Public Health

As of this draft, there were over 2.4 million confirmed cases of Covid-19 worldwide. The United States (765,000), Spain (200,000), Italy (178,972), France (152,000) and Germany (145,000). Reported deaths stood at over 164,000 making this pandemic one of the worst in the last 120 years. The average growth rate of global cases since 1/22/2020 (555 cases) and 4/13/2020 (82 days) was 10.43%. Other reported statistics and information such as case fatality rates and overall infection rates are either too preliminary or mis-measured to be reliable at this stage.

On the international scene, the first countries to impose containment and mitigation strategies were in East Asia near the epicenter of the first outbreak. Mainland China imposed a near total lockdown on Hubei province from late January 2020 and severely limited domestic movement in nearly all other provinces from then until the first week of April. Singapore, South Korea, Hong Kong, and Taiwan all maintained strict international border controls, high levels of contract tracing and testing, and monitoring or closure of international borders.

Western European nations, first with Italy (March 9th), and successively other nations, implemented strict bans on public gathering and domestic and international movement. In the United States, states initiated stay-at-home orders progressively beginning on 19 March (California) through the first week of April. Iran waited 16 days after its first case to put limits on internal/domestic movement. India announced a national shelter-in-place order on 24 March, 53 days after its first official case, and this was initially intended to have a three week duration.

We first test NPIs as determinants of the growth rate of cumulative cases or death rates across countries. On the international scene, in a sample of 73 countries for which we have complete and balanced data, we find that various NPIs had a negative and statistically significant association on the growth rate of (log) confirmed cases. Table 1 column 7 shows that the ordinal sum of the six international NPIs we use could lower the growth rate by about 2 log points (-0.0207, p-value=0.007, 95% C.I. -0.03 to -0.005).

The policies most strongly and statistically significantly associated with slowing the growth rate of (log) confirmed cases in order of magnitude of impact were public transport closures (-0.09, p-value = 0.014, 95% C.I. -0.17 to -0.02), enforced workplace closures (-0.0784, p-value =0.004 , 95% C.I. -0.131 to -0.025), limited domestic travel (-0.-650, p-value = 0.060, 95% C.I. -0.132 to 0.003), and restrictions on international travel (-0.0639, p-value = 0.009, 95% C.I. -0.11 to -0.016). School closures (p-value = 0.387) and limits on public events (p-value = 0.342) are negatively related to growth rates of confirmed cases but were not found to be statistically significant.

For the international sample, five of the six NPIs as well as the cumulative sum of all NPIs are not statistically significant determinants of the growth rate of the cumulative number of deaths. The only NPI that is significant is the closure of public transportation (point estimate: -0.09, p-value = 0.042, 95% C.I. -0.177 to -0.003). In addition the sum of all policies has a negative point estimate of -0.0123 (p-value = 0.226 95% C.I. -0.03 to 0.008), but it is not significant at conventional levels. Since we are recording event time as days since the first death in this table, the sample of countries decreased to 58 from 73 in the sample for confirmed cases. The lack of significance here could be due to our short sample and long lags between implementation of NPIs and effects on death rates.

We also tested for spillovers. Are foreign NPIs associated with lower growth rates of confirmed cases and death rates? We use the total sum of an NPI indicator across countries that share a border as a control in the same regressions as above. We find little evidence of an association for the NPIs of neighboring countries. Six of the seven NPIs, and the summed value of all NPIs in the international data set, are not statistically significant determinants of own-country outcomes for cases and deaths. The only foreign NPI that is a statistically significant of growth in cases is the limitation on internal movement in neighboring countries (point estimate: -0.043, p-value =0.003 , 95% C.I. -0.068 to -0.015).

NPIs enacted by US states are negatively correlated with the growth rate of confirmed cases of Covid-19. Table 3 shows our regression results. Column 1 of Table 3 shows that a

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state's own policy was associated with a reduction of the growth rate of 16.9 log points (p-value = 0.000, 95% C.I. -0.20 to -0.13). Figure 1 and Figure 2 show the dynamics. We compare the change in the growth rate in log confirmed cases in each day after the first day of the policy (25 coefficients) and by five-day periods to the pre-policy growth rate. The point estimates are progressively larger in absolute magnitude over time. None of the point estimates for changes in the growth rate of deaths is statistically significant. We also checked for pre-trends and reverse causality by allowing for leads of the NPI. Point estimates of the leads were not individually statistically significant.

We continue our analysis by allowing for policy spillovers between states. Figure 3 shows the path of confirmed cases for five groups of states corresponding to their calendar time adoption of stay-at-home policies. The first group is the first set of states that implemented such a policy during the week ending 21 March, 2020.[2] The following three groups are states that rolled out their stay-at-home orders during the weeks ending 28 March, 4 April, or 11 April. The fifth group (group 0) consists of states that did not have such an order as of April 13, 2020.

Next we demonstrate graphically how NPIs in group 1 and 2 might have affected other groups by plotting changes in trend growth rates of confirmed cases. Figure 3 plots the total confirmed cases within a group against event time (event day 0 is the day of the first confirmed case). We include two trend lines. This first is the average growth rate of confirmed cases since day 0. The second trend is the average growth rate of confirmed cases prior to the week in which the first group, group 1, implemented stay-at-home. If group 1 has an impact on other groups the trend could break here.

Confirmed cases decelerated following the week in which group 1 acted (groups 0, 2, and 3) or after both group 1 and group 2 had acted (groups 1, 4). From these charts, it would appear that there are spillovers, and they may be cumulative. NPI policies in group 1 and group 2 seem to be especially important for determining growth rates of new cases not only in their own states but also in other groups (i.e., 0, 3, and 4).

We test this more carefully in a linear regression in Table 3. In these regressions, we allow for stay-at-home policies in all other states to matter for state *i*. Policies in other states are population and distance weighted. We also allow for differential effects of policies in neighboring states NPIs in other states with a border state indicator dummy variable, and we allow for the level of confirmed cases in other states to affect growth of cumulative cases.

Own state policies are still associated with lower growth rates of confirmed cases after controlling for other state policies. The point is estimate is -0.034 (p-value =0.005, 95%

[2] A data appendix available upon request shows the timing for each state and their group. Group 1 includes California, Illinois, New Jersey and Maryland. Group includes 27 states including New York, Washington, Louisiana, Massachusetts , and Michigan. Group 3 includes 13 states such as Florida and Texas. Group 4 includes Alabama and Missouri. The non-adopters were: Arkansas, Iowa, Nebraska, and the Dakotas.

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C.I. -0.057 to -0.011). This is one-fifth of the magnitude of the own-state policy in Table 3 when we did not control for other state policies.

Spillovers matter. Policies in other states dating from the week ending March 21st are negatively associated with mortality even in states that had yet to impose a stay-at-home policy. The association between local growth rates of confirmed cases and the first states' policies is the largest. Column 4 shows the point estimate is -14.77 (p-value = 0.056 95% C.I. -29.93 to 0.379). An extra policy (in the first week ending 21 March) at the median distance between states is associated with a decline of about one log point or -0.009 (-0.009 = (1/1688) x -14.777). A new policy by a neighboring state, with the median in-sample centroid-to-centroid distance is associated with a decline of -0.034 (-0.034 = (1/441)*-14.777). This is about the same magnitude as the own-state point estimate. There is no statistically significant differential in the marginal impact of bordering states versus more distant states after accounting for distance between state centroids.

The association for NPI policies in weeks 2, 3 and 4 declines in absolute magnitude and statistical significance in columns 2-4. By the fourth week, the marginal effects of policies in other states are not statistically significant. This is suggestive of the idea that the first wave of stay-at home policies had a bigger impact than later waves.

We also cannot reject the hypothesis that the level of deaths in other cities (weighted by distances between cities) has no relationship with own-city growth rates of deaths *ceteris paribus*.

2.2 Policies and the Economy

Policy has been theoretically predicted to matter for the economy. A high intensity and duration of NPIs is predicted to lower cumulative mortality and peak mortality, but this comes (theoretically) at a greater cost to the economy than had NPIs not been imposed. We find no evidence of this. In

Table 4 we show that applications for unemployment insurance (i.e., jobless claims) rose at the same rate in states that adopted stay-at-home policies as in states without stay-at-home. The point estimate is -0.309 (p-value = 0.108 95% C.I. -0.675 to 0.069). Based on this, there is no evidence that stay-at-home policies led to stronger rises in jobless claims.

The results show some interesting dynamics as well showing in fact that stay-at-home was potentially associated with lower unemployment. In columns 2 (not population weighted) and 3 (population weighted regressions) the association between stay at-home policies and jobless claims is statistically significant and negative two and three weeks after implementation. The coefficient on the first week is not highly statistically significant. We also use six leads of the indicators for stay-at-home. None of these leading marginal effects is statistically significant implying that pre-policy trends are unlikely to account for the post-policy rises in initial jobless claims.

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We also interact state-fixed effects with the stay-at-home policy which allows for heterogeneous impacts by state. A potential concern is that the adoption of stay-at-home was economically less costly, and therefore adopted sooner in places where the occupational structure allowed telecommuting or where the structure of employment was less sensitive to the stay-at-home demand shock. This would bias the impact of such policies downwards. For instance, restaurants, retail and other 'in-person' services may have been more vulnerable to the drop in demand from stay-at-home and states that rely on these industries more heavily may have delayed. Figure 4 shows that the association between jobless claims and stay-at-home varies by state. It is difficult to see a clear pattern here however.

We attempt to see where stay-at-home mattered most by checking for a relationship between stay-at-home and industry-level employment-to-population shares as well as an interaction for the share of jobs in a state that were "telecommutable".[3] We include separate effects for industries that are most likely to be "in-person". For the main effects, we find jobless claims grew most strongly in states with higher shares of employment in the leisure and recreation industry and in wholesale distribution and smaller where employment shares in retail were higher.

In terms of interactions between industry and stay-at-home there are interesting findings. Stay-at-home had a smaller impact on jobless claims where oil and petroleum sectors were more prevalent and where arts and recreation had a higher share of employment. Other sectors like food preparation, retail sales and wholesale were not differentially affected by stay-at-home orders. This suggests common shocks and cross-state trade may matter. At the very least, there is little straightforward evidence linking stay-at-home to industries that are most obviously in-person like retail, food and leisure.

We do however find a more straightforward interaction with stay-at-home and telecommuting. Stay-at-home has a smaller impact I proportion to the share of jobs that can be done remotely. When we include a control for this and an interaction effect, the un-interacted stay-at-home main effect is associated with higher jobless claims with a point estimate of 2.55 (p-value = 0.064, 95% C.I. -0.159 to 5.27). However, the interaction with the share of jobs that can telecommute is large and negative at -4.93 (p-value = 0.063, 95% C.I. -10.15 to 0.28). The average share of telecommutable jobs is 0.38 implying that states above average and near the top, at a share of say 0.48, felt an impact on jobless claims from stay-at-home roughly 1/3 as large as states at the mean.

3. Discussion and comment

[3] These data are from Dingel and Neiman downloaded from https://github.com/jdingel/DingelNeiman-workathome on April 17, 2020.

We have studied a range of Non-Pharmaceutical Interventions in the early stages of the global Covid-19 pandemic. We assess the epidemiological and economic implications of these policies. NPIs reduce growth rates of confirmed cases of Covid-19. The reductions apply to local jurisdictions but also "spillover" to geographically proximate units. Spillovers in policy seem to work more strongly domestically (according to US data) than across international borders.

On average, stay-at-home policies are not associated with higher joblessness in the US states that imposed them than in states that did not. We interpret this as evidence that the negative economic shocks were national and not local. There is however some evidence that stay-at-home has sectoral and occupational impacts. States with more jobs that can be done remotely seem to have lost fewer jobs after implementing stay-at-home than states with fewer such jobs.

During Covid-19, NPIs appear to spillover across states in the US data. These spillovers could arise due to direct limitations on contact with infected individuals from other jurisdictions. However, it could also be because of a psychological or expectational effects. We find evidence that policies in the first-moving states matter more for other states than policies from later-moving states. This implies that part of the impact is due to reaction to news of NPIs in other states. Such news may indicate the severity of an outbreak or a pandemic leading to decreases in labor supply and reactive social distancing even without policies in the locality. Reduced demand for other states products and services from places with stay-at-home could spillover to states without policy too. State-to-state trade or shipment data would be required to verify and validate this channel.

The association between own-state policy and growth of new cases of Covid-19 is weakened once accounting for neighboring state policies. This does not imply that local policy is un-necessary or fruitless. Indeed, the opposite may be true. Neighbors of states not implementing NPIs evidently face greater challenges containing and mitigating disease. This implies there is justification for policy coordination if the objective is to mitigate the spread of disease and to reduce mortality. Externalities imply coordination as per standard economic theory.

In terms of the tradeoff between the economy and public health, similar lessons apply. There is no "free lunch" in a connected and open economy. Once a pandemic is underway and some states have implemented NPIs, then the economic spillover is likely to be strong. This occurs as NPIs in one state, region or country reduce local demand as well as demand for goods and services from other localities. NPIs also disrupt supply chains and contribute to a generalized supply shock in an open-economy setting. Information flows between localities means non-local policies could limit economic participation and labor supply even in localities without NPIs.

Could a state or locality do better by not implementing an NPI while others did? Free-riding is tempting, but it may have un-intended impacts. Assume people can move between places. States with NPIs, realizing that the pandemic could be more severe globally due to

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non-compliance with public health recommendations may be forced to keep their own NPIs in place longer or more intensively. These NPIs reduce the demand for services and products from the non-complier for longer or in greater proportion. The negative impact is in proportion to the level of trade and economic inter-dependence between the two areas. International retaliation with travel bans on non-NPI territories could also limit the economic opportunities of non-complying states. The economic effects would spillover as well. Finally, agents in the non-complying locality may react to information coming from other localities. These reactions will have to be stronger and more intense since the local outbreak would be more intense than if the locality had implemented an NPI.

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Table 1 Mitigation Policies and the Growth Rate of Confirmed Cases of Covid-19: Cross Country Evidence

	(1) School Closures	(2) Workplace Closures	(3) Public Events Limits	(4) Public Transportation Closed	(5) Public Information Campaign	(6) Domestic Travel Limited	(7) International Travel Limited	(8) Sum of all policies
Policy	-0.0230	-0.0784***	-0.0233	-0.0953**	-0.0274	-0.0650*	-0.0639***	-0.0207***
	(0.0264)	(0.0267)	(0.0244)	(0.0376)	(0.0357)	(0.0339)	(0.0236)	(0.00751)
Event time	-0.00611**	-0.00563**	-0.00625**	-0.00585**	-0.00633***	-0.00590**	-0.00524**	-0.00452*
	(0.00259)	(0.00239)	(0.00249)	(0.00248)	(0.00234)	(0.00236)	(0.00257)	(0.00247)
$(\text{Event time})^2$	0.0000984***	0.0000997***	0.000101***	0.0000924***	0.0000991***	0.000101***	0.0000926***	0.0000926***
	(0.0000345)	(0.0000343)	(0.0000342)	(0.0000345)	(0.0000335)	(0.0000341)	(0.0000343)	(0.0000337)
Constant	0.253***	0.251***	0.254***	0.252***	0.270***	0.251***	0.265***	0.269***
	(0.0318)	(0.0311)	(0.0319)	(0.0316)	(0.0434)	(0.0313)	(0.0315)	(0.0307)
Observations	2346	2346	2346	2346	2346	2346	2346	2346
R^2	0.108	0.115	0.108	0.112	0.108	0.112	0.112	0.115
Countries	73	73	73	73	73	73	73	73

Notes: Dependent variable is the daily change in the logarithm of deaths from Covid-19. Estimation is by OLS. All models include country fixed effects and calendar day dummies. Event time is defined as number of days since the first official case of Covid-19. Standard errors in parentheses are clustered at the country level. * p < 0.1, ** p < 0.05, *** p < 0.01

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Table 2 Mitigation Policies and the Growth Rate of Deaths from Covid-19: Cross Country Evidence

	(1) School Closures	(2) Workplace Closures	(3) Public Events Limits	(4) Public Transportation Closed	(5) Domestic Travel Limited	(6) International Travel Limited	(7) Sum of all policies
Policy	0.0340	-0.000391	0.0156	-0.0900**	-0.0496	-0.0414	-0.0123
	(0.0320)	(0.0264)	(0.0279)	(0.0432)	(0.0553)	(0.0315)	(0.0101)
Event time	-0.124**	-0.119**	-0.122**	-0.108*	-0.118**	-0.117**	-0.103
	(0.0581)	(0.0587)	(0.0576)	(0.0563)	(0.0573)	(0.0575)	(0.0624)
$(\text{Event time})^2$	0.0000110	0.00000252	0.00000533	-0.0000169	-0.00000419	-0.000000779	-0.0000230
	(0.0000289)	(0.0000322)	(0.0000282)	(0.0000299)	(0.0000321)	(0.0000289)	(0.0000356)
Constant	2.107**	2.058**	2.086**	1.897**	2.080**	2.049**	1.864*
	(0.906)	(0.918)	(0.902)	(0.887)	(0.896)	(0.901)	(0.962)
Observations	948	948	948	948	948	948	948
R^2	0.303	0.302	0.302	0.306	0.302	0.303	0.303
Countries	58	58	58	58	58	58	58

Notes: Dependent variable is the daily change in the logarithm of deaths from Covid-19. Estimation is by OLS. All models include country fixed effects and calendar day dummies. Event time is defined as number of days since the first official death from Covid-19. Standard errors in parentheses are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 Change in (log) Confirmed Cases versus Stay-at-Home Orders and Neighboring States' Stay-at-Home Policies.

	(1)	(2)	(3)	(4)
S_i = Stay-at-home	-0.170***	-0.0284**	-0.0335**	-0.0338***
	(0.0197)	(0.0124)	(0.0155)	(0.0114)
$S_{i,-i}$ = (Stay-at-home$_{-i}$) x week ending 21 Mar.		-4.020	-8.018	-14.78*
		(2.952)	(4.909)	(7.538)
$S_{i,-i}$ = (Stay-at-home$_{-i}$) x week ending 28 Mar.		-2.045**	-3.099***	-4.226***
		(0.941)	(0.997)	(1.109)
$S_{i,-i}$ = (Stay-at-home$_{-i}$) x week ending 4 Apr.		-1.527*	-1.684*	-2.385**
		(0.832)	(0.894)	(1.040)
$S_{i,-i}$ = (Stay-at-home$_{-i}$) x week ending 11 Apr.		-0.486	-0.673	-1.379
		(0.892)	(0.935)	(1.070)
$S_{i,-i}$ = (Stay-at-home$_{-i}$) x week ending 18 Apr.		-0.273	-0.532	-1.294
		(0.878)	(0.892)	(1.035)
$S'_{i,-i}$ = (Stay-at-home- border states) x week ending 21 Mar.			0.0452	0.0552
			(0.0457)	(0.0464)
$S'_{i,-i}$ = (Stay-at-home- border states) x week ending 28 Mar.			0.0115*	0.0148**
			(0.00573)	(0.00576)
$S'_{i,-i}$ = (Stay-at-home- border states) x week ending 24 Mar.			0.00222	0.00551
			(0.00563)	(0.00579)
$S'_{i,-i}$ = (Stay-at-home- border states) x week ending 11 Apr.			0.00344	0.00556
			(0.00671)	(0.00729)
$S'_{i,-i}$ = (Stay-at-home- border states) x week ending 18 Apr.			0.00516	0.00712
			(0.00657)	(0.00687)
ln (confirmed cases$_{-i}$/distance)				0.0516
				(0.0461)
ln (confirmed cases, border states)				-0.00881
				(0.0393)
Observations	2175	2175	2175	2175
R^2	0.213	0.282	0.316	0.322
States	49	49	49	49
Week Dummies	NO	YES	YES	YES

Notes: Dependent variable is the daily change in the logarithm of confirmed cases of Covid-19. Estimation is by OLS. All models include state fixed effects. Event time trend and a quadratic term in event time are included. Event time is defined as number of days since the first official case of Covid-19. Week indicators for all weeks after the week ending 28 March are included. The week ending March 21 is the policy reference group. All regressions are weighted by state population. Standard errors in parentheses are clustered at the country level. * p < 0.1, ** p < 0.05, *** p < 0.

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Table 4 Initial jobless claims and the Dynamics of Own-State Stay-at-Home Orders

	(1)	(2)	(3)
Stay-at-home	-0.309*		
	(0.179)		
Stay-at-home (3 weeks after)		-0.629***	-0.494***
		(0.230)	(0.164)
Stay-at-home (2 weeks after)		-0.427**	-0.398***
		(0.166)	(0.121)
Stay-at-home (initial week)		-0.304	-0.166**
		(0.188)	(0.0782)
Stay-at-home (2 weeks before)		-0.00315	-0.00453
		(0.124)	(0.122)
Stay-at-home (3 weeks before)		-0.0176	0.0286
		(0.0907)	(0.105)
Stay-at-home (4 weeks before)		0.0356	0.0409
		(0.117)	(0.0853)
Stay-at-home (5 weeks before)		-0.0400	-0.00228
		(0.0509)	(0.0651)
Stay-at-home (6 weeks before)		-0.0658*	-0.0571
		(0.0385)	(0.0448)
N	459	459	459
Number of States + DC	51	51	51
R^2	0.975	0.976	0.977

Notes: Dependent variable is the logarithm of initial jobless claims in the previous week (not seasonally adjusted). Estimation is by OLS. Data is a panel of states + District of Columbia by week. All models include state fixed effects and calendar week fixed effects. Regressions (1) and (2) are weighted by state population. Column (3) is an unweighted regression. In columns (2) and (3) week t is the first week for the stay-at-home order. Week t – 3 denotes three weeks after stay-at-home was initiated, t – 2 two week etc. The week prior to initiation of the stay-at-home order is the reference group. Standard errors in parentheses are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 5 Initial jobless claims, Stay-at-Home Orders and Sectoral Employment

	(1)	(2)	(3)	(4)
Stay-at-home	-0.303	0.537	2.403*	2.559*
	(0.185)	(0.367)	(1.355)	(1.353)
Average Share of Jobs-at-home		4.644	6.315	0.0706
		(3.689)	(3.974)	(4.373)
Stay-at-home x Average Share of Jobs-at-home			-4.927	-4.937*
			(3.559)	(2.599)
Share of Jobs in Oil & Gas				55.43
				(169.0)
Share of Jobs in Arts, Rec. and Entertainment				255.8***
				(86.32)
Share of Jobs in Food & Accommodation				-10.73
				(17.72)
Share of Jobs in Retail				-189.4***
				(38.91)
Share of Jobs in Wholesale				149.9***
				(41.93)
Share of Jobs in Oil & Gas x Stay-at-home				-316.3***
				(89.42)
Share of Jobs in Arts, Rec. and Entertainment x Stay-at-home				-124.7**
				(55.04)
Share of Jobs in Food & Accommodation x Stay-at-home				-2.579
				(10.13)
Share of Jobs in Retail x Stay-at-home				9.512
				(17.31)
Share of Jobs in Wholesale x Stay-at-home				-6.138
				(27.31)
N	267	267	267	267
R^2	0.971	0.662	0.663	0.849

Notes: Dependent variable is the log of initial jobless claims (not seasonally adjusted). Estimation is by OLS. Data is a panel of states + District of Columbia by week. Column (1) includes state fixed effects and all models have calendar week fixed effects. Regressions are weighted by state population. Standard errors in parentheses are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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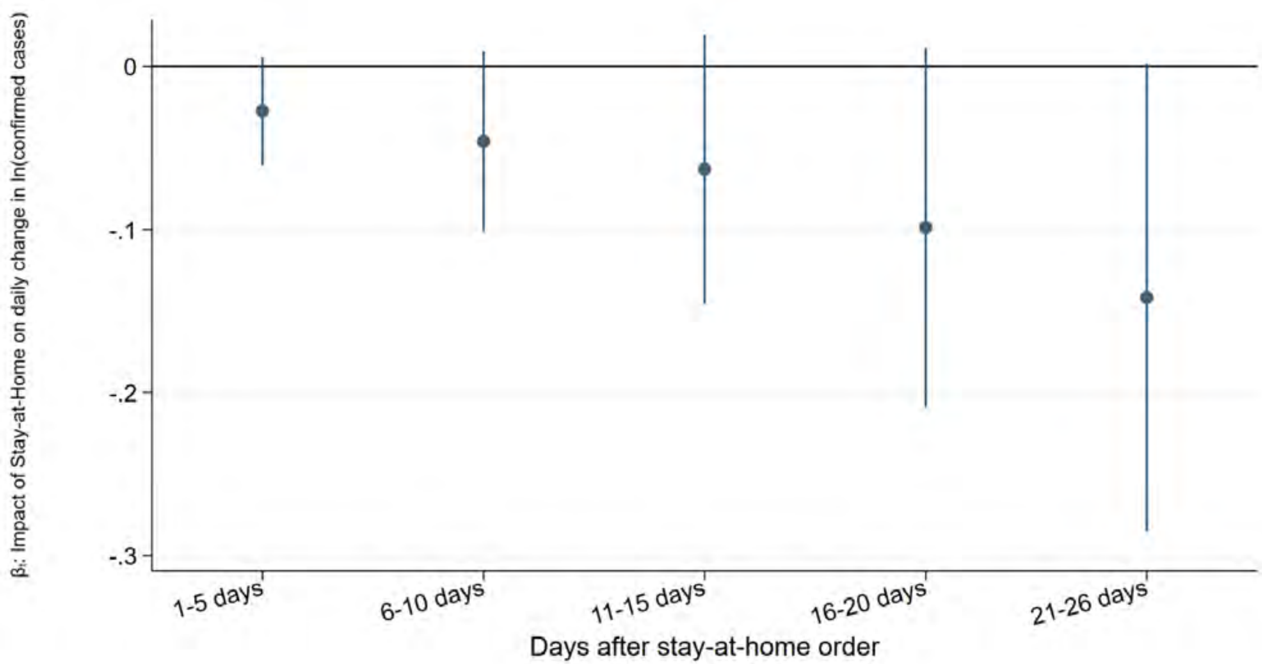
Figure 1 Stay-at-Home and the Growth Rate of Cumulative Cases of Covid-19: Dynamics Post-Policy



Notes: Chart shows the average level of the daily change in the log of confirmed cases of Covid-19 in periods after implementing a stay-at-home order with 95% confidence bars. The levels (dots) are the coefficients from OLS regressions where the dependent variable is the logarithm of confirmed cases. Regressions include state fixed effects, event time trend and quadratic effect and calendar day dummies. Event time is counted in days since the first case of Covid-19 within a state. Standard errors are clustered at the state level.

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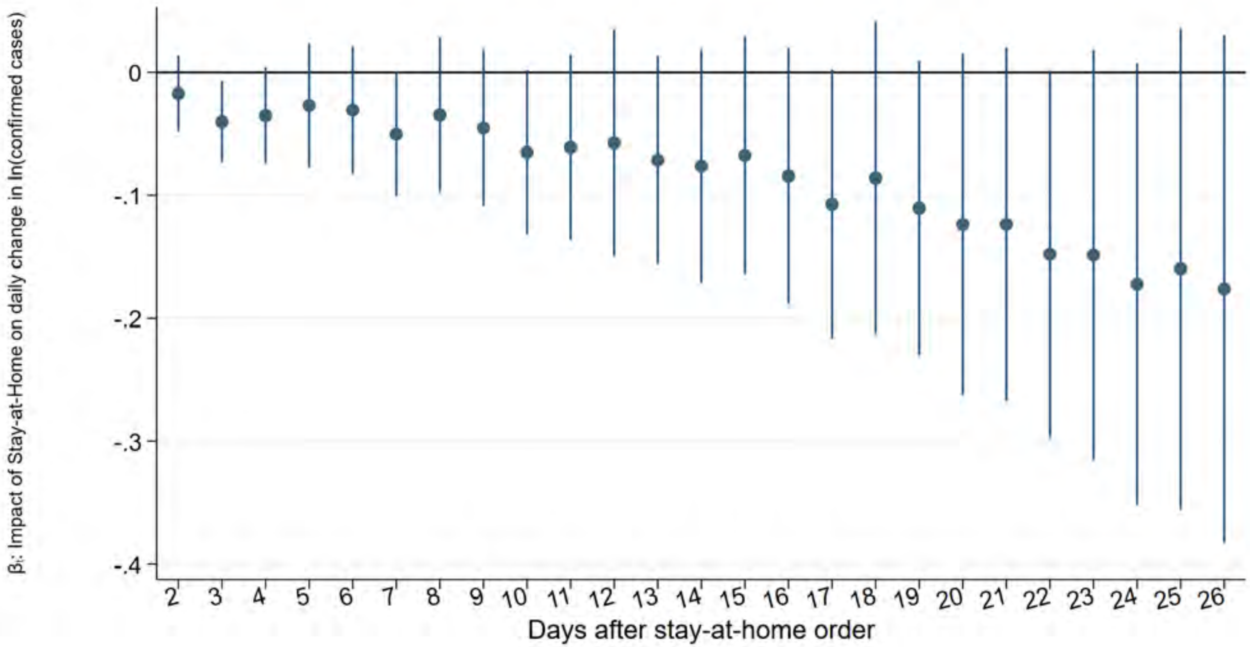
Figure 2 Stay-at-Home and the Growth Rate of Cumulative Cases of Covid-19: Daily Dynamics Post-Policy



Notes: Chart shows the average level of the daily change in the log of confirmed cases of Covid-19 in days after implementing a stay-at-home order with 95% confidence bars. The reference category is the first day of the stay at home order. The levels (dots) are the coefficients from OLS regressions where the dependent variable is the logarithm of confirmed cases. Regressions include state fixed effects, event time trend and quadratic effect and calendar day dummies. Event time is counted in days since the first case of Covid-19 within a state. Standard errors are clustered at the state level.

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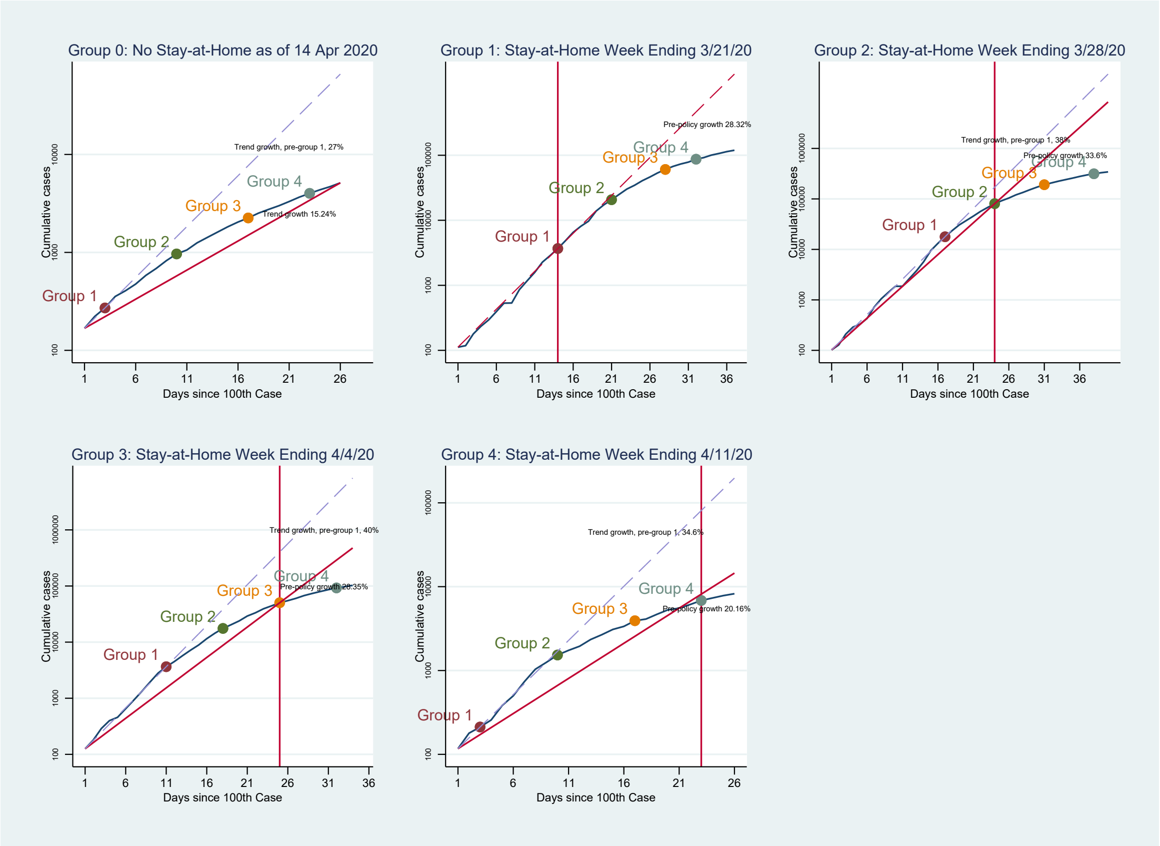
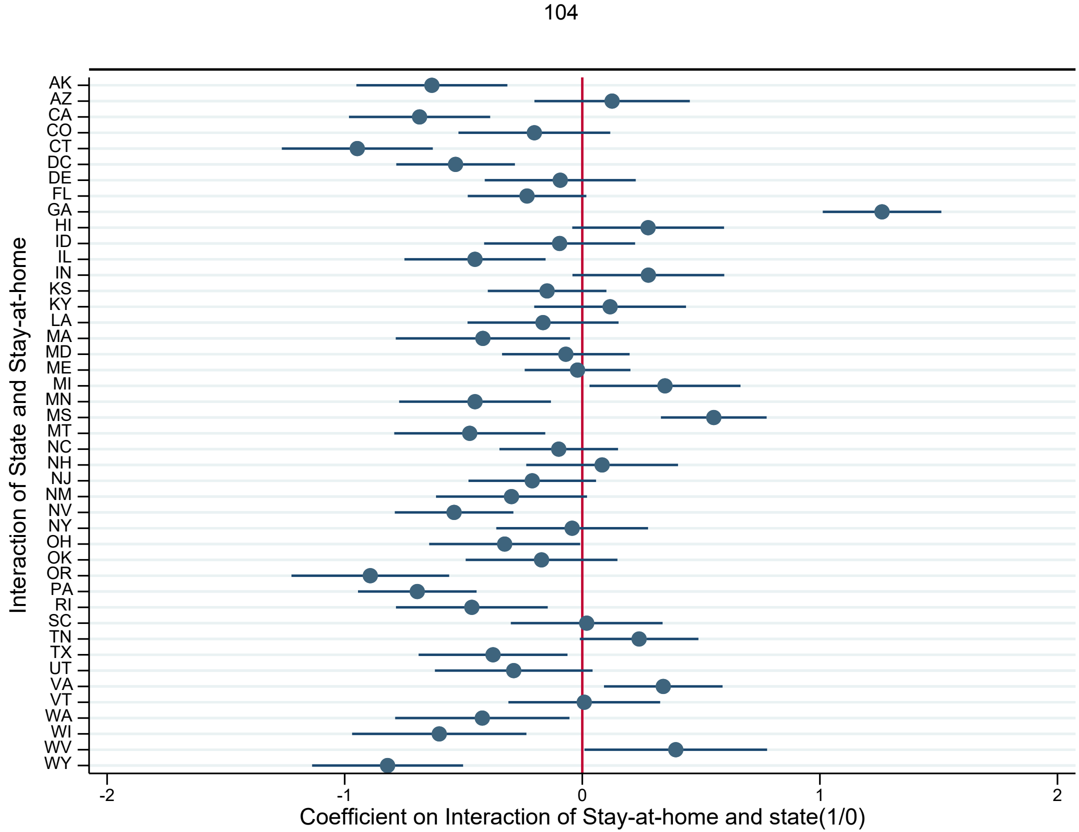
Figure 3 Cumulative Cases of Covid-19 and Stay-at-Home Orders



Notes: Figures plot cumulative cases of Covid-19 for five groups of states. Group 1 -4 implemented stay-at-home orders in successive weeks. Group 0 did not initiate stay-at-home within the sample. Data are plotted on a logarithmic scale. Vertical line denotes the end of the week in which all states in the group implemented stay-at-home. Dotted trend line is the average rate of growth of conformed cases prior to week ending 3/21. Solid line is the trend growth rate prior to implementation of own-group policies.

Figure 4 Impact on Initial Jobless claims of Stay-at-Home Orders by State



Notes: Chart shows the average level of the log of initial jobless claims after implementing a stay-at-home order with 95% confidence bars. Data is a panel of states + District of Columbia by week. All models include state fixed effects and calendar week fixed effects. The regression is weighted by state population. Standard errors are clustered at the state level.

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Covid Economics Issue 14, 6 May 2020

When the markets get Covid: Contagion, viruses, and information diffusion[1]

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We quantify the exposure of major financial markets to news shocks about global contagion risk accounting for local epidemic conditions. For a wide cross section of countries, we construct a novel data set comprising (i) announcements related to COVID-19, and (ii) high-frequency data on epidemic news diffused through Twitter. Across several classes of financial assets, we provide novel empirical evidence about financial dynamics (i) around epidemic announcements, (ii) at a daily frequency, and (iii) at an intra-daily frequency. Formal estimations based on both contagion data and social media activity about COVID-19 confirm that the market price of contagion risk is very significant. We conclude that prudential policies aimed at mitigating either global contagion or local diffusion may be extremely valuable.

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1 Introduction

COVID19 has manifested itself as a very aggressive and fast epidemic that—at the time of the first draft of this paper—has brought major economic countries to their knees.[1] Given the fast-increasing contagion curve of COVID19 and its global scale, this epidemic event is challenging common economic policy interventions and depressing the global value of our assets, i.e., the wealth of millions of households all over the world.

Given that severe virus-related crises are expected to become more frequent, we find it relevant to use COVID19-related data to ask the following broad questions about financial market reactions to viral contagion risk. First, what is the average impact of medical announcements on financial returns? Equivalently, is the diffusion of this information wealth-enhancing or adding risk? Second, what is the market price of risk of news related to global contagion dynamics? Third, can local contagion conditions help us to predict expected returns?

Last but not least, can we use social media activity to measure production and diffusion of information about epidemic risk? This question is important for at least two reasons. First, fast epidemic outbreaks tend to get investors off guard and hence real-time indexes based on social media news may function as a useful predictive tool. Second, the estimation of multidimensional models requires many observations that we may gather by using high-frequency data, as opposed to waiting for daily medical bulletins.

In this study, we address these questions by quantifying the exposure of major financial markets to news shocks about global contagion risk accounting for local epidemic conditions. For a wide cross section of countries, we construct a novel data set comprising (i) medical announcements related to COVID19; and (ii) high-frequency data on epidemic news diffused through Twitter. Across several classes of financial assets and currencies, we provide novel empirical evidence about financial dynamics (i) around epidemic announcements, (ii) at a daily frequency, and (iii) at an

[1] Our first draft is dated 3/23/2020. To assess the severity of COVID19, see the 3/11/2020 WHO Director-General's opening remarks (`https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020`).

intra-daily frequency. Formal estimations based on both contagion data and social media activity about COVID19 confirm that the market price of epidemic risk is very significant. We conclude that prudential policies aimed at mitigating either global contagion or local diffusion may be extremely valuable.

Current results in detail. An important contribution of our work is the collection of a novel dataset on the COVID19 pandemic that includes both (i) a very large set of official announcements on medical conditions, and (ii) news diffused on Twitter in real-time by major newspapers. We identify major newspapers for a large cross section of major countries in the spirit of Baker et al. (2016). In contrast to Baker et al. (2016), we do not analyze articles, rather we track news published on Twitter in real time, so that we can produce high frequency data when needed.

More specifically, we track tweets posted by major newspapers with key words such as 'coronavirus' and 'covid19'. For each newspaper, we identify the location of its headquarters so that we can identify its specific time-zone. As a result, we gather thousands of tweets for a large cross section of countries that we can aggregate at different frequencies and across regions.

Given this data set, we document several important facts about news diffusion. First, both Twitter-based news diffusion (measured by number of tweets) and attention (measured by number of retweets) spike upon contagion-related announcements. Second and more broadly, the diffusion of information increases substantially in each country in our data set as soon as that country goes into an epidemic state.[2] Third, our measured increase in information diffusion is particularly pronounced precisely during the hours in which financial markets are open. All of these empirical facts suggest that tracking Twitter-diffused news can be a reliable way to characterize the information set of investors at high frequency.

Turning our attention to financial dynamics, we look at equity returns around announcements, that is, in a ±90 minute window. We find that cumulative equity returns have no clear pattern

[2] We identify the beginning of the epidemic state with the day in which the number of confirmed COVID19 cases becomes greater or equal to 100.

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before the announcement, as they tend to be relatively flat and indistinguishable from zero. In the post-announcement time window, instead, cumulated returns jump upward upon the announcement and then they exhibit a significant downward path for about 60 minutes.

We note that this time behavior of returns is not present in the pre-epidemic state and is quite different from that documented in Lucca and Moench (2015). Lucca and Moench (2015) shows a slow and persistent accumulation of positive returns before monetary policy announcements. In our case, instead, the increase in the cumulative returns at the announcement is consistent with the Ai and Bansal (2018) model. When the representative investor cares about the timing of resolution of uncertainty, prices jump upward when uncertainty is resolved along the information cycle and then they start to decline.

Furthermore, we conduct the same analysis looking at the government bond market. The response of bonds is less severe than that observed in equities. In a ± 60-minute window around the announcement, there is no significant adjustment in bonds returns. This observation is important as, by no-arbitrage, it suggests that cash-flow uncertainty is an important determinant of the market fluctuations observed during the COVID19 crisis. This high-frequency result is consistent with the results documented by Gormsen and Koijen (2020) looking at dividend futures.

In the last step of our analysis we focus on European countries whose markets are open simultaneously. Specifically, we focus on ITA, ESP, UK, FRA, DEU, CHE, and SWE. Every day, we group them into three portfolios according to their relative number of COVID19 cases. The H (L) portfolio comprises the equity returns of the top-2 (bottom-2) countries for COVID19 contagion cases.

We then estimate a no-arbitrage based model in which we allow for time-varying betas with respect to global contagion risk. Specifically we allow equity returns to respond to global viral contagion news according to the relative share of official COVID19 cases associated to each portfolio. Global contagion risk is measured either by innovations in the growth rate of global COVID19 contagion cases or by innovations in the tone of our COVID19-related tweets.

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This model can potentially capture many of the features of equity returns that we document in our descriptive analysis. First, this model captures predictability through contagion-based time-varying betas. Second, this specification has the potential to capture higher negative skewness for countries that go through more severe contagion paths. Consider the case of portfolio H comprising countries receiving a sequence of relatively more severe contagion news. This portfolio will have greater exposure to adverse news as the relative contagion share of the portfolio grows. As the relative contagion share starts to flatten out and eventually decline, the sensitivity of this portfolio to good news is reduced ($|\beta_{H,t}|$ shrinks), meaning that returns will be less sensitive to positive news and hence the right tail of their distribution will not be very long.

Third, this model accounts for heterogeneous exposure to global contagion news and hence it enables us to identify the market price of risk of this global contagion component. Across all of our specifications, the market price of contagion risk is both statistically significant and extremely high.

Related literature. Due to its relevance, the COVID19 crisis has spurred a lot of contemporaneous research. Macroeconomic studies are focusing on both the aggregate and distributional dynamic implications of the epidemic crisis (Eichenbaum et al. 2020; Fornaro and Wolf 2020; Chiou and Tucker 2020; Barrot et al. 2020; Alon et al. 2020; Glover et al. 2020; Corsetti et al. 2020; Caballero and Simsek 2020; Coven and Gupta 2020). Other studies assess policy concerns (Alvarez et al. 2020; Jones et al. 2020; Bahaj and Reis 2020; Elgin et al. 2020; Faria-e Castro and Louis 2020; Krueger et al. 2020; Farboodi et al. 2020). Correia et al. (2020) and Barro et al. (2020) provide evidence using data from the 1918-Flu epidemic. We differ from these studies for our strong attention to asset prices and COVID19-driven risk.

Other studies at the intersection of macroeconomics and econometrics focus on forecasting the diffusion of both contagion cases and COVID19-implied economic activity disruptions (Favero 2020; Atkeson 2020; Atkeson 2020; Ma et al. 2020; Ludvigson et al. 2020). We focus on both the cross sectional and time series implications for asset prices across different asset classes.

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An important strand of the literature focuses on the measurement of both COVID19-induced uncertainty and firm-level risk exposure by utilizing textual analysis and surveys (Baker et al. 2020; Hassan et al. 2020; Bartik et al. 2020). Giglio et al. (2020) use a survey to study investor expectations over different horizons. Lewis et al. (2020) provide a novel weekly measure of economic activity using several labor market-based timeseries. We focus on high-frequency data, Twitter-based news diffusion, epidemic announcements, and country-level asset price dynamics.

Gerding et al. (2020) look at equity market dynamics and link the epidemic risk exposure to country-level fiscal capacity. Albuquerque et al. (2020) focus on the performance of firms with high environmental and social ratings during the COVID19 outbreak. They do not study announcements and they do not assess the market price of viral contagion risk. Ramelli and Wagner (2020) study equity returns across firms accounting for international trade, financial strength, and investor attention. They use both Google search volume and conference calls as a measure of attention, whereas we use high-frequency data on retweets of tweets issued by news provider. We provide novel evidence about both (i) market reactions around contagion-related announcement times, and (ii) the market price of contagion risk at high frequency.

Schoenfeld (2020) examines buy-and-hold returns for many assets and finds that managers systematically underestimate their exposure to COVID19. Alfaro et al. (2020) focus on the link between aggregate equity market returns and unanticipated changes in predicted infections during the SARS and COVID19 pandemics. We differ in our attention to medical announcements; our social media-based measures of information diffusion and attention; and our high frequency analysis. Our work complements the evidence in Gormsen and Koijen (2020) who extract relevant information about expectations and risk premia from dividend futures.

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2 Data

Twitter-based news. In the spirit of Baker et al. (2016), we identify major newspapers for a large cross section of major countries (see table A.1 in the appendix). In contrast to Baker et al. (2016), we do not analyze articles, rather we track news published on Twitter in real time, so that we can produce high frequency data when needed. More specifically, we track the news related to the COVID19 viral infection posted by major newspapers on Twitter. We do so by searching for key words such as 'coronavirus' and 'covid19'. For each newspaper, we identify the location of its headquarter so that we can identify its specific time-zone.

In table 1, we report a summary of our social media–based dataset. It is very comprehensive and it features several dimensions that enable us to study both information production and diffusion. Specifically, our ability to track retweets and likes gives us a high-frequency measure of attention. Google searches are often used to measure attention (Da et al. 2011; Ramelli and Wagner 2020), but to the best of our knowledge they are not provided minute-by-minute and they do not account for the timing of initial production of the news, an aspect that is very important when analyzing capital market reactions.

The time series behavior of our news indicators is depicted in figure 1. For each country, we also depict the beginning of the epidemic period which we identify on the day in which the number of confirmed cases of COVID19 becomes greater than 100. We note several interesting patterns. First of all, there is significant heterogeneity across countries in the timing of the information diffusion. Across several countries, information diffusion becomes more intense after the beginning of the local epidemic period. We note that both the diffusion of news, that is, number of tweets, and the attention to the news, that is, number of retweets, increase rapidly after the beginning of the local epidemic period.

Figure 2 shows both diffusion and attention to the news at the global level, that is, when we aggregate all of our tweets and retweets across countries. The right panel of this figure provides

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Table 1. Newspapers Dataset

Country	No. News Providers	Tweets	Retweets	Likes	Topics			
					Mortality	Symptoms	Quarant.	Med. Supply
Australia	4	3307	34318	66187	29%	9%	40%	22%
Canada	5	10271	88295	177900	23%	10%	26%	41%
China	3	13943	660194	1770485	27%	8%	27%	38%
France	4	15717	678873	1127045	41%	4%	36%	20%
Germany	4	3264	64197	122710	19%	18%	34%	28%
Hong Kong	3	8059	280160	394609	16%	5%	46%	33%
India	4	25250	321797	1728467	28%	5%	47%	20%
Italy	3	13145	154141	429069	54%	7%	21%	18%
Japan	4	4227	57999	78475	21%	9%	30%	40%
Korea	4	4198	42859	58386	30%	6%	24%	41%
New Zealand	4	5657	59774	114832	33%	8%	39%	20%
Spain	4	13173	1190005	1847935	46%	19%	13%	22%
Switzerland	4	2313	21237	26376	33%	8%	37%	24%
UK	4	7412	386741	854359	23%	14%	41%	22%
USA	11	28505	2477861	5104485	26%	15%	20%	39%
Total	65	158441	6518451	13901320				

Notes: This table shows summary statistics of COVID19-related news data that we collect for a large cross section of countries. Our real-time data range from January 1st 2020 to the date of this manuscript. For each country, we report number of news providers and number of tweets collected. We also report the total number of retweets and likes as measures of attention. The last four columns report the share of tweets mentioning number of deaths, symptoms, quarantine measures, and medical supply, respectively.

a breakdown of the most prominent topics addressed in the COVID19 tweets, namely, symptoms, death risk, quarantine measures, and availability of medical supply. The attention to all of them increased substantially, except for the number of tweets devoted to the discussion of the symptoms of COVID19 which has increased only slightly.

Figure 3 shows the intraday pattern of the diffusion of COVID19 news for each country. This figure is not based on universal time, rather it accounts for country-specific time. In each country, we consider two country-specific subsamples, that is, the pre-epidemic and epidemic period. There are two main takeaways from this picture: (i) the diffusion of COVID19-related news increases significantly with local epidemic conditions; (ii) a significant share of the diffusion takes place while the local capital markets are open. This observation is important because it suggests that monitoring media activity can be a very useful tool to track in real-time the information set of financial market participants.

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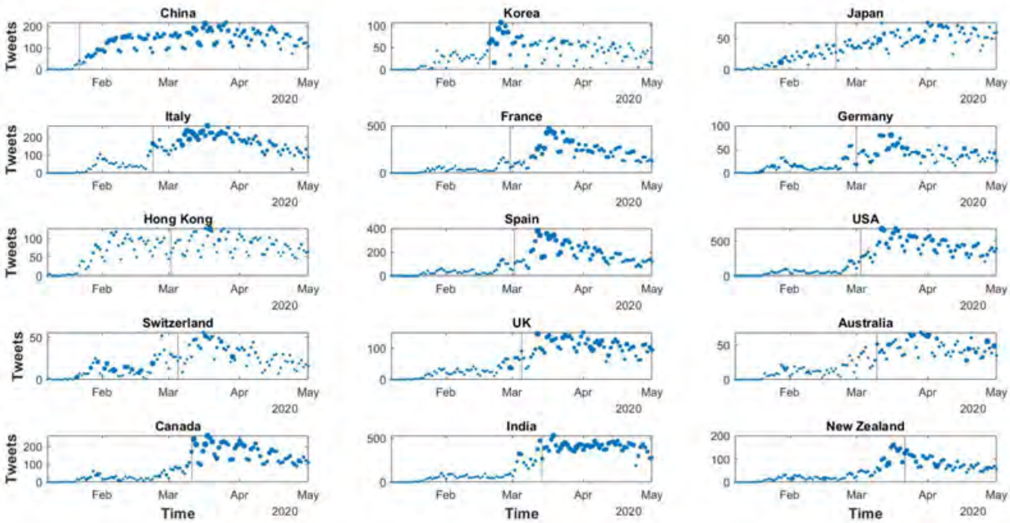

Fig. 1. Information Diffusion and Attention across Countries

Notes: This figure shows the daily number of tweets posted in each country by major newspapers. The vertical axis shows the daily number of tweets. The size of each data point represents the number of retweets scaled by the maximum daily number of retweets for each country. The sample starts on January 8th 2020 and ends on the date of this draft. The vertical line depicts the date that each country had more than 100 confirmed cases of COVID19. More details on the data collection are reported in the Appendix.

Tweet Tone. Since we use Twitter activity to form a high-frequency risk factor, we need to identify the tone of the tweets, that is, we need to know whether they relate to either good or bad news. Given (i) the high volume of tweets that we collect, and (ii) the fact that our tweets are written in different languages, we use Polyglot (available at `https://pypi.org/project/polyglot/`), i.e., a natural language pipeline that supports multilingual applications with polarity lexicons for 136 languages. This computer-based mapping algorithm reads our text and classifies the words into three degrees of polarity: +1 for positive words, -1 for negatives words and 0 for neutral words. We provide two examples in table A.2 (see our appendix).

Our measure of the tone of the tweets is based on the count of positive words minus the count of negative words, divided by the sum of positive and negative word counts (Twedt and Rees, 2012).

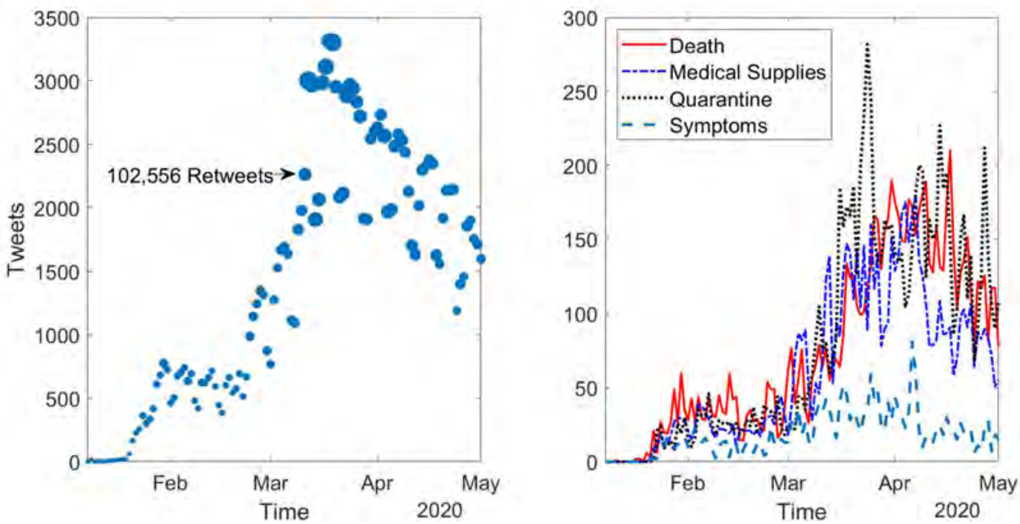

Fig. 2. Global Information Diffusion

Notes: The left panel of this figure shows the daily total number of tweets posted across countries by major newspapers. The vertical axis shows the daily number of tweets. The size of each data point represents the number of retweets scaled by the maximum daily number of retweets. The right panel shows the daily number of tweets related to death-risk, (scarcity of) medical supplies, quarantine, and symptoms. The tweets were identified using a multilingual bag-of-words approach. The sample starts on January 8th 2020 and ends on the date of this draft. More details on the data collection are reported in the Appendix.

We compute this measure at the country level at both the hourly and the daily frequency. We then aggregate this measure across countries in order to obtain a global measure.

We depict our global tone factor in figure 4, left panel. Its time-pattern is consistent with the observed contagion dynamics. Specifically, the tone became very negative by the end of January as the conditions in China started to precipitate. It improved in early February, when there was still no sign of massive contagion in Europe, and it declined again when the epidemic started in Italy. The slow improvement of the tone of our tweets observed after the beginning of March pairs well with the observed flattening of the contagion curves in many of the countries in our dataset. We find these results reassuring as they confirm that our text analysis algorithm tracks the contagion dynamics in a reliable manner.

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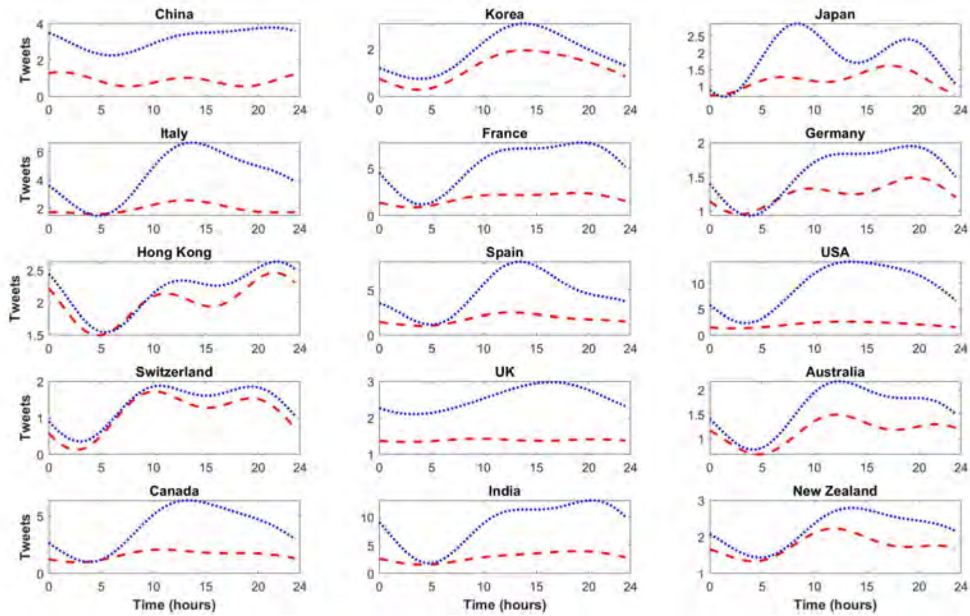

Fig. 3. Intraday Information Diffusion

Notes: This figure shows the intra-day trend of the number of tweets posted every 30 minutes across several countries in our dataset. The dotted line represents the intra-day trend in the epidemic period, identified when a country has more than 100 cases of COVID19. The dashed line represents the intra-day trend in the pre-epidemic period. The sample starts on January 8th 2020 and ends on the date of this draft. Time refers to local time zone of each newspaper. More details on the data collection are reported in the Appendix.

For the sake of our asset pricing analysis, we focus on the innovations to the tone of our tweets. One simple way to extract these innovations is to consider the difference in the tone at day t and its 5-day backward looking moving average assessed at time $t-1$. We depict this time series in the right panel of figure 4 and note that (i) it has become progressively less volatile; and (ii) it is basically serially uncorrelated.

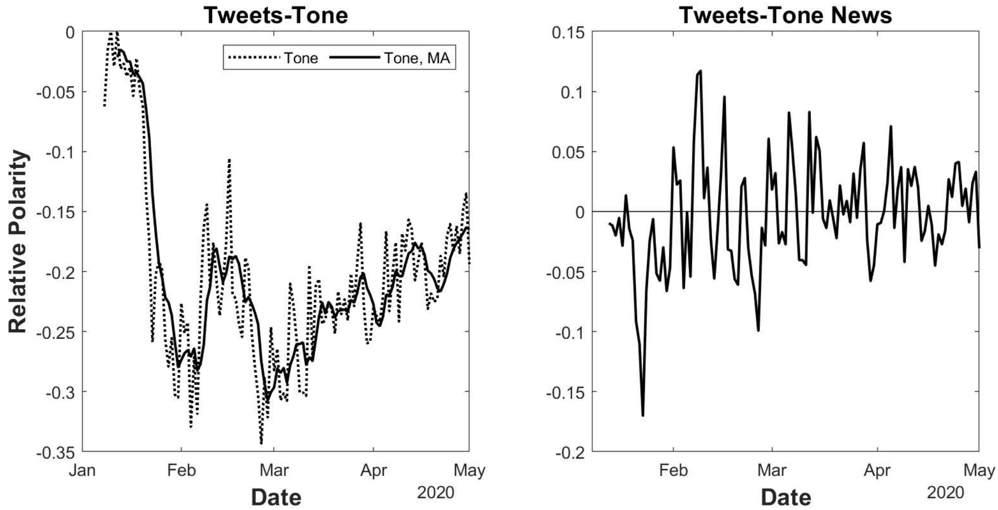

Fig. 4. Twitter-Based COVID19 Factor

Notes: This figure shows our daily global Twitter-based COVID19 factor. We use Polygot to measure the polarity of our tweets and compute the tone of each tweet according to Twedt and Rees (2012). We aggregate the tones at a daily frequency and across countries. MA refers to a backward looking 5-day moving average. The news at time t is computed as the difference between the tweets-tone at time t and their MA at time $t-1$. The sample starts in early January 2020 and ends on the date of this draft.

Contagion data. Contagion data are from official medical bulletins. Our primary source is CSSE at Johns Hopkins University.[3] Since we are interested in the timing of the announcements, we complement this information with hand-collected official press statements publicly available on the webpage of the Ministry of Health (or, equivalently, Health Department) of each country in our data set. When the time stamp of the announcement is not reported on the official report, for each country we investigate the twitter accounts of both the Ministry of Health and major newspapers releasing news with the content of the reports. Hence in our data collection we select the effective date and time of release of the news.

[3] https://github.com/CSSEGISandData/COVID19/tree/master/csse_covid_19_data/csse_covid_19_time_series

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Table 2. Summary Statistics for Announcements

Country	No. Announcements	Governments & Central Banks	Med. Bulletins & Lockdowns
Australia	117	0.00%	100.00%
Canada	52	0.00%	100.00%
China	107	0.00%	100.00%
France	89	7.87%	92.13%
Germany	41	17.07%	82.93%
Hong Kong	87	0.00%	100.00%
India	68	5.88%	94.12%
Italy	96	22.92%	77.08%
Japan	15	6.67%	93.33%
Korea	156	0.64%	99.36%
New Zealand	63	0.00%	100.00%
Spain	122	5.74%	94.26%
Sweden	34	0.00%	100.00%
Switzerland	90	2.22%	97.78%
UK	128	4.69%	95.31%
USA	106	8.49%	91.51%
Total	1371	4.82%	95.18%

Notes: This table shows summary statistics for COVID19-related announcements that we collect for a large cross section of countries. Our real-time data range from 1/1/2020 to the date of this manuscript. For each country, we report the total number of announcements, the fraction related to either medical bulletins or lock-down measures, as well as the fraction of other announcements issued by governments and central banks about fiscal and monetary policy, respectively.

Announcements. For the sake of our intraday analysis, we treat the release of each medical bulletin as an announcement. The same applies to travel limitations and lock down policies related to COVID19. We note that we have manually tracked these policy interventions on a daily basis and hence we have constructed a novel dataset important to study real-time high frequency reactions of financial markets to epidemic risk.

Since in our sample we have also witnessed important announcements related to both monetary and fiscal policy interventions, we complement the medical announcements with major policy-related announcements as well. Our data collection is very comprehensive, as documented in table 2. An example of COVID19-related announcement follows:

2020-03-14 15:35:00; Vice President @Mike_Pence and members of the

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Coronavirus Task Force will hold a press briefing at 12:00 p.m. ET. Watch LIVE: `http://45.wh.gov/RtVRmD`

In this case, we set the time of the announcement at 12:00 p.m. ET. To clarify further our methodology, we also give an example of an announcement related to a monetary policy intervention in response to COVID19:

2020-03-18 23:05:00; FT Breaking News; ECB to launch €750bn bond-buying programme.

In this case, the time of the announcement is 11:05p.m. CET.

Sometimes, we may have two consecutive related announcements in the same country (for example, an official medical bulletin released by the Health Department immediately followed by a press conference of the Prime Minister). To avoid redundant information, we only consider announcements non-overlapping over a 60 minute window. In table 2, we report our effective number of announcements that we use for each country.

Most importantly, we show that the vast majority of the announcements that we gather are solely related to medical bulletins and policy measures to fight the epidemic. This is an important point, as the returns reaction in our study is different from that observed with respect to other economic announcements.

Financial Data. All data are from Eikon, Thomson Reuter. Equity and currency data are obtained at the minute frequency and then aggregated at lower frequency when necessary. We measure the risk-free rate by focusing on the yield of 3-month government bills. We also focus on treasury bonds with a 10-year maturity. All details about our data can be found in table A.3 (see appendix).

In order to show the relevance of local epidemic conditions, in figure 5 we show the intra-day behavior of returns pre- and post-epidemic for equities, bonds, and currencies. We focus on two groups of countries with similar stock exchange timing, namely US and Canada (EST timezone),

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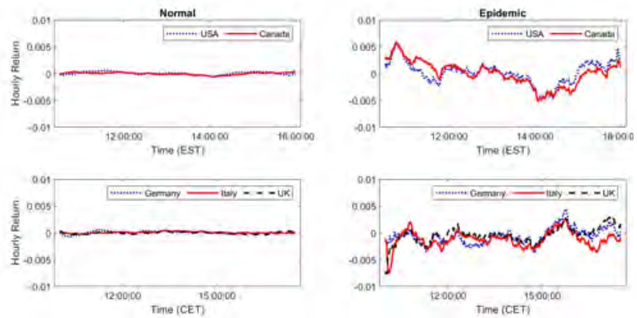
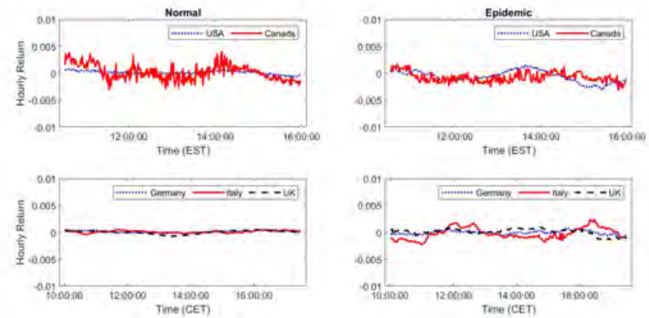
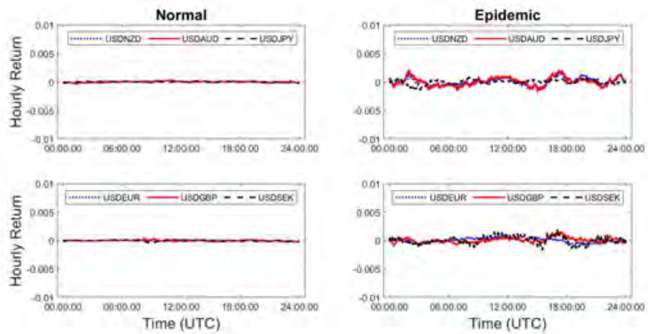


Equity



Bonds



Currencies

Fig. 5. Intra-day Returns Behavior and Epidemic Conditions

Notes: For each asset class, we depict per- and post-pandemic intra-day return patterns. Data are averaged across days. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The sample starts in October 2019 and it ends on the date of this draft. Bond and stock hourly returns start one hour after the opening of the markets. All returns are in raw units. **Sentence deleted**

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and Italy, UK, and Germany (CET timezone). The countries in the second group are interesting because they have experienced very different exposures to COVID19. Italy has been affected first and in an intensive way. Germany has been able to mitigate the contagion and has seen a pick up in contagion numbers as soon as it lessened the lockdown measures. The UK has changed its strategic response to the crisis in the middle of the epidemic period.

We note that equity returns have been much more volatile in the epidemic period. Most importunately, the intra-day patterns have become much more correlated once all countries have gone into an epidemic state. This result suggests that we can think of the epidemic as a slowly diffusing global factor. Our empirical asset pricing analysis is based on this observation.

When we turn our attention to bonds in the epidemic period, we see more volatile patterns than in the pre-epidemic period. In contrast to equities, we see no substantial change in their commonalities across countries. Currencies, instead, tend to be more volatile and more correlated in epidemic subsamples, similarly to equities. We see this as consistent with COVID19 being a global risk factor that affects countries at different times and with different intensities.

3 Empirical Findings

In this section, we report our major empirical findings. We first look at the behavior of asset prices around announcement time. We then turn our attention to the study of a conditional linear factor model which accounts for heterogeneous exposure to COVID19. The latter approach produces interesting results both when we use daily medical bulletins and when we use higher frequency data based on our social media measures. The last subsection highlights our next research steps.

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3.1 Announcements

Our novel social media-based data set enables us to measure the diffusion of information at a very high frequency. For each announcement in our data set, we collect all tweets issued in a ±90-minute window around announcement time. For the sake of statistical power, we aggregate all of these tweets across all of our countries and we call the resulting aggregate 'World'.

In the left panel of figure 6, we show per-country per-minute average number of tweets around announcement time during epidemic periods in excess of the same average measured in the pre-epidemic samples (dots). As before, the start of the epidemic period is country-specific and is identified with the day when the number of COVID19 cases becomes greater than 100. This procedure enables us to capture news diffusion patterns specific to the epidemic period. The right panel refers to retweets, that is, our measure of attention to the news.

We interpolate our data with a quadratic function of time and include dummy variables to account for post-announcement jumps in both the level and the slope. Formal tests reject the null of a common time-behavior before and after the announcement for information diffusion. We depict our results in figure 6, where the solid line denotes our estimate whereas the shaded area refers to our confidence intervals. Importantly, both information diffusion and attention to the news increase significantly in the aftermath of the announcements.

Note that we assign to retweets the time of the original tweet they refer to. This means that we match attention level with the original time of the news diffusion. As a result, the lack of a jump in attention is likely due an underestimation issue with respect to the timing of the retweets since many retweets refer to pre-announcement tweets but happen post-announcement.

This pattern pairs nicely with that of equity returns depicted in figure 7. Specifically, the panel on the left shows the average cumulative returns obtained from buying country-specific equities 90 minutes before a country-specific announcement and holding them over an increasing horizon of 180

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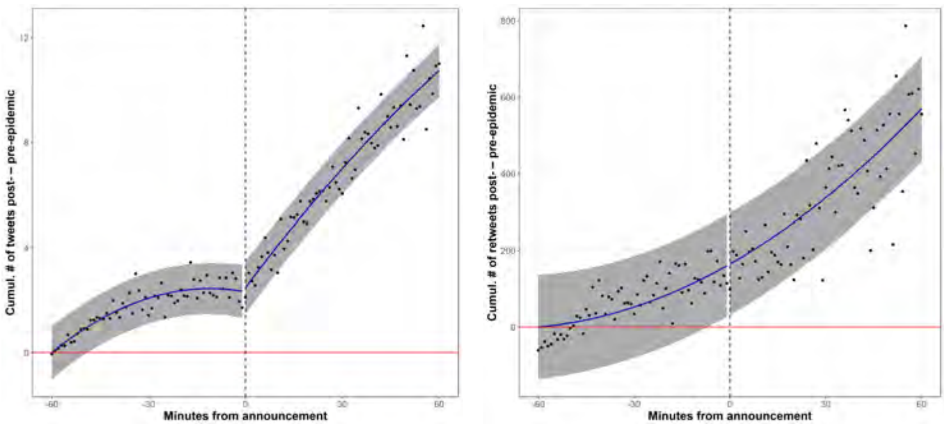

Fig. 6. Information Diffusion and Attention around Announcements

Notes: The left (right) panel of this figure shows the average per-minute and per-country number of tweets (retweets) around announcement time in excess of the same average in the pre-epidemic period. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The solid line comes from a quadratic interpolation estimated before and after the announcement. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

minutes. Our results are averaged across both countries and announcements.[4]

In this picture, we plot the behavior of the returns in both the normal and the epidemic states or, equivalently, subsamples. In both cases, cumulative returns have no clear pattern before the announcement, as they tend to be relatively flat and indistinguishable from zero. In the post-announcement time window, instead, the dynamics become quite different across the normal and the epidemic state. Specifically, in the epidemic state, cumulated returns jump upward upon the announcement and then they exhibit a significant downward path for about 60 minutes.

We note that this figure shows a time varying behavior of returns quite different from that documented in Lucca and Moench (2015). Lucca and Moench (2015) show a slow and persistent accumulation of positive returns before monetary policy announcements. In our case, instead, the

[4] If a country-specific announcement happens when the exchange of the country is closed, we consider the 90 minutes prior to the closing time of the previous day and the first 90 minutes after the opening of the exchange in the next day. This is, for example, what we do with the ECB announcement made at 11:05pm on 3/18/2020.

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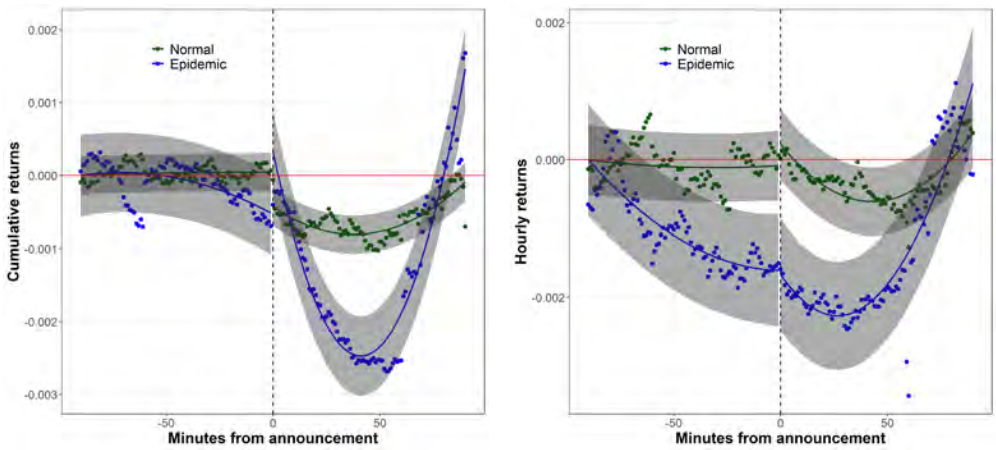

Cumulative Returns Hourly Returns

Fig. 7. Equity Returns around Announcements

Notes: The panel on the left shows the average cumulative returns obtained from buying equities 90 minutes before an announcement and holding them over an increasing horizon of 180 minutes. The panel on the right shows the average realized returns from holding equities for 60 minutes at the end of the investment strategy, that is, the value reported at +30 minutes refers to an investment started 30 minutes before the announcement. Returns are in raw log units. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The solid line comes from a quadratic OLS augmented with post-announcement dummies. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

increase in the cumulative returns at the announcement is consistent with the Ai and Bansal (2018) model. When the representative investor cares about the timing of resolution of uncertainty, prices jump upward when uncertainty is resolved along the information cycle, and then they start to decline.

After about 60 minutes returns start to pick up again. There are two possible explanations at the moment. First, since we consider non-overlapping announcements over a 60-minute window when forming our dataset, we may start to pick the componded effect of multiple announcements. Alternatively, such under-shooting and recovery behavior could be consistent with behavioral finance models. A possible way to test the second exaplanation is to look at volumes and liquidity around announcement time. We are currently working on this issue.

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To further validate this point, in the right panel we plot hourly returns computed on a backward looking rolling window. For example, a data point reported at the time of the announcement refers to the returns from an investment strategy started 60 minutes before the announcement time and liquidated at the announcement time. Given this construction, we can also think of these values as a measure of 60-minute ahead expected returns.

Our results indicate that there is no significant pattern in the pre-epidemic period. Most importantly, in the epidemic subsample, expected returns are stable up to an hour prior to the announcement, they jump upward when the hour ahead includes the announcement time, and then they decline and start to revert half an hour prior to the announcement. In our graph, this means to look at at $t = +30$ minutes from announcement.

Figure A.3 (see Appendix) shows the difference in cumulative returns and hourly returns across normal and epidemic subsamples. Formal tests confirm substantial differences in the time behavior of returns pre- and post-announcement across the normal and the epidemic samples, consistent with our discussion of figure 7.

Figure 8 shows our results for bonds returns. The construction of the depicted data is identical to that used for equities. We note that the dynamics in the bond markets are less severe than those observed from equities. In a $\pm$60-minute window around the announcement, there is no significant adjustment in bonds returns. This observation is important as, by no-arbitrage, it suggests that cash-flow uncertainty is an important determinant of the market fluctuations observed during the COVID19 crisis. This high-frequency result is consistent with the results documented by Gormsen and Koijen (2020) looking at dividend futures.

An alternative explanation for this muted response is that bond markets are subject to two offsetting forces. Specifically, flight to safety may promote bond appreciation but, simultaneously, sovereign default risk may increase and and push bond prices downward. We are working on this issue by collecting country-level data on both trade volume and CDS spreads. Given that different countries entered this crisis with different levels of fiscal capacity, exploring country-level

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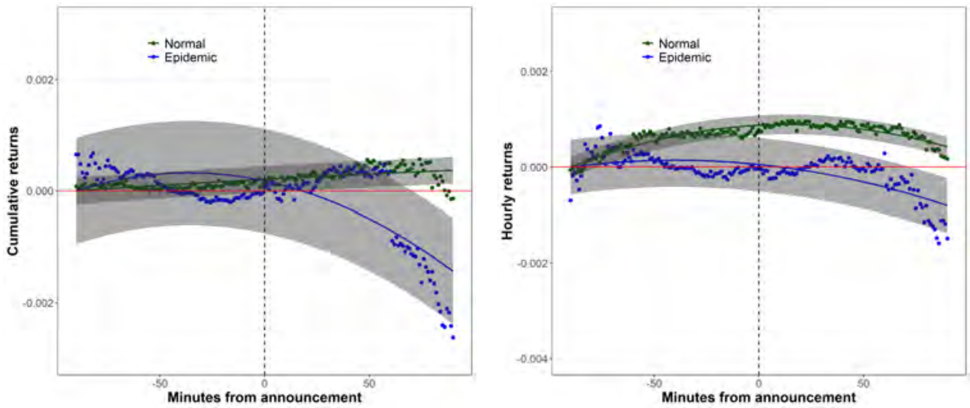

Cumulative Returns Hourly Returns

Fig. 8. Bond Returns around Announcements

Notes: The panel on the left shows the average cumulative returns obtained from buying 10y government bonds 90 minutes before an announcement and holding them over an increasing horizon of 180 minutes. The panel on the right shows the average realized returns from holding bonds for 60 minutes at the end of the investment strategy, that is, the value reported at +30 minutes refers to an investment started 30 minutes before the announcement. Returns are in raw log units. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The solid line comes from a quadratic OLS augmented with post-announcement dummies. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

heterogeneity is important.

3.2 Cross Sectional Results: HML$_{COVID19}$

Daily News. We start by focusing on European countries whose markets are open simultaneously. Specifically, we focus on ITA, ESP, UK, FRA, DEU, CHE, and SWE. Every day, we group them into three portfolios according to their relative number of COVID19 cases. The H (L) portfolio comprises the top-2 (bottom-2) countries in terms of COVID19 cases. We also consider an investment strategy long in the H portfolio and short in the L portfolio. We refer to the returns of this portfolio as HML-COVID19.

We report common summary statistics for these portfolios in table 3. The in-sample average

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Table 3. Summary Statistics for Portfolios

	Low	**Medium**	**High**	**HML$_{COVID19}$**
Mean	-0.026	-0.028	-0.062	-0.036^{**}
	(0.041)	(0.038)	(0.045)	(0.016)
StDev	0.912	0.843	0.942	0.472
First Quartile	-0.271	-0.312	-0.328	-0.181
Median	-0.004	-0.005	-0.023	-0.009
Third Quartile	0.263	0.268	0.246	0.14
Avg. N. Countries	2.088	2.923	1.989	-
Turnover (%)	2	5.2	4.1	-
International-CAPM α	0.012	0.007	-0.024^{**}	-0.036^{**}
	(0.009)	(0.006)	(0.009)	(0.015)

Notes: This table shows summary statistics for the equity excess returns of portfolios formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation. Hourly excess returns are in log units and multiplied by 100. Portfolios are obtained from equity indexes for ITA, ESP, UK, FRA, DEU, CHE, and SWE. Our real-time data range from February 2020 to the date of this manuscript. Turnover measures the number of countries entering or exiting a portfolio relative to the total number of countries in a specific portfolio $\times$ number of days in our sample. International-CAPM α is the intercept obtained by regressing the portfolio returns on the average equity return across the above mentioned countries. Numbers in parenthesis are HAC-adjusted standard errors.

of the returns in all portfolios is negative. Given our sample, this not surprising. Focusing on the quartiles of the returns distribution, we see that the portfolio comprising the more exposed countries tends to have more severe negative skewness. This is an aspect that we capture in our conditional no-arbitrage model.

The turnover in each portfolio is not excessive and, most importantly, our HML-COVID19 returns are not explained by an international CAPM model. Specifically, when we regress our HML returns on the excess returns of an equity index including all of our countries, the alpha estimated from the timeseries is statistically significant.

We consider the following conditional asset pricing model,

$$
\begin{aligned}
r^{ex}_{f,t+1} &= \overline{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\}, && (1) \\
\beta_{f,t} &= \beta_0 + \beta_{f,1} X_{f,t}, && (2) \\
\frac{\partial \overline{r}^{ex}_{f,t}}{\partial X_{f,t}} &= \lambda \beta_{f,1}, && (3)
\end{aligned}
$$

where X_t is the share of contagion cases associated to portfolio f at time t, and λ is the market price of risk of the global news factor $news^{glob}_{t+1}$.

This model can potentially capture many of the features of returns seen so far. First, it captures predictability through contagion-based time-varying betas. Second, it has the potential to capture higher negative skewness for countries that go through more severe contagion paths. Consider the case of portfolio H comprising countries receiving a sequence of relatively more severe adverse contagion news. This portfolio will have severe exposure to adverse news as the relative contagion share of the portfolio grows. When the relative contagion share starts to flatten out and decline, the sensitivity of this portfolio to good news is reduced ($|\beta_{H,t}|$ shrinks). This means that returns become less sensitive to positive news and hence the right tail of the returns distribution is shortened.

Third, consistent with our previous descriptive returns, it accounts for heterogenous exposure to global contagion news. Last but not least, it enables us to identify the market price of risk of this global contagion component, λ. By no-arbitrage, the extent of time-series predictability of our excess returns must equal $\lambda\beta_{f,1}$, and $\beta_{f,1}$ can be easily estimated in the time-series by considering the multiplicative factor $X_{f,t} \cdot news^{glob}_{t+1}$.

We report our main results obtained from daily data in table 4. In the first two specifications, the news to the contagion factor are obtained by computing the difference between the daily growth rate of contagion cases at time t and its backward-looking time $t-1$ moving average computed over the previous 5 days. We choose a 5-day window because it matches the number of days of a typical trading week.

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Table 4. Conditional Linear Factor Model

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
News about Covid Cases							
coef	-0.049	-51.489^{***}	-13.400^{***}	-7.233^{***}	-0.012^{***}	61	3
se	(0.034)	(11.985)	(3.663)	(1.690)	(0.003)	61	3
News about Covid Cases, adjusting for FX							
coef	-0.044	-48.681^{***}	-11.222^{***}	-5.582^{***}	-0.012^{***}	61	3
se	(0.028)	(10.881)	(3.016)	(1.264)	(0.004)	61	3
News from Twitter							
coef	0.129^{**}	17.219^{***}	4.864^{***}	2.001^{***}	0.037^{***}	61	3
se	(0.050)	(4.669)	(1.133)	(0.500)	(0.009)	61	3
News from Twitter, adjusting for FX							
coef	0.091^{**}	25.736^{***}	6.527^{***}	2.236^{***}	0.029^{***}	61	3
se	(0.037)	(6.016)	(1.116)	(0.512)	(0.006)	61	3

Notes: This table shows the results of the conditional linear factor model described in equations (1)–(3). Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). The coefficient $\beta_{f,t} = \beta_0 + \beta_f X_{f,t}$ refers to the exposure of the equity portfolio $f \in \{H, M, L\}$ to the COVID19 factor. When we measure the COVID19 news as unexpected number of contagion cases (unexpected improvement in COVID19-related tweets), we expect a negative (positive) market price of risk (MPR). Both daily excess returns and market prices of risk are in log units. Our real-time data range from February 2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

Since our contagion-based factor spans a 7-day week, we assign to Friday the average growth rate of global contagion cases that occurred on Friday, Saturday, and Sunday.[5] Note that the set of countries that we consider provide daily updates about contagion cases at the end of the day. In order to properly represent the information set of investors, in our asset pricing model we lag the news by one day, i.e., we assume that day-t returns respond to news released in the evening of day $t-1$.

We estimate our asset pricing model through GMM and notice that all portfolios have a significant negative exposure to our contagion-based news, $\beta_{f,t}$. This sign is consistent with our expectations since positive news about global contagion growth refers to an adverse shock. Most importantly, the implied daily market price of risk is negative and significant. This means that the

[5]For the Easter Holiday, we assign to Thr 4/9/2020 the average daily growth rate of global cases from Thr 4/9/2020 to Mon 4/13/2020.

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relative share of contagion cases forecasts an increase in expected future returns across all portfolios.

We note that the share of contagion cases across our three portfolios have very different scales and variability. As a result, the coefficients $\beta_{f,1}$ are not revealing of the sorting of $\beta_{f,t}$ across portfolios. In our sample, the portfolio of countries with the highest share of COVID19 cases tends to be more exposed to contagion news.

Both Sweden and Switzerland have their own local currencies. Given the spirit of our analysis, it is important to understand whether adjusting for exchange rates our results continue to hold. When we express all returns in euros, our estimated time-varying betas change slightly, but the market price of risk remains unchanged.

Next, we replicate our estimation procedure using our daily measure of innovations in the global factor derived from our tweets' tone. In this case, positive news should be interpreted as good news. As a result, both our estimated beta and the market price of risk are positive. Equivalently, the share of contagion cases is a relevant positive predictor of future expected returns. Looking at theoutput of our four specifications and accounting for estimation uncertainty, we conclude that 1% is a reasonable lower bound on the daily market price of risk of daily contagion news. We consider this estimate as very significant, consistent with the great contraction experienced in equity markets during the epidemic period.

An important advantage of our Twitter-based risk-factor is that we can measure it at very high frequencies, in contrast to daily contagion cases. Using higher frequency data helps sharpen the estimate of the market price of risk because it provides an increased number of observations and hence it gives us enough degrees of freedom to control for other relevant factors, i.e, to estimate a multi-factor conditional model.

In table 5, we show our results when we link hourly equity excess returns to hourly Twitter-based news. Our implied betas continue to be positive, but our inference is less precise as hourly returns are much noisier than daily returns. The implied market price of risk is positive, well identified,

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Table 5. Conditional Linear Factor Model

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
News from Twitter, hourly							
coef	-0.011	1.068	0.606**	0.201*	0.057***	549	3
se	(0.008)	(1.322)	(0.307)	(0.118)	(0.018)	549	3
News from Twitter, hourly, adjusting for FX							
coef	0.003*	0.202*	0.049**	0.001	0.280***	549	3
se	(0.001)	(0.114)	(0.023)	(0.008)	(0.107)	549	3
News from Twitter, hourly, controlling for MKT							
coef	-0.013**	1.040	0.699***	0.252***	0.015***	549	3
se	(0.005)	(0.677)	(0.234)	(0.094)	(0.006)	549	3

Notes: This table shows the results of the conditional linear factor model described in equations (1)–(3). Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). The coefficient $\beta_{f,t} = \beta_0 + \beta_f X_{f,t}$ refers to the exposure of the equity portfolio $f \in \{H, M, L\}$ to the COVID19 factor. When we measure the COVID19 news as unexpected number of contagion cases (unexpected improvement in COVID19-related tweets), we expect a negative (positive) market price of risk (MPR). Both hourly excess returns and market prices of risk are in log units. Our real-time data range from February 2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

and sizeable. When we express al returns in Euros, the market price of risk becomes enormous. We interpret this preliminary result as suggesting that our factor may remain very relevant even after controlling for other relevant sources of risk highlighted in the literature.

In our last specification. Specifically, we regress our portfolio returns on the excess returns of an equity index including all of our countries and use the residuals of this regression in our conditional one-factor model. Consistent with the failure of the international-CAPM documented in table 3, our the implied market price of risk is still positive and sizeable.

3.3 Next steps

We are working on addressing the following questions:

1. What happens to the estimate of the market price of contagion risk if we include information from bond returns?

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2. Is the $HML_{COVID19}$ factor spanned by currencies? If so, we can use currencies to track this factor across time zones (UTC time), as currencies are traded all day long.

3. Is the $HML_{COVID19}$ factor that we can construct from either America or Asia equity markets similar to the one constructed using European data? If not, why?

4. How would our portfolio results change if we focused on winners and losers in terms of daily contagion changes, as opposed to the share of the total 'stock' of cases?

5. Do different news shocks (mortality, contagion, ...) have a different impact on the MPR of our COVID19 factor?

6. Given the heterogeneous response of equity and bonds to the same factor, what are the resulting prescriptions for the construction of a high-performance portfolio?

7. As the contagion risk tapers off in Europe, will announcements have a different impact on equity returns?

4 Conclusion

In this study, we quantify the exposure of major financial markets to news shocks about global contagion risk accounting for local epidemic conditions. We construct a novel data set comprising (i) medical announcements related to COVID19 for a wide cross section of countries; and (ii) high-frequency data on epidemic news diffused through Twitter. Across several classes of financial assets and currencies, we provide novel empirical evidence about financial dynamics (i) around epidemic announcements, (ii) at a daily frequency, and (iii) at an intra-daily frequency. Formal estimations based on both contagion data and social media activity about COVID19 confirm that the market price of epidemic risk is very significant. In the spirit of Mulligan (2020), we conclude that policies related to prevention and containment of contagion could be first-order, that is, extremely valuable, for global wealth.

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Appendix A. Data Sources

TABLE A.1: **News Papers**

Country	Newspaper	Twitter Account	BBD	Language
USA	LA Times	@latimes	Yes	English
USA	USA Today	@USATODAY	Yes	English
USA	Chicago Tribune	@chicagotribune	Yes	English
USA	Washington Post	@washingtonpost	Yes	English
USA	Boston Globe	@BostonGlobe	Yes	English
USA	Wall Street Journal	@WSJ	Yes	English
USA	Miami Herald	@MiamiHerald	Yes	English
USA	Dallas Morning News	@dallasnews	Yes	English
USA	Houston Chronicle	@HoustonChron	Yes	English
USA	San Francisco Chronicle	@sfchronicle	Yes	English
USA	New York Times	@nytimes	Yes	English
Italy	Corriere Della Sera	@Corriere	Yes	Italian
Italy	La Repubblica	@repubblica	Yes	Italian
Italy	Il Sole 24 ORE	@sole24ore		Italian
Canada	Gazette	@mtlgazette	Yes	English
Canada	Globe and Mail	@globeandmail	Yes	English
Canada	Ottawa Citizen	@OttawaCitizen	Yes	English
Canada	Toronto Star	@TorontoStar	Yes	English
Canada	Vancouver Sun	@VancouverSun	Yes	English
China	People's Daily, China	@PDChina		English
China	China Xinhua News	@XHNews		English
China	China Daily	@ChinaDaily		English

(To be continued)

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Country	Newspaper	Twitter Account	BBD	Language
France	Le Monde	@lemondefr	Yes	French
France	Le Figaro	@Le_Figaro		French
France	Liberation	@libe		French
France	Le Parisien	@le_Parisien		French
Germany	Handelsblatt	@handelsblatt	Yes	German
Germany	Frankfurter Allgemeine Zeitun	@faznet	Yes	German
Germany	BILD	@BILD		German
Germany	Zeit Online	@zeitonline		German
India	Economic Times	@EconomicTimes	Yes	English
India	Times of India	@timesofindia	Yes	English
India	Hindustan Times	@htTweets	Yes	English
India	The Hindu	@the_hindu	Yes	English
Japan	Asahi Shimbun AJW	@AJWasahi	Yes	English
Japan	The Japan News by Yomiuri	@The_Japan_News	Yes	English
Japan	The Japan Times	@japantimes		English
Japan	Japan Today News	@JapanToday		English
Korea	Yonhap News Agency	@YonhapNews		Korean
Korea	The Korea Times	@koreatimescokr		Korean
Korea	Korea JoongAng Daily	@JoongAngDaily		English
Korea	The Korea Herald	@TheKoreaHerald		English
Spain	EL MUNDO	@elmundoes	Yes	Spanish
Spain	EL PAIS	@el_pais	Yes	Spanish
Spain	ABC.es	@abc_es		Spanish
Spain	La Vanguardia	@LaVanguardia		Spanish
UK	The Times	@thetimes	Yes	English

(To be continued)

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Country	Newspaper	Twitter Account	BBD	Language
UK	Financial Times	@FinancialTimes	Yes	English
UK	BBC News (UK)	@BBCNews		English
UK	Guardian news	@guardiannews		English
Switzerland	Neue Zurcher Zeitung	@NZZ		German
Switzerland	20 Minuten	@20min		German
Switzerland	24 Heures	@24heuresch		French
Switzerland	Le Temps	@LeTemps		French
Hong Kong	South China Morning Post	@SCMPNews	Yes	English
Hong Kong	Hong Kong Free Press	@HongKongFP		English
Hong Kong	RTHK English News	@rthk_enews		English
Australia	The Age	@theage		English
Australia	The Australian	@australian		English
Australia	The Daily Telegraph	@dailytelegraph		English
Australia	Financial Review	@FinancialReview		English
New Zeland	The New Zealand Herald	@nzherald		English
New Zeland	The Sydney Morning Herald	@smh		English
New Zeland	Herald Sun	@theheraldsun		English
New Zeland	Guardian Australia	@GuardianAus		English

Notes: This table reports our newspaper sources. For each newspaper, we specify headquarter location, original language, and twitter account. A 'Yes' under the column BBD denotes a newspaper used also in Baker et al. (2016).

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Table A.2. Computing Tweets' Tone: Two Examples

Tweet Text	Positive Words	Negative Words	Tone
The coronavirus pandemic has been particularly devastating to the United States's biggest cities. It comes as the country's major urban centers were already losing their appeal for many Americans.	"devastating", "losing"	"appeal"	$\frac{-2+1}{3} = -0.33$
A shortage of test kits and technical flaws in the U.S. significantly delayed widespread coronavirus testing. This is how testing has increased since the beginning of March — and how far it still needs to go, according to the Harvard estimates	"shortag", "flaws", "delayed"		$\frac{-3}{3} = -1$

Notes: This table shows two examples of the computation of the tone of a tweet using Polyglot.

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Table A.3. Data Sources

Country	Equity Index	Long Term Bond Index	Short Term Bond Index	Currency
Australia	ASX Index	AU 10y benchmark	AU 1Y benchmark rate	AUDUSD
Canada	SPTSX Composite Index	CA 10y benchmark	CA 3M benchmark rate	USDCAD
China	Shanghai Shenzen Composite Index	CN 10y benchmark	CN 1Y benchmark rate	USDCNY
France	CAC Index	FR 10y benchmark	FR 3M benchmark rate	EURUSD
Germany	DAX Index	DE 10y benchmark	DE 3M benchmark rate	EURUSD
Hong Kong	Hong Kong Hang Seng Index	CN-HK 10y benchmark	HK 3M benchmark rate	USDHKD
Italy	FTSE MIB Index	IT 10y benchmark	IT 3M benchmark rate	EURUSD
India	BSE Senex Index	IN 10y benchmark	ES 3M benchmark rate	USDINR
Japan	Nikkei 225 Index	JA 10y benchmark	JP 3M benchmark rate	USDJPY
Korea	KOSPI Index	KR 10y benchmark	KR 1Y benchmark rate	USDKRW
New Zealand	NZX 50 Gross Index	NZ 10y benchmark	NZ 3M benchmark rate	NZDUSD
Spain	IBEX 35	ES 10y benchmark	ES 3M benchmark rate	EURUSD
Switzerland	SMI Index	CH 10y benchmark	CH 3M benchmark rate	USDCHF
Sweden	OMX Stockholm 30 Index	SE 10y benchmark	SE 3M benchmark rate	USDSEK
USA	SPX Index	US 10y benchmark	US 3M benchmark rate	USD
UK	FTSE Index	UK 10y benchmark	GB 3M benchmark rate	GBPUSD

Notes: This table shows our data sources. All data are obtained from Eikon, Thomson Reuter.

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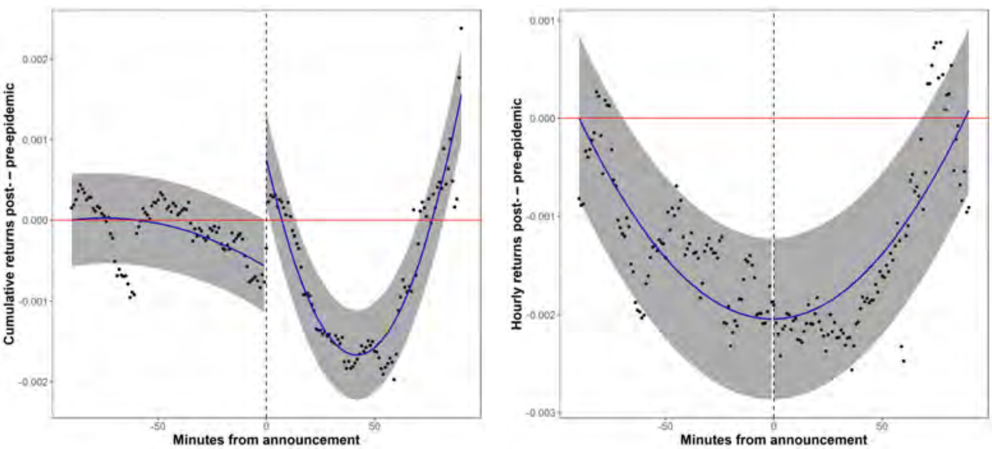

Cumulative Returns Hourly Returns

Fig. A.3. Equity Returns around Announcements

Notes: The panel on the left shows the average cumulative returns obtained from buying equities 90 minutes before an announcement and holding them over an increasing horizon of 180 minutes in the epidemic period minus that obtained in the pre-epidemic sample. The panel on the right shows the difference in the average realized returns from holding equities for 60 minutes across the pre-epidemic and the epidemic sample. We report realized returns at the end of the investment strategy, that is, the value reported at +30 minutes refers to an investment started 30 minutes before the announcement. Returns are in raw log units. In each country, the epidemic period starts when there are more than 100 cases of COVID-19. The solid line comes from a quadratic OLS augmented with post-announcement dummies. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

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Inequality of fear and self-quarantine: Is there a trade-off between GDP and public health?

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Date submitted: 28 April 2020; **Date accepted:** 30 April 2020

We construct a quantitative model of an economy hit by an epidemic. People differ by age and skill, and choose occupations and whether to commute to work or work from home, to maximize their income and minimize their fear of infection. Occupations differ by wage, infection risk, and the productivity loss when working from home. By setting the model parameters to replicate the progression of COVID-19 in South Korea and the United Kingdom, we obtain three key results. First, government-imposed lock-downs may not present a clear trade-off between GDP and public health, as commonly believed, even though its immediate effect is to reduce GDP and infections by forcing people to work from home. A premature lifting of the lock-down raises GDP temporarily, but infections rise over the next months to a level at which many people choose to work from home, where they are less productive, driven by the fear of infection. A longer lock-down eventually mitigates the GDP loss as well as attens the infection curve. Second, if the UK had adopted South Korean policies, its GDP loss and infections would have been substantially smaller both in the short and the long run. This is not because Korea implemented policies sooner, but because aggressive testing and tracking more effectively reduce infections and disrupt the economy less than a blanket lock-down. Finally, low-skill workers and self-employed lose the most from the epidemic and also from the government policies.

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However, the policy of issuing "visas" to those who have antibodies will disproportionately benefit the low-skilled, by relieving them of the fear of infection and also by allowing them to get back to work.

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1 Introduction

As the COVID-19 pandemic went under way, with no known vaccine or cure, most governments turned to quarantine policies to “flatten the curve.” Some of the policies are selective and targeted, based on testing and tracing, while others were more blunt, indiscriminately imposing social distancing and lock-downs. The urgency of the situation and the lack of real-time data have not allowed a thorough analysis of the economic and epidemiological impact of such policies. Which policy is more effective in arresting the epidemic? How big are the economic costs of the quarantine policies that disrupt most economic activities? How are the impacts of the epidemic and the governments’ countermeasures distributed across people of different socioeconomic standings? These questions remain largely unanswered. In the midst of the intense debates on whether to open up to save the economy or to stay locked down till the epidemic further subsides, addressing these questions is of paramount importance.

To answer the questions, we develop a quantitative economic-epidemiological model, in which the progression of the epidemic affects people’s economic decisions and vice versa. The model has several novel features that make it unique in the nascent but fast growing literature of epidemic economics. First, to evaluate how the impact of the epidemic and the policies are distributed, the model incorporates rich heterogeneity: People differ by skill and age, and there are multiple sectors and occupations. Second, people choose their occupations and whether to commute to work or work from home, to maximize income and minimize the fear of infection. Occupations are different in terms of earnings, infection risks, and the productivity loss when working from home. Working from home entails lower earnings but curtails the risk of infection. Third, true health states are not observable, and people have to be tested to find out their current infection status (or past status, if antibody tests are available) subject to false negatives. Finally, governments have access to three policy tools: testing, tracking (targeted quarantine), and broad lock-downs. The intensive margins of these tools are adjustable, and so is their timing.

Our model provides a framework for *quantitative* analysis and can be used to evaluate and predict the aggregate and distributive effects of real-world policies in various economic settings. The quantitative nature of our analysis sets it apart from most other works in the literature, which tend to be either empirical or theoretical. In this paper, we choose the model parameters to replicate the progression of COVID-19 in South Korea and the United Kingdom (henceforth SK and UK, respectively). These two make an interesting and informative contrast. SK responded early with aggressive testing and tracking, and largely contained the epidemic. The UK on the other hand belatedly imposed a blanket lock-down, and its containment efforts have not been as successful.

Based on our quantitative analysis of the two countries, we obtain three key results.

First, contrary to the common view, there may not be a clear trade-off between GDP and public health after all. It is true that, since a lock-down prevents people from working normally, it can slow down the rise in infection at the expense of lower economic output. It is also true that a premature lifting of the lock-down increases GDP initially at the expense of rising infections. However, if the lock-down is lifted too soon, infections can rise to a level at which most people voluntarily work from home out of fear of infection, and this would happen in a matter of months. The government may try to impose another round of lock-downs, but all the countermeasures lose their

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potency once infections reach a certain threshold. For the UK, an extended lock-down pushes peak infection from early to late autumn, and 5-percent *higher* GDP throughout the summer. In other words, a stricter and longer lock-down can deliver both higher GDP and better public health outcomes.

Second, if the UK had adopted the SK policies, its GDP loss would have been smaller by two-thirds both in the short and the long run, and the cumulative infections through November would have been three orders of magnitude smaller. This is not merely because SK implemented policies sooner: The model shows that an earlier implementation of the lock-down in the UK has minor effects on GDP and infection. Rather, it is because aggressive testing and tracking can more effectively isolate the infected and hence reduce their chance of infecting other people, without forcing everyone, including the large majority that is not infected, to work from home where they are less productive.

Third, the epidemic or the policies implemented to counter it do not affect people equally. Low-skill jobs tend to be more contact-intensive (e.g., restaurants and retail), which means that (i) low-skill individuals face higher infection risks and hence suffer more from the fear of infection, and (ii) it is hard to do their work from home and hence their earnings loss when working from home is larger. For these reasons, low-skill workers and self-employed are disproportionately affected by the epidemic and the government's countermeasures that make them work from home (be it through testing, tracking and/or lock-down), and some low-skill workers in particular switch jobs in response. One exception is the potential policy of issuing "virus visas" to those who have antibodies: This policy will disproportionately benefit the low-skill workers and self-employed, by relieving them of the fear of infection and also by allowing them to get back to work. A visa policy can raise UK's GDP by 2 percent compared to its baseline lock-down policy in our model, entirely driven by a 5-percent higher output in low-skill sectors. This result suggests that antibody tests should prioritize the low-skilled, not only to help those most in need, but also to have a maximal positive effect on aggregate GDP.

Related literature Our paper belongs to the new strand of literature that incorporates the SIR epidemiology model by Kermack et al. (1927) or its variants into economic environments. Our innovation on the epidemiology side is to consider asymptotic carriers, which is crucial in the evaluation of testing policies, and heterogeneous infection rates by worker type, which can alter the spread of the virus depending on which people are quarantined. For the production structure, we use a simplified version of our existing work on sector/occupational heterogeneity in Lee and Shin (2017), and refer to Hensvik et al. (2020); Mongey et al. (2020) to guide our choice of work-from-home productivity differences across sector-occupations, as well as which jobs are more "essential" in the event of a lock-down.

Insofar as we focus on the quantitative impact of virus containment policies to gauge the interaction between economic activities and the spread of the virus, our paper is related to the more theoretical papers such as Alvarez et al. (2020), Eichenbaum et al. (2020), and Piguillem and Shi (2020) that analyze optimal quarantine policies considering similar trade-offs. In particular, Piguillem and Shi (2020) is closest to our work in that theirs is the only other model that is calibrated to actual data moments (Italy) and highlights the effectiveness of testing policy under the possibility of asymptotic car-

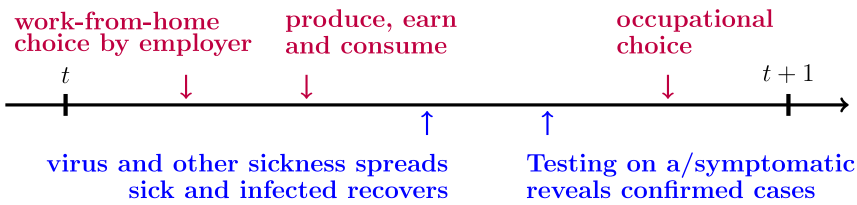

Fig. 1: Model Timeline

riers. We expand on such papers by considering a more elaborate heterogeneous-agent equilibrium model of production in which people voluntarily choose to self-quarantine themselves out of fear and are unaware of their own infection status without testing. We also consider different dimensions of government-enforced quarantines (ordering people to stay home is different from enforcing that order, e.g. lock-down orders vs. SK-style digital tracking).

The potential importance of voluntary self-quarantine in response to the epidemic shock is also emphasized in Farboodi et al. (2020) and Chudik et al. (2020). The latter argues that self-quarantine is unlikely to lower infection rates unless the epidemic approaches very high levels, so that mandated social distancing could be required to flatten the epidemic curve, which we find to be true in our calibration. While Chudik et al. (2020) focus on the estimation of the epidemiology parameters, we focus on the quantitative impact on GDP and inequality. Krueger et al. (2020) consider heterogeneity in individuals' consumption choices, and show that an endogenous shift of consumption toward low contact goods from high contact goods can mitigate the negative impact on the economic activity. In contrast, we focus on the heterogeneity in individuals' labor supply choices, and delve deeper into distributional issues in addition to the aggregate impact of COVID-19.

We explicitly model the fact that high levels of voluntary self-quarantine leads to GDP losses, as well as how self-quarantine interacts with various policy options, concluding that the combination of test/trace/tracking is the most effective tool from both an economic and epidemiology perspective. To our knowledge, this paper is the first quantitative analysis that explicitly fits both country level data on GDP and employment in conjunction with COVID infection/death counts, as well as inequality in both economic and epidemiological outcomes.

2 Model

Time is discrete, and one model period is one day. At $t = 0$, there is an influx of infected agents into the economy, but nobody is aware of it until the government starts testing at some later date $\tau > 0$. We allow for asymptomatic carriers and also for similar symptoms not caused by the coronavirus: People could show no symptom when infected with the coronavirus, and could exhibit similar symptoms without the coronavirus (e.g., sick with the flu). People start the day with a health status and in the job they chose last night, and in the morning, decide whether to commute or work

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from home. Then they work and consume, and prices are determined to clear markets. Over the course of the day, the virus spreads, and some of the infected people recover. Their health status (symptomatic/asymptomatic) also gets updated. In the evening, if $t \geq \tau$, people may get tested. Given the test results and their updated health status, they decide whether to stay in their job or switch to a new job. The whole cycle repeats itself the next day.

Below, we describe the model details without a time-subscript. The model's daily timeline is shown in Figure 1.

2.1 Individual States

Immutable states People are either young or old, and given the focus on the short-term dynamics, we ignore aging. People do die with or without COVID-19 and exit from the model. The old are all retired and do not work. We will also assume that all of the old are in self-quarantine in the presence of COVID-19. These assumptions imply that the model treats the old as a single block, although their epidemiological states to be defined below will differ from one another and change over time.

On the other hand, the young are either high-skilled or low-skilled, indexed by $x \in \{l, h\}$, which is a permanent characteristic. In every period, they choose occupations and, unlike the old, may or may not be in quarantine. Like the old, their epidemiological states are heterogeneous and change over time.

In summary, one's age (young or old) and skill (only for the young) are held permanently constant.

True epidemiological states The true epidemiological side of the model extends the SIR model, and we have four states: susceptible (S), infected (I), recovered (R) and dead (D). Needless to say, death is an absorbing state. We assume that those recovered will not be infected again, although this is not a foregone conclusion in the medical literature.

One important distinction we make is that these true epidemiological states, with the exception of death, are not observable to the people or the government in the model. As a result, they will make decisions based on observed epidemiological states defined below.

Observed epidemiological states People are either healthy (asymptomatic, a) or sick (symptomatic, s), both with and without the SARS-CoV-2 ("the virus" hereafter). By now it is well known that some people with the virus exhibit no symptom. In addition, in the model it is possible that someone without the virus can be sick with symptoms (for example, because of the flu) similar to those of COVID-19. In terms of testing for the virus, people fall into three categories: untested or tested negative (superscript 0), tested positive (superscript c), and confirmed remission (superscript r). False negative is a possibility, but false positive is not. As a result, we have seven observed epidemiological states: two symptom categories by three test categories, plus death: $\{a^0, s^0, a^c, s^c, a^r, s^r, d = D\}$. The true and observed epidemiological states coincide perfectly only at death. The two diverge because not everyone is tested and also false negative is possible.

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2.2 The Economic Model

Preferences and Technology For utility out of consumption, we assume that

$$u(c) = \log(1 + c),$$

which is somewhat unconventional but it is equivalent to Stone-Geary log-preferences with one unit of "free consumption." This is to allow for zero earnings. We will also introduce additively-separable disutility terms coming from the epidemiological side.

There are three sectors of production. Two of them produce intermediate inputs and are labeled "high-skill" and "low-skill" in reference to the skill levels of the people who work in them. The other is the final good sector, combining the output of the high- and the low-skill sectors with a constant-return-to-scale production function:

$$Y = Y_l^{\theta} Y_h^{1-\theta} \tag{1}$$

where $0 < \theta < 1$ is a share parameter. The production is done by a perfectly-competitive, representative firm, and the final good price p is normalized to one.

For the high-skill and the low-skill sectors, indexed by $x = h, l$, there are two modes of production. First, a healthy self-employed person who commutes to work produces $z_{x,1}$ units of the skill-x good without hiring any additional labor, where the subscript 1 denotes self-employment. Second, a healthy manager who commutes to work, and whose skill is x can hire workers of the same skill and operate a span-of-control production function:

$$y_{x,2} = z_{x,2}^{\alpha_x} l_{x,3}^{1-\alpha_x}, \tag{2}$$

where $z_{x,2}$ is the efficiency unit as a manager (subscript 2) of skill x and $l_{x,3}$ is the efficiency units of the workers (subscript 3) of the same skill x hired. The parameter $1 - \alpha_x$ is the span of control. The skill-x output produced by the two modes are perfectly substitutable. The price of the high- and the low-skill goods are denoted by p_h and p_l respectively, and all producers are price takers.

2.2.1 Individual Choices

In the model, the old are retired and always in self-quarantine, and hence have no decision to make. The young will choose their occupation and quarantine status based on their skill and observed epidemiological states.

Work-from-home decision Our timing convention is such that the young choose an occupation at the end of each period. There are three occupations for each of the two skill levels: self-employment (non-employer), manager, and worker, which we index by $j = 1, 2, 3$. The self-employed decide whether to work from home (self-quarantine) or work normally (not in quarantine), and the managers decide whether they and/or their workers will work from home or not. Workers do not have such a decision—they are told by their managers to either work normally or work from home.

Working from home makes people less productive, and their efficiency units are multiplied by a factor $\psi_{x,j}$ that is less than one, which varies by the two-by-three skill-occupation groups.

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Sick people are less productive whether they work normally or from home, so the efficiency units are multiplied by a factor ϕ that is less than one if and only if sick (symptomatic, $e \in \{s^0, s^c, s^r\}$), regardless of whether or not they have the virus. In addition, working normally (not in quarantine) while sick causes disutility κ. This productivity loss and the disutility from working while sick are the same for all skill-occupation groups.

The wage per efficiency unit of high-skill labor is w_h and that of low-skill labor is w_l. For tractability, we assume that when making the work-from-home decision, the self-employed and managers use adaptive expectations and base their decisions on the equilibrium prices from the previous period.

The self-employed (subscript 1) with skill x and observable epidemiological state e choose to work normally (n) or work from home (q):

$$V_{x,1}(e;\mathbf{p}) = \max_{\iota \in \{n,q\}} \left\{ V^n_{x,1}(e;\mathbf{p}) + \epsilon_n, V^q_{x,1}(e;\mathbf{p}) + \epsilon_q \right\}, \tag{3}$$

where ϵ_ι for $\iota = n, q$ is i.i.d. extreme value preference shocks. The work location choice is made *after* the realization of the preference shocks. The aggregate state $\mathbf{p}$ is the vector of market-clearing prices and wages from the previous period. The two values of working normally and from home are

$$\begin{aligned} V^n_{x,1}(e;\mathbf{p}) &= u\left[\phi(e) \cdot p_x z_{x,1}\right] - \kappa(e) - \chi_{x,1}\left(\mathbf{I}, e\right) \\ V^q_{x,1}(e;\mathbf{p}) &= u\left[\psi_{x,1}\phi(e) \cdot p_x z_{x,1}\right] - \chi_q\left(\mathbf{I}, e\right). \end{aligned} \tag{4}$$

The self-employed with skill x produce $z_{x,1}$ units of output without using any input, and the output price is p_x. The parameter $\psi_{x,1} < 1$ discounts their productivity when working from home, which differs by skill x. The reduced productivity for being sick $\phi(e)$ is less than one for $e \in \{s^0, s^c, s^r\}$ and equal to one otherwise. The utility from hand-to-mouth consumption is the first term. Individuals also dislike working normally while sick and would rather work from home, as measured by $\kappa(e)$.[1] The last term $\chi(\mathbf{I}, e)$ is the disutility from the fear of infection, which differs depending on whether or not an individual chooses to stay at home (effectively quarantining oneself).[2] Fear depends on the entire distribution of the masses of the infected across all groups (the vector notation $\mathbf{I}$, whose i-th element is the mass of those infected in group i). However, if $e \in \{a^r, s^r\}$, the individual knows that he is immune and no longer has this fear.[3]

Similarly, the values of managers of skill x (subscript $x,2$) working normally (n) or from home (q) are:

$$\begin{aligned} V^n_{x,2}(e;\mathbf{p}) &= u\left[\phi(e) \cdot \pi_x z_{x,2}\right] - \kappa(e) - \chi_{x,2}\left(\mathbf{I}, e\right) \\ V^q_{x,2}(e;\mathbf{p}) &= u\left[\psi_{x,2}\phi(e) \cdot \pi_x z_{x,2}\right] - \chi_q\left(\mathbf{I}, e\right). \end{aligned} \tag{5}$$

[1] This is distinct from a general disutility from being sick, which we ignore as it does not alter choices.

[2] Our reduced form specification can capture a direct disutility from high infections, but also the expected loss in future earnings from becoming infected tomorrow.

[3] People do not know whether they are infected/recovered without testing, and the government does not know who is infected either. However, they still know the total number of infected by skill, occupation, and observed health status, as long as they know the deterministic epidemiological laws of motion in Section 2.3 and the history of confirmed cases. This is why $\mathbf{I}$ is an admissible argument of individual preferences.

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The main difference from the self-employed is the return to their skill π_x:

$$\pi_x = \alpha_x p_x \cdot \left[\frac{(1-\alpha_x)p_x}{w_x} \right]^{\frac{1-\alpha_x}{\alpha_x}},$$

which is the maximized profit per efficiency unit of managerial skill. The managers' productivity discount when working from home, $\psi_{x,2}$, and their fear from infection, $\chi_{x,2}(\mathbf{I}, e)$, differ by skill x and also from those of the self-employed or the worker (hence subscript 2).

In addition, managers decide whether their workers will work normally or work from home. For this decision, managers act like a "paternalistic planner" and maximize a modified version of the workers' objective function. Specifically, a manager's problem regarding a worker with skill x and observed health status $e_{x,3}$ is:

$$\max_{\iota \in \{n,q\}} \left\{ u\left[\phi(e) \cdot w_x z_{x,3}\right] + \epsilon_n, u\left[\psi_{x,3}\phi(e) \cdot w_x z_{x,3}\right] + \epsilon_q \right\}, \tag{6}$$

where the $u[\cdot]$ term is the worker's utility from consuming his labor income, which is the product of the wage w_x and his labor efficiency units $z_{x,3}$, discounted by ϕ for being sick and/or $\psi_{x,3}$ for working from home. For each worker, the manager draws i.i.d. extreme value preference shocks ϵ_ι and make the worker's work location decision.

We compare this objective function of the "paternalistic" manager with the actual values of a worker with skill x and observed epidemiological state e for the period:

$$\begin{aligned} V^n_{x,3}(e; \mathbf{p}) &= u\left[\phi(e) \cdot w_x z_{x,3}\right] - \kappa(e) - \chi_{x,3}(\mathbf{I}, e) \\ V^q_{x,3}(e; \mathbf{p}) &= u\left[\psi_{x,3}\phi(e) \cdot w_x z_{x,3}\right] - \chi_q(\mathbf{I}, e). \end{aligned} \tag{7}$$

We see that the paternalistic managers ignore the disutility from working normally while sick κ as well as their fear when making the work-from-home decision.

Due to the extreme value assumptions on the preference shocks for work location, the fraction of the self-employed, managers and workers working from home, $\Pr^q_{x,j}(e, \mathbf{p})$ for $j = 1, 2, 3$, can be easily calculated from the values in equations (4), (5) and (6) as conditional choice probabilities (CCP). Because the workers do not make the work location decision themselves, the values in (6) are used, not those in (7). To be specific, for $j = 1, 2$,

$$\Pr^q_{x,j}(e, \mathbf{p}) = \frac{1}{1 + \exp\left[V^n_{x,j}(e; \mathbf{p}) - V^q_{x,j}(e; \mathbf{p})\right]}. \tag{8}$$

In the event of a lock-down, the government force people to work from home. Let $\rho_{x,j}(e)$ denote the fraction of people of skill-occupation x-j with epidemiological state e prevented from commuting to work. Then the actual fraction of people who stay home is

$$\overline{\Pr}^q_{x,j}(e, \mathbf{p}) = \max\left\{\rho_{x,j}(e), \Pr^q_{x,j}(e, \mathbf{p})\right\}. \tag{9}$$

Occupational choice At the end of each period, after production takes place and everyone's true and observable epidemiological states are updated, the young choose occupations for the next period subject to an important friction: Only a fraction

$\nu < 1$ of those who want to switch occupations can do so. This assumption prevents unrealistically high volumes of occupation changes at a high frequency. (A period in the model is a day.)

The occupation choice is myopic: People will choose the occupation that maximizes the current period profit/wage minus the disutility of working while sick and the disutility from the fear of getting infected. This is a static choice but the last term captures a notion of continuation value. When making the decision, they have updated information about their status $\bar{e}$, which they know from testing, and also about realized market clearing prices of today, $\bar{\mathbf{p}}$.[4] The values also include i.i.d. extreme value preference shocks ϵ_j for each occupation, and people are aware that tomorrow's work-from-home decision will be subject to the same i.i.d. extreme value preference shock ϵ_ι. To be specific, the occupation choice is

$$\max_{j=1,2,3} \left\{ \overline{\Pr}^q_{x,j}(\bar{e},\mathbf{p}) \cdot V^q_{x,j}(\bar{e},\bar{\mathbf{p}}) + \left[1 - \overline{\Pr}^q_{x,j}(\bar{e},\mathbf{p})\right] \cdot V^n_{x,j}(\bar{e},\bar{\mathbf{p}}) + \epsilon_j \right\}.$$

The values of working normally or from home ($\iota = n, q$) for a skill-occupation combination x-j, $V^\iota_{x,j}$ are defined in equations (4), (5) and (7). The probability of working from home for each occupation is in equations (8) and (9). Note that the realized price vector $\bar{\mathbf{p}}$ that clears the market, and used for occupation choice, is different from the price $\mathbf{p}$ that individuals use to make their work-from-home decisions.

We reiterate that only a fraction $\nu < 1$ of those who want to switch occupations are given the opportunity to do so.

2.2.2 Equilibrium

Once the work location choices are made as in equations (4)–(6), the wages and the output prices are determined to clear labor and goods markets. The wage per efficiency unit of skill x is

$$\bar{w}_x = (1-\alpha_x)\bar{p}_x \cdot \left(\frac{\Lambda_{x,2}}{\Lambda_{x,3}}\right)^{\alpha_x}$$

where $\Lambda_{x,j}$ is the total efficiency units of skill x and occupation j supplied, taking into account the occupation-specific productivity $z_{x,j}$, the fraction of sick individuals and sickness discount ϕ, and the fraction of those working from home and the home discounts $\psi_{x,j}$.

Since the two intermediate goods indexed by skill x are combined by a CES function to produce the final good, the intermediate good market clearing condition is

$$\frac{\bar{p}_h}{\bar{p}_l} = \frac{1-\theta}{\theta} \cdot \frac{y_l}{y_h},$$

where y_x is the total output of the self-employed and managers of skill x, or occupations $(x,1)$ and $(x,2)$, taking into account the skill-occupation-specific productivity $z_{x,j}$, the fraction of sick individuals and sickness discount ϕ, and the fraction of those working from home and the home discounts $\psi_{x,j}$. The final good is the numeraire and its price, p, satisfies

$$1 = \bar{p} = \left(\frac{\bar{p}_l}{\theta}\right)^{\theta} \left(\frac{\bar{p}_h}{1-\theta}\right)^{1-\theta}.$$

[4] This is a form of "adapted expectations" since the occupation choice is for tomorrow and the resulting market clearing wages and profits will be different from the current values on which the decision is based.

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2.3 The Epidemiological Model

The epidemiological side of our model is a heterogeneous-agent version of the SIR model. To be specific, there are eight distinct groups to keep track of: six skill-occupation groups working normally, all the young people working from home (or in quarantine), and the old. For the economic side of the model, we need to keep track of who works normally or at home for each skill-occupation group. However, the epidemiological law of motion applies equally to all the young working from home, regardless of their skill or occupation. As a result we have seven groups for the young rather than twelve (six skill-occupations by two work locations). The old are also in quarantine, but subject to a different epidemiological law of motion.

2.3.1 True Epidemiological States

For each of the eight group indexed by i, there are four true epidemiological states and their respective mass is denoted by S_i (susceptible), I_i (infected), R_i (recovered), and D_i (dead). Let $\mathbf{I} \equiv (I_i)$ be the vector of the masses of the infected across all eight groups. We use bars on the masses to denote the masses at the end of the period. The true epidemiological states for each group i evolve as follows.

$$\begin{aligned}
\frac{\bar{S}_i}{1-\delta_i} &= [1 - v_i(\mathbf{I})]\, S_i \\
\frac{\bar{I}_i}{1-\delta_i} &= v_i(\mathbf{I}) S_i + (1-\gamma_i)(1-m_i) I_i \\
\frac{\bar{R}_i}{1-\delta_i} &= \gamma_i (1-m_i) I_i + R_i \\
\bar{D}_i &= D_i + \delta_i (S_i + I_i + R_i) + (1-\delta_i) m_i I_i
\end{aligned}$$

The baseline death rate is δ_i and the group-specific infection rate as a function of the masses of the infected across the eight groups is $v_i(\mathbf{I})$. The recovery rate is γ_i and the added mortality from the virus is m_i. In essence, we have eight separate SIR models for the eight groups, linked by the dependence of the infection rates on all groups' infected masses. Note that we assume complete immunity once a patient recovers.

Each period, a fraction of the susceptible dies or becomes infected, and the infection rates depend on the distribution of infected masses across the eight groups. The dependence itself varies across the eight groups (hence $v_i(\mathbf{I})$). These assumptions allow us to capture the facts that people can get infected more easily by their coworkers (including managers) than by the general public and that sectors may differ in how often their workers may infect their customers. They can also capture the obvious fact that people in quarantine are both less likely to get infected and infect others (those in quarantine are one of the eight groups). Moreover, the function can also capture the effectiveness of tracking or lock-down policies: That is, the government has some control over how much it can socially isolate people in quarantine, as we explain in the next section when we specify functional forms for $v_i(\mathbf{I})$.

While some of the infected die (baseline death rate δ_i plus the additional mortality from the virus m_i), a fraction γ_i recovers.

2.3.2 Observed Epidemiological States

The true epidemiological states are not observed (with the exception of death), and hence people do not know whether they are susceptible, infected or recovered without testing. Even then, we allow for false negatives. Infected people may not show any symptoms, and the susceptible and even the recovered may show symptoms.

We now explain how we keep track of the observed epidemiological states. We define the mass of the infected that are unconfirmed after infection and recovery take place but before testing is done at the end of the period:

$$\hat{I}_i = \bar{I}_i - (1-\delta_i)(1-m_i)(1-\gamma_i)c_i,$$

where c_i is the mass of the confirmed infected at the beginning of the period. Similarly, we define the mass of the recovered that are unconfirmed after infection and recovery take place but before tests are done at the end of the period:

$$\hat{R}_i = \bar{R}_i - (1-\delta_i)\left[\gamma_i(1-m_i)c_i + r_i\right],$$

where r_i is the mass of the confirmed recovered at the beginning of the period. A person is confirmed recovered either if he tests negative after having tested positive or if his recovery is confirmed by an antibody test.

Then at the end of a period, after tests are administered, the mass of the unconfirmed without symptoms $\bar{a}_i^0$ and the mass of the unconfirmed with symptoms $\bar{s}_i^0$ for each group indexed by i are

$$\bar{a}_i^0 = (1-f_i)\bar{S}_i + (1-\omega\tau^a)(1-\eta_i)\hat{I}_i + (1-\mathbb{I}_{AB}\omega\tau^a)(1-f_i)\hat{R}_i, \tag{10a}$$

$$\bar{s}_i^0 = f_i\bar{S}_i + (1-\omega\tau^s)\eta_i\hat{I}_i + (1-\mathbb{I}_{AB}\omega\tau^s)f_i\hat{R}_i, \tag{10b}$$

where f_i is the probability of getting sick (symptomatic) when susceptible or recovered and η_i is the probability of getting sick when infected. Fractions τ^a and τ^s of the asymptomatic unconfirmed and the symptomatic unconfirmed are tested, respectively, and ω is the probability that the test correctly detects the virus. The indicator function $\mathbb{I}_{AB}$ is one if anti-body tests are available and zero if not. The mass of the asymptomatic unconfirmed $\bar{a}_i^0$ consists of (i) the susceptible who are not sick, (ii) the asymptomatic unconfirmed infected who get either untested or get a false negative result, and (iii) the asymptomatic unconfirmed recovered who get either untested or get a false negative result for antibody, if antibody tests are available. Similarly, the mass of the symptomatic unconfirmed $\bar{s}_i^0$ is the sum of (i) the sick susceptible, (ii) the symptomatic unconfirmed infected who are untested or given false positive, and (iii) the symptomatic unconfirmed recovered untested or tested false negative for antibodies.

The masses of the confirmed infected $\bar{c}_i$ and the confirmed recovered $\bar{r}_i$ after testing at the end of the period are

$$\bar{c}_i = (1-\delta_i)(1-m_i)(1-\gamma_i)c_i + \omega\left[\tau^a(1-\eta_i) + \tau^s\eta_i\right]\hat{I}_i, \tag{11a}$$

$$\bar{r}_i = (1-\delta_i)\left[r_i + \gamma_i(1-m_i)c_i\right] + \mathbb{I}_{AB}\cdot\omega\left[\tau^a(1-\eta_i) + \tau^s\eta_i\right]\hat{R}_i. \tag{11b}$$

The mass of the confirmed infected is the previous period's mass net of death and recovery, plus the newly confirmed of the unconfirmed infected. The mass of the confirmed recovered is the previous period's mass net of death, plus those of the confirmed infected who recover this period and, when antibody tests are available, the newly confirmed of the unconfirmed recovered. Obviously, c_j and r_j are zero from $t = 0$ to $t = \tau$, assuming that the virus hits at time 0 and testing begins at time τ.

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2.3.3 Infection Rates

Let I (with no subscript) denote the total mass of infected in the population, i.e., $I \equiv \sum_i I_i$ for all $I_i \in \mathbf{I}$. We denote by Q the effectiveness of quarantine policies and assume that the mass of the infected who actually spread the disease is

$$I^* = I - QI_q, \quad 0 \leq Q \leq 1, \tag{12}$$

where I_q is the mass of the infected in the quarantine group, $i = q$. In this setup, Q is a policy variable that controls the *intensive margin* of quarantine policies.[5] For example, the government can regularly check if people in quarantine are actually staying home by means of digital tracking, such as in SK, or by police-enforced lock-downs, as in most other countries. This is different from the *extensive margin* of quarantines, which bars people from commuting to work but not checking whether they actually stay home. For example if $Q = 1$, all the young people working from home (I_q) are staying home and not infecting anyone. On the other hand, if $Q = 0$, all the people working from home actually go around socializing and infecting others.

We now specify the infection rates $v_i(\mathbf{I})$ for the eight groups indexed by i. First, for the old, those in quarantine, and the self-employed ($i \in \{o, q, (l,1), (h,1)\}$), we assume:

$$v_i(\mathbf{I}) = \bar{v}_i \cdot \frac{I^*}{N},$$

where N is the population size. So their infection rates depend only on the total mass of the infected, net of those effectively quarantined.

For managers and workers working normally, $i \in \{(l,2), (l,3), (h,2), (h,3)\}$:

$$v_i(\mathbf{I}) = \bar{v}_i \cdot \left[\beta_i^i \cdot \frac{I_i^*}{N_i} + \beta_i^k \cdot \frac{I_k^*}{N_k} + (1 - \beta_i^i - \beta_i^k) \cdot \frac{I^*}{N}\right],$$

where $k = (x,3)$ if $i = (x,2)$ and $k = (x,2)$ if $i = (x,3)$, I_i^* is the effective mass of infected people still commuting in occupation i, taking into account government enforcement, and N_i is the mass of individuals in occupation i (that is, those working normally and those working from home combined). This captures the idea that the infection rates can be more sensitive to the mass of infected coworkers (managers and workers) than the mass of the infected general public.

2.4 Government Policies

We consider three types of government policies in the model: testing, tracking, and lock-down.

1. **Testing.** Equations (10) and (11) introduced τ^a and τ^s, the fractions of asymptomatic and symptomatic people who are tested, after the spread of the virus within a period. Testing the asymptomatic can be viewed as "tracing," a policy testing all the people who have come into contact with a positively confirmed person even if they are asymptomatic.

[5] The government cannot observe anyone's true epidemiological state either. The enforcement applies equally to everyone in quarantine (group $i = q$).

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2. **Tracking.** Tracking means an effective enforcement of quarantine, as measured by the variable Q in (12). An effective tracking ensures that those who should be home are indeed staying home and not infecting others.
3. **Lock-down.** A lock-down forces people to work from home, as operationalized by $\rho_{x,j}$ in equation (9). People in our model decide whether to work normally or from home, so if a large enough a share of people are already voluntarily working from home, this policy is not binding. Furthermore, a lock-down mandates that certain people work from home but does not automatically ensure that they do not go out socializing and infecting others. In our language, tracking ensures that those in quarantine do indeed stay home.

The three policies are distinct and enter the model via separate sets of variables. A government can choose to implement any combination of them.

3 Quantitative Analysis: SK vs UK

SK's response to COVID-19 has been lauded for its successful test and tracking policies. Thus, our benchmark calibration will be targeted to SK data on infections, recoveries and GDP losses. But precisely because its suppression of COVID was so successful, we find that the fear factor (as measured by the parameter χ in our model) plays no role in explaining SK data. Thus, we calibrate the fear factor along with an additional set of parameters for the UK, including its lock-down policy.

We then check the importance of the fear factor and the benefits of each country's policy by simulating the following counterfactual scenarios:

1. No intervention, SK and UK
2. SK's policy (high test and tracking) on UK
3. UK's policy (lock-down) on SK
4. Early or extended lock-down for UK
5. UK lock-down followed by virus "visas" on June 20th

Scenario 1 will illustrate how far-reaching the epidemic would have been absent any intervention. The remaining scenarios will show that, at least in our model, tracking is better than lock-downs, with a minimal effect on GDP. The last scenario will show that virus visas based on antibody tests are disproportionately beneficial for the low-skilled. This calls for redistributive antibody testing aimed at the low-skilled rather than random testing, as is called for in Germany.

3.1 Calibration

Economic parameters All the economic parameters are calibrated to SK. We fix the mass of the young population (ages 25-64) at 1 at time 0, and the old (age 65+) at 0.26, according to the population data from the Korean Statistical Information Service. Employment shares are computed from the Korea Labor Force Survey (KLFS), a monthly employment survey equivalent to the Current Population Survey in the United States. As shown in Table 1, the survey records whether an individual is self-employed with no workers (non-employers or single-worker firms) or an employer. We can also

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August 2019	Self-employed	Employer	Manager	Worker
Low-wage industries	3,522	1,152	159 (2.46)	11,068 (1.66)
High-wage industries	605	382	205 (2.86)	9,127 (2.04)
February 2020	Self-employed	Employer	Manager	Worker
Low-wage industries	3,398	1,109	148	10,942
High-wage industries	626	351	192	9,110
March 2020	Self-employed	Employer	Manager	Worker
Low-wage industries	3,510	1,072	150	10,719
High-wage industries	629	325	198	8,989

Table 1: Employment in SK (in thousands)

Self-employment: single employer-employee; Employer: self-employed with non-zero employees; Manager: employees in a managerial position. Monthly wage information (in parentheses, million KRW) is only included in the August supplement. Both employment counts and wages are inferred by using sample weights on 35,000 observations. Source: Korea Labor Force Survey.

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identify employees in a managerial position using their occupation code. Only the August includes a wage supplement and March is the most recently available iteration.

Low- and high-skill workers in our model are differentiated by effective productivity (z), as well as their productivity when working from home. Since the latter largely varies by industry (Mongey et al., 2020), we broadly classify industries into low- and high-wage industries as follows so that low-skill industries' employment share is approximately 60 percent:

1. Low-skill (l): Transportation & warehouses, Construction, Retail & wholesale, Real estate, Support, Personal services, Health & social assistance, Arts, sports & Entertainment, Agriculture, Foods and accommodations
2. High-skill (h): Utilities, Finance, Professional, Information, Manufacturing, Mining, Public, Education

High-skill industries generally require less social interaction at the workplace. However, since we also let home-productivity vary by occupation, we will discount high-skill workers' productivity more than the high-skill self-employed and managers.

As shown in the table, employment shares remained roughly constant in SK, despite its early COVID-19 outbreak in February (compared to the UK) and the drop in industrial production of approximately 3.5 percent in February 2020 (month-to-month, seasonally adjusted). Thus, we consider the August employment and wage statistics to constitute the initial steady state.

We use the August KLFS to calibrate a subset of the economic parameters as follows. First, we initialize employment shares, $L^0_{x,j}$ by skill and by assuming the self-employed ($j = 1$) and workers ($j = 3$) in the model respectively correspond to self-

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Parameter	Value	Description
L_y	1	Mass of young
L_o	0.2562	Mass of old
$L^0_{l,j}$	[0.1343, 0.0500, 0.4221]	Initial employment share
$L^0_{h,j}$	[0.0231, 0.0224, 0.3481]	by industry/occupation
$\psi^0_{l,j}$	[0.10, 0.10, 0.07]	Home productivity discounts
$\psi^0_{h,j}$	[0.70, 0.70, 0.49]	by industry/occupation
ϕ	0.7	Sick productivity discount
$z_{l,j}$	[0.9167, 1.0, 1.0]	Effective productivities
$z_{h,j}$	[1.3594, 1.3, 1.3]	by industry/occupation
κ	0.1115	Sickness disutility
α_l, α_h	[0.1493, 0.0827]	Manager income share by industry
θ	0.4540	Low-skilled share in final good production
μ_q, σ	[0.4667,0.3333]	Extreme value distribution for home-work choice
$\mu_{l,j}$	[0,-0.9832,1.2349]	Extreme value distribution
$\mu_{h,j}$	[0,-0.0145,2.8562]	for occupation choice
ν	0.01	1% of individuals can switch occupation

Table 2: Economic Parameters

employed and to non-manager employees in the KLFS, and managers ($j = 2$) in the model to employers and employees in managerial positions in the KLFS. Employment shares are shown in the second panel of Table 2.

We then set, for now, the home and sick productivity discounts arbitrarily, making sure that low-skill jobs and workers suffer heavier discounts, as shown in the third panel. Given these parameters, we calibrate $z_{x,j}$, κ, α_x and θ as follows. Suppose that there is no epidemic, so the fear factor is irrelevant. Also suppose that there is no preference shock, neither for working from home decisions nor occupation choices.

1. We normalize manager-worker productivities to be equal and set high-skill workers to be 30 percent more productive than low-skill workers.[6] We then choose the self-employed productivity, $z_{x,1}$, so that they are indifferent between staying self-employed or becoming a manager.
2. We choose κ so that high-skilled are indifferent between working from home or not when sick. This ensures that low-skilled would never work from home, before realization of the i.i.d. preference shock to stay home.
3. We assume that only high-skill self-employed and managers work from home when sick. Then we can compute the manager share parameter α_x to match manager income shares from the KLFS. We can also set θ to match the low-skill income share in the KLFS, assuming that self-employed and employer mean wages are

[6] These normalizations are innocuous, since in our model, the productivity parameters are not separately identified from the manager share α_x and the low-skill sector share θ.

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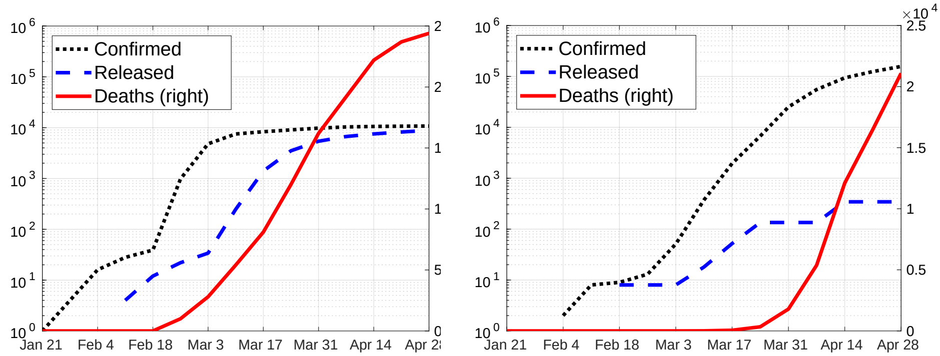

(a) South Korea (b) United Kingdom

Fig. 2: Infections, Recoveries and Deaths, Cumulative: SK vs. UK
Confirmed and released in log-10 scale (left), death counts on the right axis. Source: Korea Center for Disease Control and Prevention, UK Department of Health and Social Care

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equal to managers'.

Given these parameter values, we then simulate the economy with no epidemic. We assume that the i.i.d. preference shocks for the work-from-home choice are drawn from extreme value distributions with location parameters (μ_n, μ_q) and scale parameter σ, with the normalization $\mu_n = 0$. For the preference shocks when making occupation choices, we normalize the scale parameter to one and the self-employment location parameter to $\mu_{x,1} = 0$. We calibrate these location and scale parameters as follows:

1. Choose μ_q, the location parameter of the home preference shock, so that approximately 15 percent of high-skill self-employed and managers work from home. Then choose the scale parameter, σ, so that approximately 10 percent of low-skill self-employed and managers work from home (Eurostat, 2020; Hensvik et al., 2020).
2. Choose $\mu_{x,2}, \mu_{x,3}$, the location parameters for becoming a manager or worker, to match initial employment shares $L^0_{x,j}$.

Last, we arbitrarily assume that only $\nu = 0.01$ of individuals can switch occupations. The resulting parameters are shown in the bottom panel of Table 2.

Epidemiology and policy parameters Figure 2 shows the path of SK's confirmed infections, recoveries and deaths from COVID-19 from January 21 to April 21. We show the same data for the UK for comparison.

Since policies affect the course of the epidemic, for the model to match the paths observed in Figure 2, the infection, recovery and mortality rates must be jointly calibrated with the policy parameters. Several of the SIR parameters are fixed loosely based on what is known up to now about SARS-CoV-2.

1. Assume a natural death rate of 0 for the young, and a 2 percent annual death rate for the old, based on SK mortality rates.

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2. Uniformly set a recovery rate of $\gamma = 1/14$ for the young, so that the infected remain infectious for two weeks. We then assume that it takes twice as long for the old to recover, or $\gamma_o = 1/28$.
3. Assume that the old experience a 10 times higher mortality rate, conditional on contracting the virus (Center for Disease Control and Prevention, 2020).
4. Fix the infection rate of low-skill equal to the old. Fix the high-skill infection rate to 90 percent of the old, and those in quarantine to 1/7 of the old. This assumes that a person in quarantine makes one day worth of social contact per week compared to a low-skill worker who commutes to work. High-skill jobs face lower infection rates to capture the fact that they are in better health in general and have better healthcare (Case and Deaton, 2020), and also require less social interaction at the workplace (Mongey et al., 2020).
5. Suppose that workers and managers socialize more amongst themselves, and more so for high-skilled. This is to capture the fact that high-skill industries are more hierarchical.

Once these assumptions are made, there are four remaining parameters that determine the progression of the virus absent any policy intervention: the COVID-19 mortality rate of the young, the COVID-19 infection rate of the old, the initial date the coronavirus is introduced, and the initial mass of the infected on that day (I_0). Since the latter two are not separately identified (we can always choose an earlier date assuming a lower mass of initially infected, and or the other way around), we arbitrarily set the initial date to December 22, 2019, which is exactly one month before SK starts publishing infection counts. Thus, confirmed cases start appearing on $\tau = 30$.

We find that we cannot match the UK data using the same additional mortality rate due to the virus for the old (m_o) as SK, even taking into account different policies.[7] So while we let this parameter differ between SK and UK, to more easily compare the effect of policies, we keep all other epidemiology parameters equal between them.[8] Of course, to the extent that UK employment shares and earnings are different from SK's, some of the results should be viewed with caution. However, the comparative dynamics does not vary much with the initial distribution of jobs and wages, as long as they are qualitatively similar.

Then we make the following assumptions on the testing technology, as well as the fraction of individuals who fall sick with or without the virus:

1. A fraction $1 - \omega = 0.2$ of test results are false-negative (Yang et al., 2020).
2. Rather optimistically assume that antibody testing becomes universal on June 19, 2020, or 180 days after the emergence of the virus.
3. Assume that 40 and 60 percent of the young- and old-infected are symptomatic, respectively (Mizumoto and Chowell, 2020).

[7] Thus, if the low death counts in SK are due to policies, they are beyond something we can capture with our testing and tracking policies. Of course, at least some of the differences are due to different demographics, social interaction patterns, medical systems, etc., which are reflected on the mortality rate differences between the two countries.

[8] While the model is quantified to match each country, one can also view SK as a low mortality economy, and UK as a high mortality economy.

Parameter	Value	Description
δ_y	0	Young daily natural death rate
δ_o	5.48e-05	Old annual natural death rate of 2 percent
γ_y	1/14	Young recover in 2 weeks
γ_o	$\gamma_y/2$	Old recover in 4 weeks
v_o	0.1555	Old infection rate matches $R_0 = 2.18$ in SK,UK
$v_{l,j}$	$=v_o$	Low-skill infection rate equal to old
$v_{h,j}$	$=v_o \cdot 0.9$	High-skill infection rate 90% of low-skill
v_q	$=v_o/7$	Reduce social contact to 1 day a week in quarantine
$[\beta^2_{l,2}, \beta^3_{l,2}]$	[0.4,0.2]	Low skill manager interaction with managers and workers
$[\beta^2_{l,3}, \beta^3_{l,3}]$	[0.2,0.4]	Low skill worker interaction with managers and workers
$[\beta^2_{h,2}, \beta^3_{h,2}]$	[0.5,0.1]	High skill manager interaction with managers and workers
$[\beta^2_{h,3}, \beta^3_{h,3}]$	[0.1,0.5]	High skill worker interaction with managers and workers
m_o	(0.003,0.041)	Old COVID mortality to match observed death counts in SK,UK
m_y	$=m_o/10$	Young mortality from COVID one-tenth of the old
I_0	1.27e-05	500 people infected in SK on Dec 22nd ($t = 0$) (assume same fraction of population for UK)

Table 3: Epidemiology Parameters

4. Arbitrarily assume that 10 and 20 percent of the young and old are sick when uninfected, respectively.

Moreover, policy variables do not remain constant but change over time according to observed reactions of the SK and UK governments. All dates are number of days since December 22, 2019.

Jan 21 First confirmed case in SK. Thus, we set $\tau = 30$ for SK.

Jan 31 First confirmed case(s) in the UK. Two people test positive. Thus, we set $\tau = 40$ for the UK.

Feb 10 UK health secretary announces strengthened quarantine policies ($t = 50$).

Feb 19 Shincheonji outbreak in SK, number of confirmed cases surge and country intensifies testing and tracking ($t = 59$).

Mar 15-23 UK announces the possibility of, then implements, a lock-down ($t = 84$)

We assume that the date of the first confirmed case is the date testing commences in the model, from which time onward all untested symptomatic and confirmed are quarantined. The test probabilities (τ^a, τ^s), as well as quarantine enforcement Q, change values at each node of each country's timeline, but remain constant until another action is taken. The values of the parameters in each time interval are chosen to match the observed path of confirmed infections in each country in each time interval.

To capture the effect of testing, tracking, lock-downs, and virus visas, we specify the function $\rho_{x,j}(e)$, the intensity at which the government prevents people from working

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Parameter	Value	Description		
$\bar{\chi}$	500	Fear factor: 20 percent GDP drop in UK at peak infection		
ω	0.8	20 percent false negatives		
t_{AB}	180	Antibody test becomes universal		
(f_y, f_o)	(0.10,0.20)	Old and young uninfected but sick		
(η_y, η_o)	(0.40,0.60)	Young and old infected with symptoms		
$\rho_{l,j}$	[0.5,0.7,0.5]	Fraction low-skill locked-down		
$\rho_{h,j}$	[0.9,0.9,0.9]	Fraction high-skill locked-down		
λ_0	-0.15	20 percent GDP drop upon lock-down		
λ_1	0.01	1 percent decay in lock-down		
(τ_a, τ_s)	[timeline below]	Test rates for a/symptomatic		
$Q = \bar{Q}$	[timeline below]	Tracking policy		
Country	**Date**	**Event**	**Testing**	**Tracking**
	Dec 22, $t = 0$	No detection	$(\tau_a, \tau_s) = 0$	$Q = 0$
SK	Jan 21, $t = 30 = \tau$	First detection	$(\tau_a, \tau_s) = 0.0004$	$Q = 0.4$
	Feb 19, $t = 59$	Shincheonji outbreak	$(\tau_a, \tau_s) = 0.1$	$Q = 0.9$
	Dec 22, $t = 0$	No detection	$(\tau_a, \tau_s) = 0$	$Q = 0$
	Jan 31, $t = 40 = \tau$	First detection	$(\tau_a, \tau_s) = (0, 0.0004)$	$Q = 0$
UK	Feb 10, $t = 50$	First quarantine	$(\tau_a, \tau_s) = (0, 0.0004)$	$Q = 0$
	Mar 15, $t = 84 = t_\lambda$	Effective lock-down	$(\tau_a, \tau_s) = (0, 0.3)$	$Q = 0.3$
	Jun 20, $t = 180 = t_{AB}$	Hypothetical virus-visas	$(\tau_a, \tau_s) = (1.0, 1.0)$	$Q = 0.3$

Table 4: Fear Factor and Policy Parameters

in equation (9), as

$$\rho_{x,j}(e) = \begin{cases} \max\left\{\frac{\bar{\rho}_{x,j}}{1+\exp(\lambda_0+\lambda_1(t-t_\lambda))}, \bar{Q}\right\} & \text{if } e \in \{s^0, a^c, s^c\} \\ \frac{\bar{\rho}_{x,j}}{1+\exp(\lambda_0+\lambda_1(t-t_\lambda))} & \text{otherwise.} \end{cases} \tag{13}$$

where t_λ is the date a lock-down commences.

1. **Tracking:** Absent a lock-down, $\bar{\rho}_{x,j} = 0$ for all (x, j). Thus, the government can only quarantine the untested and confirmed with intensity $\bar{Q}$. Since $\bar{Q}$ is also a measure of testing and tracking policies, we simply set $\bar{Q} = Q$.
2. **Lock-down:** Implemented at time $t = t_\lambda$, a fraction $\bar{\rho}_{x,j}(e)$ individuals of skill x in occupation j are told to stay home, regardless of their symptoms. The function varies by skill and occupation, but not by observed epidemiological status. If more people in a certain state are voluntarily staying home, this policy is not binding. However, the intensity at which this is enforceable decays over time, where λ_0 measures the intensity of the policy upon impact and λ_1 the duration.[9]
3. **Virus visas:** The government sets $\bar{\rho}_{x,j}(e)$ to 0 for $e \in \{a^r, s^r\}$, while maintaining the same intensity as a lock-down for everyone else.

[9] Thus, λ_1 not only measures how strongly the government implements a lock-down, but also how willingly people follow the rules.

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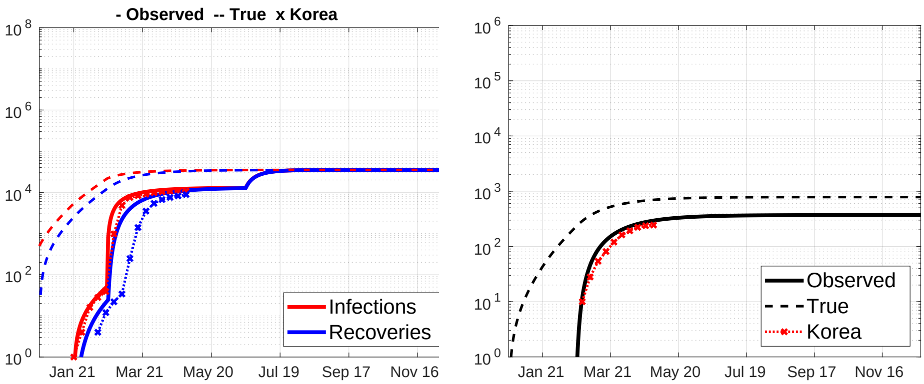


(a) Infections and Recoveries (b) Deaths

Fig. 3: SK SIR Model vs. Data

"Observed" corresponds to confirmed cases in the model. Counts are cumulative and in log-10 scale. Data source: Korea Center for Disease Control.

We set $\rho_{x,j} = 0.5$ for low-skill self-employed and workers, 0.7 for low-skill managers, and 0.9 for all high-skill. While somewhat arbitrary, this captures the fact that the "essential workers" during the COVID-19 crisis are concentrated among low-skill industries and sectors, such as grocery workers, deliverers and security staff.

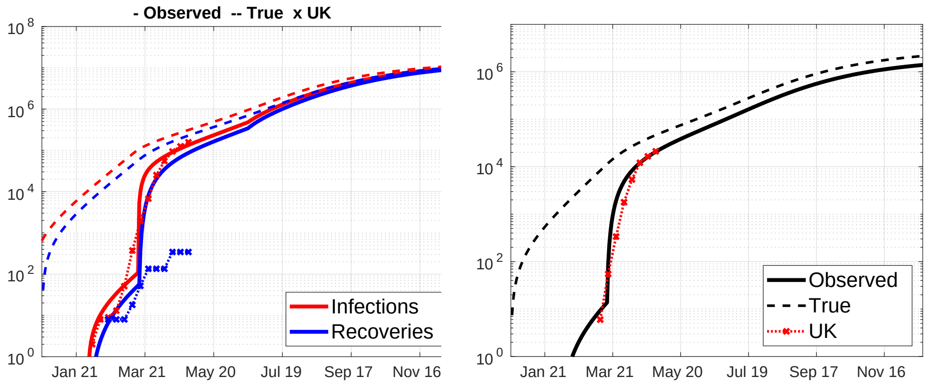
Finally, the fear factor itself plays a similar role as policy: If people fear the infection enough, they will voluntarily stay home, and more so when infection rates are higher. This would reduce the spread of the virus, but also drag down the economy. For simplicity, we assume that

$$\chi_i(\mathbf{I}, e) = \begin{cases} 0 & \text{if } e \in \{a^r, s^r\} \\ \bar{\chi} \cdot v_i(\mathbf{I}) & \text{otherwise.} \end{cases} \tag{14}$$

Thus the constant $\bar{\chi}$ measures the fear factor. The fear factor and the lock-down parameter λ_0 jointly determine the initial drop in GDP upon implementation of the lock-down. Since the exact magnitude is yet unknown, we target a 20-percent drop in GDP both upon implementation of the lock-down and at the peak of infection, which is about the average of the IMF and UK Office for Budget Responsibility's GDP forecasts for the UK of 6.5 and 35 percent, respectively.[10] The duration parameter λ_1 is set arbitrarily at 0.01, so that the effectiveness of the lock-down decays by 1 percent daily.

The resulting epidemiology, policy and fear factor parameters are summarized in Tables 3 and 4. While the test rates are chosen to match the observed infection counts, the mass of people tested should not be taken literally. As a policy, it measures how available tests are. In SK, for example, testing costs approximately \$40, which is reimbursed if tested positive, so the actual cost is low. This made testing available to the general public regardless of symptoms, but at the same time, the government

[10]Because SK effectively contains the virus early on, the fear factor never becomes quantitatively operational. Thus we cannot use SK moments to discipline $\bar{\chi}$.



(a) Infections and Recoveries

(b) Deaths

Fig. 4: UK SIR Model vs. Data

"Observed" corresponds to confirmed cases in the model. Counts are cumulative and in log-10 scale. Data source: UK Department of Health and Social Care.

traced all individuals who came into contact with a confirmed person. Thus we set testing rates to $\tau^a = \tau^s = 0.1$ in SK from February 19 onward. The fact that $Q = 0.9$ in SK captures its digital tracking system, which may be infeasible if infections grew larger but near perfect at its current level.

In contrast, tracing was never done in the UK, and strict self-quarantines are still more or less voluntary even in the midst of the lock-down. So we maintain Q at a low level, even as more people are told to go home following the lock-down. The difference between the $t = 40$ and 50 in the UK is that in 10 days, the UK commences isolating the symptomatic and confirmed: Before that, no action is taken beyond minimal testing. Moreover, testing is still symptoms-based ($\tau^a = 0$) and not readily available even for many people with symptoms even now. Thus while $\tau^s = 0.3$ during the lock-down is an optimistic representation of its policy, we maintain its high level both to match the data but also to give the lock-down policy a chance.[11] In any case, we find that both a high τ_a (testing of asymptomatic) and high Q were necessary for SK's successful containment of the virus.

The results of our calibration are shown in Figure 3 and 4, for SK and UK, respectively.[12] There are several points to note. First, the kinks in the model infection curves represent a change in policy in each country, which do not perfectly align with the data but track its general path. Second, for a fair comparison, we have chosen parameters so that our model slightly overshoots SK and undershoots UK, especially given that the latter has higher infection and mortality rates. Third, there are discrepancies in UK's data reporting, for both recoveries and deaths. It is quite clear that recoveries are not being reported daily, and also that information on deaths were not released

[11]We are still able to match UK's infection path with slightly lower levels of τ_s, but that would lead to higher calibrated values for UK's infection probability parameters.

[12]The model is in masses, while data is in integer counts. We blow up the mass for SK by 39,314,000, its age 25+ population in 2018. For the UK, we blow up this number further by 29.32 percent, according to the population size from the Office of National Statistics.

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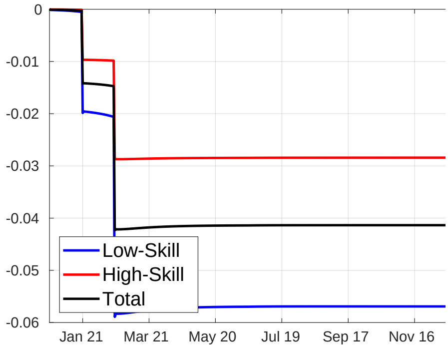
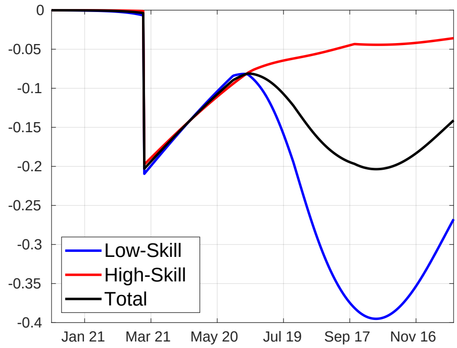
until later. Finally, the model captures that both SK's testing and tracking policy and UK's lock-down have effectively "flattened the curve," at least for now.

3.2 GDP and Inequality

Given that the model matches infection and death counts for each country, how much did the containment policies matter for economic outcomes? First, in Figure 5, we plot together low-skill, high-skill and aggregate GDP (not in per capita, to capture the deaths from the virus), for both countries.



(a) SK



(b) UK

Fig. 5: GDP Losses: SK vs UK

Model implied GDP by skill, and total. GDP is in log-point changes and not normalized per capita, so includes GDP losses from COVID-19 deaths (the working-young has a zero natural death rate).

SK's GDP loss from January to March rises from 1.5 percent to 4.1 percent, which is very close to the actual industrial production drop of 3.5 percent in the data. Since this drop was not a targeted moment, it is a success of our model. In contrast, the 20 percent drop in the UK GDP was a target moment. But notice that GDP starts dropping slightly even before the lock-down on March 15, which is partly due to the (weak) quarantine policies put in place before the lock-down but mostly due to the fear factor. Since the lock-down weakens after impact, there is a small recovery until April, but then as the virus further progresses, GDP falls again due to the fear factor (calibrated to reach a trough of 20 percent).

The fear factor is also why GDP falls between January and February in SK. However, the fact that GDP remains constant afterward implies that SK's policy successfully contained the virus, so that the fear factor is no longer binding for most people (and therefore there is no subsequent drop in GDP).

Perhaps more important, the drop in low-skill GDP is much larger than high-skill for both countries. This is because the low-skill are less productive from home. The relative drop is even larger when it is due to the fear factor. Even as high-skill GDP recovers in the UK, low-skill GDP continues to drop because low-skill workers face higher risks of infection at work and are thus more sensitive to the fear at very high infection rates. In fact, high-skill GDP recovers almost entirely before the lock-down

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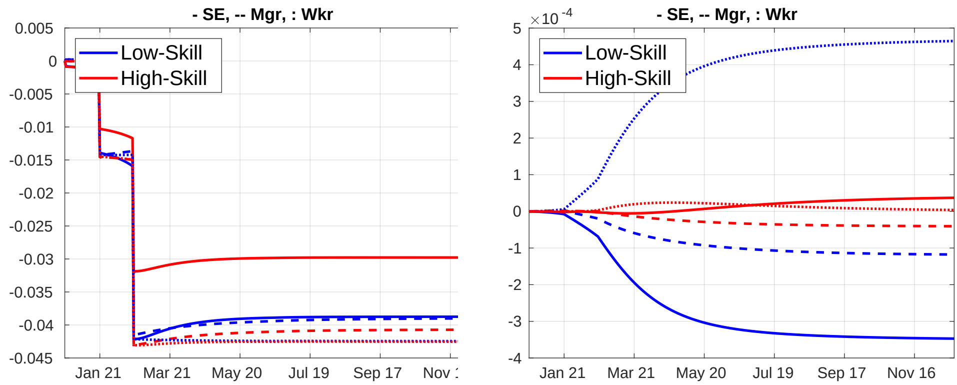
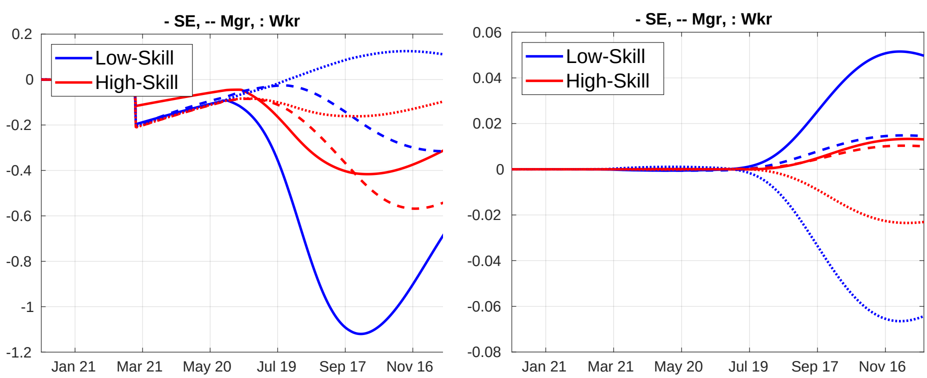


(a) Earnings (b) Employment Shares

Fig. 6: SK Dynamics by Skill-Occupation Group

SE: Self-employed, Mgr: Managers, Wkr: Workers. The left panel is changes in earnings in log points, and the right panel is changes in employment shares.



(a) Earnings (b) Employment Shares

Fig. 7: UK Dynamics by Skill-Occupation Group

SE: Self-employed, Mgr: Managers, Wkr: Workers. The left panel is changes in earnings in log points, and the right panel is changes in employment shares.

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fades away on June 20, so the only reason total GDP remains low afterward is because low-skill GDP continues to drop to more than 40 percent below its initial value.

Earnings vary by occupation as well. In Figures 6 and 7, we plot together the earnings and employment shares of each skill-occupation group for SK and UK, respectively.

Employment shares in SK are close to constant, consistent with SK data in Table 1.[13] Again, this implies that the fear factor is barely operational for individuals to switch jobs (from the steady state shares at $t = 0$). However, earnings losses still vary considerably by occupation. Workers and the self-employed stand to lose the most because of the tracking policy (as more of them are infected, more are enforced to stay home). In contrast, high-skill self-employed earnings drop little upon policy impact, and rise modestly over time.

The changes in the UK are more dramatic, and it is still the low-skill self-employed who lose the most. And despite the large loss in earnings, their employment share goes up: This is due to low-skill workers switching into self-employment at high rates of infection. Workers are forced to work by their managers, so earnings drop by less no matter the rate of infection. But since they face higher rates of infection, workers value the option to stay home more than their earnings, so switch toward self-employment, as shown in Figure 7(b). And because so many workers switch to other jobs, their relative wages go up in equilibrium, a form of compensating differential.

Thus, the rise in workers' earnings in Figure 7(a) must be viewed with caution. At high infection rates, workers would rather stay at home but are not given the choice. And in our model, the only way for workers to avoid infection is to switch jobs. Although we do not explicitly model unemployment, workers' switch toward self-employment would show up exactly as unemployment in the data. Those workers in our model who switch their jobs to self-employment make close-to-zero earnings, which can be viewed as unemployment benefits or other government subsidies that are issued universally.

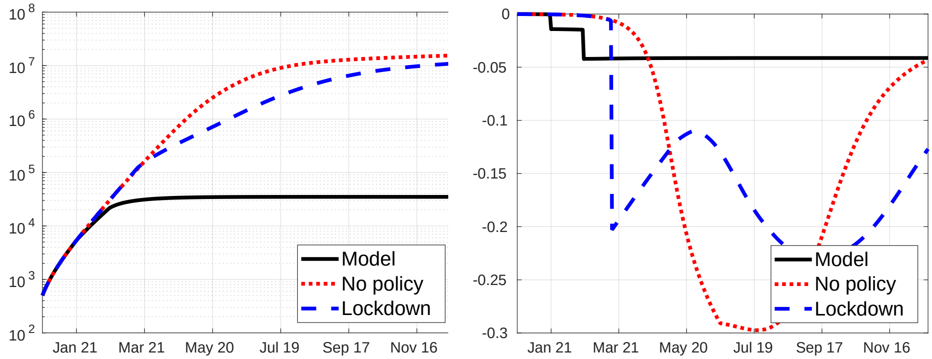
3.3 Counterfactual Policy Analysis

How effective were each country's policies? While SK's policy is deemed successful, would it work for other countries as well? And could an early lock-down have contained the outbreak better (or worse)? We address these questions by simulating the path of infections and GDP if each country had implemented no policies, and then applying the UK's policies on SK and the other way around.

In Figure 8, we compare SK's baseline policy against the hypothetical outcome had it not done anything, and had it instead implemented UK's lock-down policy, including the exact dates of implementation. Without any intervention, the virus would have spread more by as much as three orders of magnitude (the y-axis is in log-10 scale), and GDP losses from the fear factor would have been as much as 30 percent. A UK style lock-down results in a similar outcome as the UK.

UK's lock-down is much less effective. In Figure 9, we compare UK's baseline policy against the hypothetical outcome had it not done anything, and had it instead

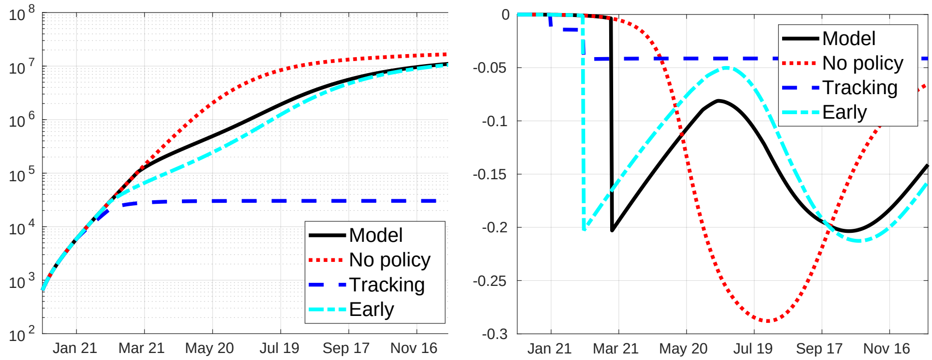
[13] Moreover, despite the small magnitude both in the data and the model, the model-predicted employment share changes by skill-occupation are qualitatively in line with the January to March changes (from the first confirmed case to peak in SK) in the KLFS as well.



(a) Infections (b) Total GDP

Fig. 8: SK Counterfactual Policies

"Model" is SK's baseline testing and tracking policy. "No policy" is doing nothing, and "Lockdown" is if SK had followed UK's policy exactly, including its lock-down date. Infection counts are cumulative and in log-10 scale. GDP is in log-point deviations and not normalized per capita, so includes GDP losses from COVID-19 deaths (the working-young has a zero natural death rate).



(a) Infections (b) Total GDP

Fig. 9: UK Counterfactual Policies

"Model" is UK's baseline lock-down policy. "No policy" is doing nothing, and "Tracking" is if UK had followed SK's policy exactly, including its timing. "Early" is if UK had implemented the same lock-down, but at the time of SK's Shincheonji outbreak. Counts are cumulative and in log-10 scale. GDP is in log-point changes and not normalized per capita, so includes GDP losses from COVID-19 deaths (the working-young has a zero natural death rate).

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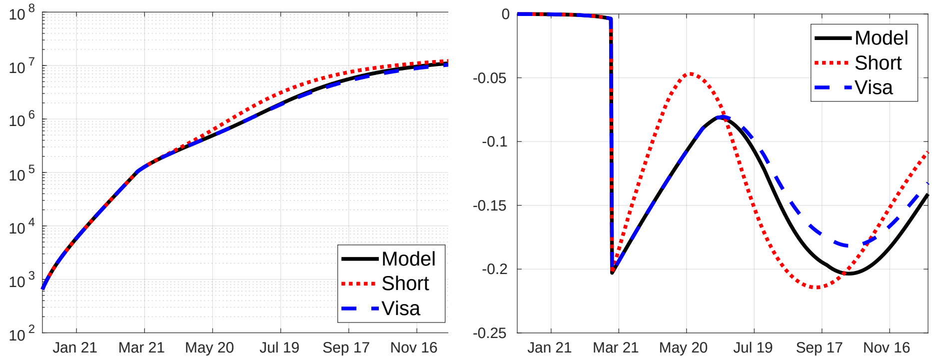

(a) Infections (b) Total GDP

Fig. 10: UK Counterfactual Policies: Extended Lock-Down and Virus Visas
"Model" is UK's baseline lock-down policy. "Short" is an earlier lifting of the lock-down. "Visa" is if UK starts issuing antibody test-based virus visas once testing becomes available on June 20, 2020. Counts are cumulative and in log-10 scale. GDP is in log-point deviations and not normalized per capita, so includes GDP losses from COVID-19 deaths (the working-young has a zero natural death rate).

implemented SK's testing and tracking policy, including the exact dates of implementation. Without any intervention, the virus would have spread nearly twice as much. Moreover, the lock-down in the UK reduces peak infection compared to doing nothing, preventing the impending 30 percent drop in GDP that would have been caused by large masses of people staying home at peak infection (August). Nonetheless, if the UK had implemented SK's testing policy, the virus would have been contained at an early stage, resulting in much fewer infections in the long-run, with only a modest drop in GDP (four percent) compared to the 20 percent drop due to the lock-down.

But is it the policy itself or the early reaction (in February rather than March) that leads to successful containment? To find out, we additionally simulate a path in which the lock-down is implemented at the same time as when SK intensified its testing. While an early lock-down is effective in preventing the spread of the virus upon impact, its efficacy wears off over time, and is not enough to avoid high infections in the long run. Consequently, infections eventually reach almost the level of the later lock-down ("Model"), as well as similar losses in GDP by September.

As of early May, the UK government decided to extend its lock-down. What would have happened if it had instead lifted the lock-down, surrendering to political pressure? While some of the decay can be due to civil disobedience, it may also be due to enforcement. So to simulate this effect, we increase the decay of its effectiveness, which we build into the model in Equation 13. In Figure 10, we simulate the paths of infections and GDP if the decay parameter, λ_1, were equal to 0.02 rather than 0.01 (two percent decay per day).

A shorter lock-down raises infections in the summer, and can raise GDP by five percent early on. But the shortening of the lock-down also hastens the fear factor to take over, increasing GDP losses at peak by about 2 percentage points in the fall. Thus the decision to extend the lockdown not only spreads out the infections, but also GDP losses, over a longer time horizon.

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An alternative policy to an extended lock-down is a "selective lifting" of the lock-down through the issuance of virus visas, considered by several European countries. Such a policy would be backed by random testing (testing also the asymptomatic) as well as antibody tests. For comparison, we simulate the infection and GDP paths of the UK under a hypothetical scenario in which it starts large-scale testing and issuing virus visas once antibody tests become universally available.

We assume that UK's baseline lock-down policy continues until June 20, at which point virus visas begin to be issued to all who have recovered from the virus. As shown in Figure 10, widespread testing reduces GDP losses at the peak by 2 percentage points by allowing all recovered to work, in addition to averting the GDP loss from the fear factor.[14] The fact that virus visas depend on antibody testing is crucial: Since more than half of eventually infected are already recovered by June 20, without it, the visa policy that can only vouch for the confirmed recovered has barely any effect.

3.4 Virus Visas and Inequality

GDP and earnings drops are always larger for the low-skilled, regardless of whether it is due to policies or the fear factor. Since virus visas are effective in reducing GDP losses, we now compare the benefits of the policy across different skill and occupation groups in the UK.

Figure 11 shows the resulting changes in GDP by skill, utility, earnings, and employment changes by skill and occupation. Figure 11(a) is to be compared with Figure 5(b), and Figures 11(c) and 11(d) with Figure 7. Before June 20, the paths are exactly same as in the baseline, since up to then agents are subject to the same lock-down policy and individuals are not forward looking.

Just as the persistent drop in GDP was entirely driven by the low-skilled in Figure 5(b), Figure11(a) shows that the recovery from the virus visa is also entirely driven by the low-skilled. The reason for this is two-fold. On the one hand, low-skill self-employed earnings recover by more than 20 log points, as those who find out they have already had the virus and recovered return to work, as shown in Figure 11(c). On the other hand, low-skill workers, who experience the smallest change in earnings due to being forced to work during the lock-down, no longer switch to self-employment to avoid infection (where they have the choice to self-quarantine themselves), and even those who previously switched return to being a worker, as shown in Figure 11(d). As discussed in Section 3.2, workers who switch to self-employment to avoid the virus in our model can be viewed as becoming unemployed. Thus, the recovery in worker shares can be viewed as furloughed or laid-off workers returning to work once the fear of infection is gone.

This latter effect is more obvious in Figure 11(b), which shows the utilities of each skill-occupation group. There, it is clear that despite the low drop in earnings, it is the workers—and especially low-skill workers—who experience the largest drop in utility from being more exposed to the virus than other groups, as they do not have the choice of staying home even at high infection rates. The rise in their utility following virus visas cannot be due to earnings, which remain flat for the duration of the lock-down. Thus, their rise in utility is entirely due to the removal of the fear factor, as

[14] Since the policy successfully contains the virus, although belatedly, we find that additional SK-style tracking ($Q = 1$) does little to affect both the infection path and GDP.

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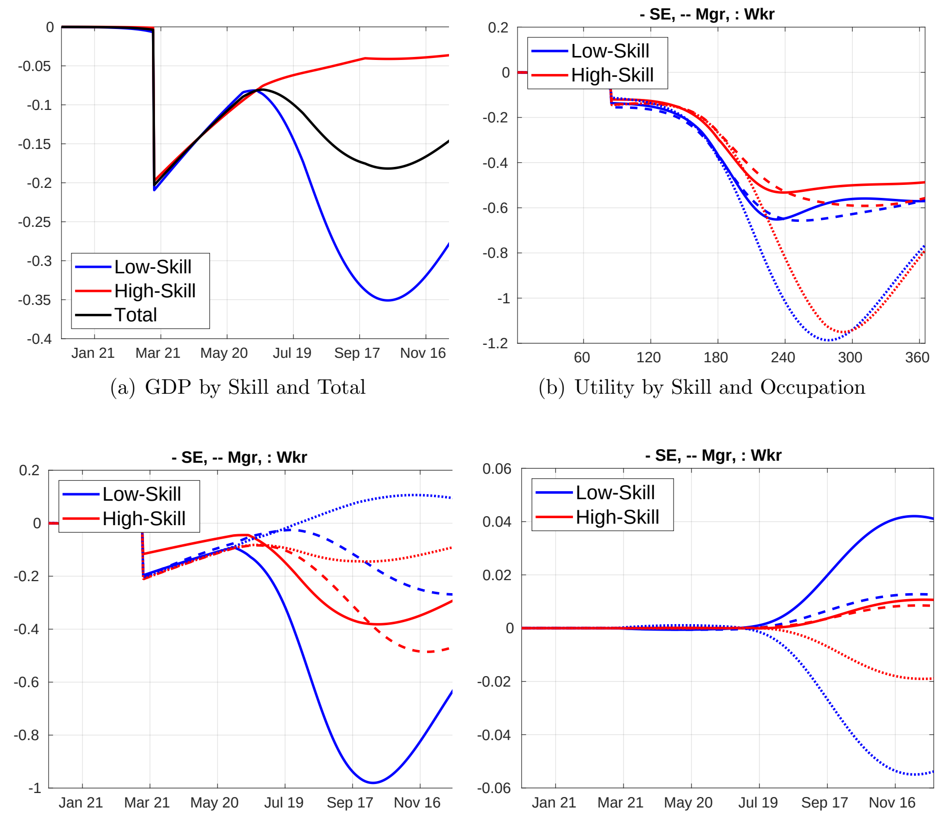

(a) GDP by Skill and Total

(b) Utility by Skill and Occupation

(c) Earnings by Skill and Occupation

(d) Employment Shares by Skill and Occupation

Fig. 11: UK Inequality using Hypothetical Virus-Visas

SE: Self-employed, Mgr: Managers, Wkr: Workers. GDP is in log-point changes and not normalized per capita, so includes GDP losses from COVID-19 deaths (the working-young has a zero natural death rate). Utilities are in per worker level changes. Earnings are in log-point changes in per worker earnings, and employment shares in level changes.

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we assumed in (14). And as their utility begins to rise, they no longer switch jobs (or become unemployed) and some of those who had left their jobs in the past, despite the low earnings in self-employment (which can be viewed as low income in unemployment), return.

In summary, to the extent that (i) low-skill workers and self-employed lose the most in all scenarios, and (ii) the high-skill benefit less from virus visas, because by now their earnings and employment have more or less recovered, our counterfactual visa policy result scall for redistributive antibody testing should it become available—disproportionately intense testing of the low-skilled. This not only helps those most in need, but also has the largest effect in recovering aggregate GDP.

4 Conclusion

We presented a quantitative economic-epidemiological model of the COVID-19 epidemic to investigate how different containment policies affect inequality and aggregate outcomes. Individuals choose whether to work from home or not, and when infection rates are high, voluntarily choose to stay home out of fear of infection despite lower earnings. We show that, contrary to common beliefs, containment policies mitigate not only infections but also long-run GDP losses, because losses would become even higher if the virus is not contained early and people start to self-quarantine themselves en masse. We also show that South Korea's testing and tracking policies are quantitatively much more effective at containing both the spread and GDP losses than a lock-down, regardless of the timing. Finally, we show that low-wage self-employed and workers suffer the most from the epidemic and a blanket lock-down, and stand most to gain from virus visas based on antibody tests, raising the possibility that redistributive testing is not only economically equitable but also efficient, in the sense that it would have a larger impact on raising aggregate GDP than randomly testing the same number of people.

Several of our parameters are chosen ad hoc and only loosely calibrated. However, as more data becomes available and allows us to use more informative numbers for calibration, our model of heterogeneous skills and occupations with observable and unobservable health status can serve as an ideal laboratory to assess how different policies have affected and will affect economic and (COVID-related) health inequality as we continue to battle the epidemic.

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COVID-19: Cross-country heterogeneity in effectiveness of non-pharmaceutical interventions

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At the onset of COVID-19 pandemic a large number of countries introduced a range of non-pharmaceutical interventions. Whereas the policies are similar across countries, country characteristics vary substantially. We examine the effectiveness of such policies using a cross-country variation in economic, geographic and public health system characteristics. The effectiveness of lockdown policies is declining with GDP per capita, population density and surface area; and increasing with health expenditure and proportion of physicians in the population. The findings can be explained by incentive-driven behaviors and resource constraints. Higher population density, larger geographical area, and a higher employment rate may require more resources to ensure compliance with lockdown policies. On the other hand, communities with access to better health care might be less likely to voluntary practice social distancing.

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1 Introduction

The outbreak of COVID-19 virus has caused major concerns about public health around the world. Since the first cases in late 2019 in China, COVID-19 has spread exponentially around the world, indicating an endemic person-to-person transmission.[1] According to statistics released by the World Health Organization (WHO), as of April 24 2020 there were 2,626,321 reported cases of COVID-19, and the death toll was 181,938. Public health officials and epidemiologists have urged governments to implement various degrees of social distancing policies in an attempt to decrease the transmission rate by reducing the exposure of uninfected individuals to the infected ones. In an attempt to reduce the population contact rates and slow the transmission of the virus, many countries implemented a range of non-pharmaceutical interventions (NPIs), including closures of schools, workplaces, public transport, cancellations of public events, restrictions of internal movement, tracing infected persons contacts, enhanced testing, and more. Timelines of these policies vary across countries, but by mid-April 2020, due to the virus crisis around 70% of countries have enacted one or more of these measures.[2] The effectiveness of each NPI may vary with a range of other actions taken by the government and communities at the time of the crisis. To assess these differences, we examine how the effectiveness of NPIs varies with country characteristics.

Using the Susceptible-Infected-Recovered (SIR) model, we examine how the impact of NPIs on transmission rate of COVID-19 varies with a range of country characteristics along economic, public health and geographic dimensions. These characteristics are associated with differences in behavioral response and differences in resources available to governments that might be required to enforce these policies. Our findings suggests that these factors play important roles in slowing down the spread of the virus during NPIs; the results also suggest that the economic and social systems as well as incentives and attitudes may lead to different outcomes of NPIs.

We account for four factors that may affect the spread of the virus when NPIs are enacted.

[1]See for example, Ghinai, et al. (2020), documenting the first known cases of person-to-person transmission of COVID-19.

[2]Authors calculations, using the Oxford COVID-19 Government Response Tracker dataset.

First, population density may affect the compliance with the social distancing rules. Higher density may increase the chances of human interactions and hence the spread of the virus and therefore make the lockdown policies less efficient than in places with low population density. It has also been previously established that an epidemic of a respiratory disease, such as influenza, initially affects the more densely populated urban areas (see for example, Zachreson et al., 2018). However, it is not clear whether the impact of non-pharmaceutical interventions varies with population density.

Second, some populations may have higher or lower incentives to comply with government policies. From the risk perspective, it was shown that deaths from COVID-19-related illness are heavily concentrated among the elderly and those with underlying health conditions (see for example, Wu and McGoogan 2020; Verity et al. 2020; CDC COVID-19 Response Team 2020). The differences in risk to be severely affected by the virus may imply higher compliance within some groups. Moreover, individuals in countries with better access to high quality health care might have lower incentives to comply with the enacted policies.

Third, lower access to leave and sick benefits may increase the incentives to work for those who already display symptoms and promote the spread of the virus. For example, Barmby and Larguem (2009) and Pichler and Ziebarth (2017) show that paid sick leave to keep contagious workers at home can mitigate the prevalence of disease transmissions. Moreover, higher employment rates may increase the risk of exposure to viruses and therefore increase the spread. For example, Markowitz et al. (2019) show that increases in employment are associated with increased incidence of influenza; Adda (2016) shows that viruses spread faster during economic booms.

Forth, government resources and favorable economic conditions prior to the pandemic have the potential to improve compliance, either through higher benefits for those on sick leave, or through increased supervision and surveillance, since patrolling and enforcing such policies may require substantial public resources.

The dataset is constructed using three data sources. The Oxford COVID-19 Government Response Tracker (OxCGRT), collected from publicly available sources, provides a systematic cross-national, cross-temporal measures of government responses to COVID-19 spread. For

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more details about the dataset, see Hale, Petherick, Phillips and Webster (2020). We obtain data on the number of recorded COVID-19 cases from the Center for Systems Science and Engineering at Johns Hopkins University. Country-level characteristics are from the World Bank data.

We show that the transmission rate is decreasing with population density, surface area of the country, air pollution, employment rate, and the proportion of elderly population; the transmission rate is increasing with the proportion of physicians in population. We test whether these channels may explain the differences in flattening the spread of COVID-19 when NPIs are enacted. Different NPIs may be more or less effective in different environments. NPIs that imply closures, such as school and workplace closures, are more effective in countries with lower population density, lower surface area, lower air pollution, higher unemployment rate, higher health expenditure, and lower proportion of elderly population. On the other hand, extensive testing for COVID-19 NPI is more effective in countries with lower GDP per capita, higher population density, larger surface area, higher air pollution, higher employment rate, lower health expenditure, lower ratio of physicians in population, and higher proportion of elderly in population.

The findings can be explained by incentives driven behaviors and public resource constraints. Compliance with closures may demand more resources in places with higher population density, larger geographical area, and higher employment rate, impairing the effectiveness of these policies. Communities with access to better health care, measured by the number of physicians and health expenditure as % of GDP, ceteris paribus, may have less incentives to voluntary reduce social interactions; therefore, lockdown measures in such communities could be more effective.

There are now a number of studies evaluating the effectiveness of NPIs. Kucharski, et al. (2020) estimate that in China, the basic reproduction rate declines from 2.35 one week before travel restrictions to 1.05 one week after travel restrictions. Friedson, McNichols, Sabia and Dave (2020), using daily COVID-19 data in California, find that the lockdown reduced the number of cases by 125.5 to 219.7 (per 100,000 population) and led to 1,661 fewer deaths during the first month following its implementation. Fang, Wang and Yang (2020) study

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the impact of lockdown in Wuhan, China enacted on January 23, 2020; they show that the COVID-19 cases would be 64.8% higher in the 347 Chinese cities outside Hubei province, and 52.64% higher in the 16 non-Wuhan cities inside Hubei, in the counterfactual world in which the city of Wuhan were not locked down. Chen and Qiu (2020) show that some NPIs are more effective than others in terms of both costs and benefits. Hartl, Walde and Weber (2020) study the effects of schools lockdown policy in Germany and show a trend break in the transmission rate on the 9th day of the policy being in place.

A number of studies examine the socio-economic inequalities associated with the COVID crisis along several dimensions. Ahmed, Ahmed, Pissarides, and Stiglitz (2020) show that addressing inequality could be important in mitigating the spread of the virus. Borjas (2020) shows that more disadvantaged populations are less likely to be tested but more likely to be infected conditional on testing. Brzezinski, Deiana, Kecht and Van Dijcke (2020) show that the more disadvantaged communities tend to have lower uptake of voluntary physical distancing in response to the outbreak of the crisis. Earlier epidemiology literature shows that there is considerable variation in individual infectiousness, model predictions that control for individual variation differ sharply from average-based approaches, with disease extinction more likely and outbreaks more rare but more explosive; suggesting that targeted control policies are more effective than general policies (see for example, Lloyd-Smith et al., 2005). Our results complement this literature showing that there is a substantial heterogeneity in the effectiveness of government response policies. This heterogeneity can be attributed to endogenous social distancing behavior; and differences in resources devoted to the policy.

The paper proceeds as follows. Section 2 describes the data. Section 3 reports estimation results. We show how transmission rate varies with country-specific characteristics and the relationships between these characteristics and the effectiveness of NPIs. Section 4 provides a discussion of the findings and concludes.

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2 Data

The dataset combines daily government response data, daily reported COVID-19 cases data, and country-level aggregate characteristics.

Government response policies data are from the Oxford COVID-19 Government Response Tracker (OxCGRT), which provides an extensive set of measures.[3] OxCGRT collects data of cross-national, cross-temporal measures starting January 2020. Hale, Petherick, Phillips and Webster (2020) provide an extensive description of data collection. The OxCGRT collects information on a range of government responses to the COVID-19 crisis. We focus on the following NPIs, closures of schools and universities, closures of workplaces, cancellations of public events, closures of public transport, restrictions in internal movements (these may include isolation of those infected and/or restrictions on movements across cities), restrictions on international travel, government information campaigns, contact tracing of infected persons and extended testing (for example, testing of persons who meet specific criteria vs. open public testing).[4] Some countries implement the closures and restrictions as a recommended measure and some as a required measure. In some countries these measures are targeted while in others they are general. We assume that targeted policies are implemented in areas with large clusters of COVID-19 and therefore these are the relevant measures for our analysis. We do not distinguish between recommended and required measures, based on the assumption that public follows the recommended measures as if these were required.[5] We model the impacts of these nine policies using the SIR framework (as described in the next Section). The OxCGRT also reports the COVID-19 Government Response Stringency Index, calculated using seven NPIs excluding contact tracing and extended testing). The value of the index on any given day is the average of the seven indicators for each policy. Each NPI receives a score between 0 and 3 (or 0 and 2), where zero implies no policy or

[3]The data is available at https://covidtracker.bsg.ox.ac.uk.

[4]Workplace closures may vary across countries and may include closures of cafes and restaurants, retail, beauty and personal care services, entertainment venues, leisure and recreation, residential facilities, outdoor recreation, non-residential institutions (such as libraries and museums and places of worship).

[5]One example of a country with recommended school closures is Australia. Based on numbers reported in the Australian media, only 15% of school age children in relevant locations were attending schools once the measure was announced.

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missing information, 1 implies targeted policy and 2 or 3 implies more general policy. The index is rescaled to create a score between 0 and 100.

There are 201 countries and territories in the dataset, 178 of which have reported at least one case of COVID-19 by April 15 2020, out of which 139 have implemented at least one of the nine listed policies. Appendix Table 1 summarizes government response policies and their average dates as reported in the OxCGRT data. Government information campaigns are the first policies that were enacted on the onset of the crisis (the average timing was 24 February 2020), followed by restrictions in internal movements, contact tracing and international travel restrictions. The more extensive closures followed about a week later, include public events cancellations, school closures, extensive testing, workplace closures and public transport closures. According to the OxCGRT, most popular policy among governments was school closures (135), cancellations of public events (134) and internal movement restrictions (133). The least popular policy is contact tracing of infected individuals (59 countries).

The number of cases of COVID-19 is provided by Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. The cumulative number of confirmed cases and deaths can be downloaded from the GitHub repository.[6] The time series starts on 22 January, 2020 and is updated daily, the analysis includes data between 22 January and 24 April. Using these data and following the SIR model, we calculate the transmission rate of COVID-19. Since the accounting of positive cases may vary substantially across countries due to different testing and reporting practices, most estimations control for country fixed effects.

A significant amount of effort has been put into creating the OxCGRT and CSSE datasets. However, data could not be collected for every day for each country. There are also differences in how COVID-19 cases are tested and reported across countries. For a number of countries response policies such as schools and workplace closures are reported as initiated on the same day as the first reported case. We assume that these reportings are due to a measurement errors and include only those countries which had at least 20 reported cases on the day of

[6]The data are available at:
https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series.

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the school closures policy implementation. This restriction leaves us with 55 countries.

The third data source is the World Bank Databank, which provides a range of aggregate measures on health, geography and the state of economy.[7] We use the most recent available measures. For aggregate health measures we use PPP health expenditure (2017), number of physicians per 1000 population (2008-2017 average), and proportion of population above 65 years old (2017). The economic indicators are GDP per capita (2017, in constant $US) and employment rate (2017). Geographic and environmental indicators are log of surface area in sq. km (2013-2017 average), population density (2017), and air pollution measured by PM2.5 (mg per cubic meter) (2017). Data are not available for every variable for each country. Our final sample that combines all three data sources includes 53 countries when including countries with at least 20 cases on the first day of school closures policy initiation. Appendix Table 2 provides summary statistics for the selected 53 countries.

3 Estimation

To assess the effectiveness of NPIs we use the Susceptible-Infected-Recovered (SIR) model with time-varying parameters. This type of model is used to analyze how infectious diseases are spread (see for example, Kermack, McKendrick and Walker 1927, and a recent application of this model in Toda, 2020). The SIR-type model assumes exponential growth dynamics in the cumulative number of cases in the absence of policy interventions.

We utilize the dynamic version of the SIR model, as in Chen and Qiu (2020), who augment this model to test for the effectiveness of various NPIs across nine countries. We apply their methodology in our analysis.

The time-varying SIR model is described by the following system of ordinary differential equations,

[7] The data are available at https://data.worldbank.org

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

The model assumes that the population, N_j, in country j is divided into three groups: susceptible, $S_j(t)$; infected, $I_j(t)$, and recovered, $R_j(t)$. Population size is assumed to be constant since we focus on a relatively short time period. The country-specific time varying parameter $\beta_j(t)$ represents the transmission rate of the virus in country j. The $I_j(t)$ infected individuals can transmit the disease with probability $\frac{S_j(t)}{N_j}$. Infected individuals recover at rate $\gamma_j(t)$.

In the classical SIR model, the reproduction rate, $R_j(t) = \beta_j(t)/\gamma_j(t)$, determines the number of additional infections by an infected person before he/she recovers. If $R_j(t) > 1$, the disease will spread exponentially and will infect a large fraction of the total population. In the dynamic SIR model, the reproduction rate, $R_j(t)$, can change over time. We assume a constant γ, therefore, by observing the change in $\beta_j(t)$ over time, we examine the effectiveness of NPI policies given varying country characteristics.

The change in the number of infected in country j is derived as follows:

$$
I_j(t+1) - I_j(t) = \frac{\beta_j(t)S_j(t)}{N_j}I(t) - \gamma_j(t)I_j(t) \tag{2}
$$

Solving for $\beta_j(t)$, leads to the following equation,

$$
\beta_j(t) = \frac{I_j(t+1) - I_j(t)}{I_j(t)}\frac{N_j}{S_j(t)} + \gamma_j(t)\frac{N_j}{S_j(t)} \tag{3}
$$

We approximate and assume that for a large N, $S(t)/N \approx 1$. We assume that the recovery rate, $\gamma_j(t)$, is constant across time and countries, we set $\gamma = 1/18$ (following findings in Atkeson (2020) and consistent with the fraction of infected that recovered or died according to the WHO as compiled in JHU CCSE).

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Following Chen and Qiu (2020), in the dynamic SIR model, the impacts of k NPIs in country j are measured as follows,

$$\beta_j(t) = \exp(\alpha_j + \sum_{k=1}^{K} \delta_{jk} NPI_{jtk}) \tag{4}$$

where α_j is a country fixed effect and

$$NPI_{j,t,k} = \begin{cases} 1 & \text{if } t < t^* \\ \exp(-\frac{(t-t^*)}{\tau}) & \text{if } t \geq t^* \end{cases} \tag{5}$$

where t^* represents the time when the NPI_k was enacted. The parameter τ controls for the time-lag effect of interventions. We assume $\tau = 8$, which reflects findings on COVID-19 incubation period in previous studies.[8]

Allowing the impacts of NPIs to vary with country-specific characteristics, the empirical specification of equation (4) takes the following form,

$$\log \beta_{jt} = \alpha_{0j} + \sum_{k=1}^{K} \alpha_{1k} NPI_{jtk} + \sum_{k=1}^{K} \alpha_{2k} \mathbb{Z}_j NPI_{jtk} + \epsilon_{jt}, \tag{6}$$

where vector $\mathbb{Z}_j$ includes a range of country specific characteristics, including aggregate health variables: health spending as a % of GDP, number of physicians per 1000 people, and the proportion of population above 65 years old in total population; economic indicators: log GDP per capita in constant $ US and ratio of employed in population; geographic and environmental indicators: log of surface area, population density (people per sq. km of land area), and air pollution measured by concentration of PM2.5. Measurement error in the data is denoted by ϵ_{jt}.

We first estimate how the transmission rate varies with country characteristics before

[8] For example, Lauer et al. (2020) and Linton et al. (2020) that find that incubation period of COVID-19 is 5.2 days on average; Li at al. (2020) reports 4.1 to 7.0 days; and Wu, Leung and Leung (2020) find this period to be 6.1 days. Combining the length of the incubation period with feeling symptoms, being tested and results reported, we set the time-lag effect of interventions at 8 days.

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most NPIs were enacted,[9]

$$\log \beta_{jt} = \lambda_0 + \mathbb{Z}_j \lambda_1 \ + u_{jt}. \tag{7}$$

Table 1 reports the results. The transmission rate varies with country characteristics. It is decreasing with population density, surface area, air pollution, employment rate and the proportion of population above 65 years old; higher proportion of physicians is positively correlated with the transmission rate.

Table 1: COVID-19 transmission rate and country characteristics, OLS, selected countries

	(1)	(2)	(3)	(4)	(5)
ln GDP per capita	-0.1194***	-0.1474***	-0.1117**	-0.0058	-0.069
	(0.0396)	(0.0556)	(0.0548)	(0.0735)	(0.0907)
Pop density		-0.1288***	-0.1399***	-0.1204***	-0.0879**
		(0.0411)	(0.0403)	(0.0412)	(0.0448)
ln surface area		-0.0886***	-0.0962***	-0.0698**	-0.0742***
		(0.0255)	(0.0250)	(0.0278)	(0.0279)
PM2.5		-0.0038	-0.0053*	-0.0063**	-0.0082**
		(0.0029)	(0.0029)	(0.0029)	(0.0035)
Employment rate			-0.0210***	-0.0273***	-0.0263***
			(0.0041)	(0.0050)	(0.0064)
Health expend, % GDP				-0.0397**	-0.0264
				(0.0184)	(0.0197)
Physicians					0.0932*
					(0.0501)
% 65 yo +					-0.0176*
					(0.0104)
const	0.5428	2.2345***	3.2386***	2.5050***	3.0459***
	(0.4028)	(0.6944)	(0.7068)	(0.7826)	(0.8191)
N	597	597	597	597	597
R2 adj.	0.015	0.04	0.082	0.089	0.096

Note: The subset of selected countries includes those with number of infected>19 when school or workplace closures are enacted, 53 countries. Observation period is between seven days after observing the first case and before the closures of schools and workplaces. Coefficients presented, standard errors in parenthesis. Statistical significance is denoted as *10%, **5%, and ***1% levels.

We estimate the effects of NPIs on transmission rate, as specified in equation (6). We first estimate equation (6) without country-specific controls, controlling for the country fixed effects. Column (1) in Table 2 reports the results. Positive coefficients imply that a given policy had a positive effect on reducing the transmission rate. It should be noted, that in most countries most of the NPIs in our dataset were enacted with very little spacing in

[9]These period may cover times when government information campaigns, contact tracing of infected, and some restrictions on international travel were in place. See Appendix Table 1 for average timings of various NPIs.

between. Appendix Table 1 shows that, on average, policies follow each other very tightly. This presents an identification challenge. Table 2 shows that we cannot identify the effects of every NPI when all of them are included in the regression. Thus, first, we combine school and workplace closures into one category (the correlation between these two NPIs is 0.87); second, we exclude NPIs which are highly correlated with the school and workplaces closures variables (correlation of 0.7 and above). This leaves the estimation with three NPIs, the combined school and workplace closures variable, contact tracing and expanded testing. Column (2) in Table 2 reports estimation results when using the subset of NPIs. The coefficient of contact tracing on transmission rate remains negative, therefore the final subset of NPIs includes the combined schools and workplaces closures and the extensive testing variables. The results using the two remaining NPIs are reported in column (3) of Table 2.

Table 2: Estimated NPI impact on COVID-19 transmission rate, fixed effects

	Selected countries, n=53			All countries, n=132		
	(1)	(2)	(3)	(4)	(5)	(6)
School closures (SC)	0.3070***			0.1720**		
	(0.1061)			(0.0851)		
Workplace closures (WC)	0.3609***			0.4578***		
	(0.0919)			(0.0665)		
Movement restrictions	0.2229**			0.2093***		
	(0.0955)			(0.0779)		
Public events cancellations	-0.7067***			-0.6690***		
	(0.0969)			(0.0820)		
Public transport closures	0.5654***			0.4909***		
	(0.0619)			(0.0508)		
Gov information campaign	-0.5346***			-0.2957***		
	(0.0746)			(0.0637)		
Contact tracing	-0.2848***	-0.2175***		-0.2770***	-0.2205***	
	(0.0771)	(0.0791)		(0.0605)	(0.0616)	
International travel restrictions	0.3065***			0.1914**		
	(0.0972)			(0.0774)		
Extensive testing (ET)	0.2470***	0.4018***	0.3623***	0.2879***	0.4095***	0.3711***
	(0.0647)	(0.0656)	(0.0641)	(0.0551)	(0.0548)	(0.0538)
School/work closures combined (SWC)		0.2896***	0.2498***		0.3054***	0.2590***
		(0.0437)	(0.0412)		(0.0375)	(0.0353)
N	3534	3534	3534	7261	7261	7261

Note: Selected countries include countries with number of infected>19 when school or workplace closures are enacted. Coefficients presented, standard errors in parenthesis. Statistical significance is denoted as *10%, **5%, and ***1% levels.

Tables 3 and 4 report estimation results of equation (6) with country-specific controls using the subset of NPIs, combined schools and workplaces closures and the extensive testing

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variables. All estimations control for the country fixed effects. In Table 3 we introduce aggregate controls separately; in Table 4 aggregate controls are added simultaneously. Extensive testing (ET) is more effective in countries with lower GDP per capita, higher population density, higher air pollution, higher employment, lower health expenditure (as % of GDP), higher proportion of physicians in population and higher proportion of older population (65 plus). On the other hand, the schools and workplace closures policy is more effective in countries with lower population density, smaller surface area, lower pollution, higher health expenditure and lower proportion of older population.

Table 3: Estimated NPI impact on COVID-19 transmission rate with country characteristics interactions, fixed effects, selected countries, N=3534

		ln GDP per capita ($US)	Pop density (people per km^2)	ln area (sq. km)	PM2.5 air poll. (mg/m3)	Empl. to pop. ratio	Health expend., % GDP	Physicians per 1000 people	% 65+ yo in pop.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ET	0.3623***	2.3782***	0.3187***	0.3062	0.1562	-0.5748	1.4281***	0.0725	0.1873
	(0.0641)	(0.7322)	(0.0670)	(0.3534)	(0.0992)	(0.3913)	(0.1742)	(0.1557)	(0.1520)
SWC	0.2498***	-0.9482**	0.2810***	1.6473***	0.3082***	0.7416***	-0.2500**	0.028	0.1740*
	(0.0412)	(0.4302)	(0.0427)	(0.2680)	(0.0623)	(0.2442)	(0.1192)	(0.1054)	(0.0918)
ET *		-0.2021***	0.0138**	0.004	0.0092***	0.0160**	-0.1365***	0.1083**	0.0122
		(0.0730)	(0.0067)	(0.0274)	(0.0034)	(0.0066)	(0.0207)	(0.0536)	(0.0099)
SWC *		0.1200***	-0.0112***	-0.1095***	-0.0024	-0.0084**	0.0671***	0.0832**	0.0053
		(0.0428)	(0.0043)	(0.0208)	(0.0021)	(0.0041)	(0.0147)	(0.0367)	(0.0060)
R2	0.042	0.045	0.045	0.054	0.044	0.044	0.054	0.048	0.043

Note: Subset of countries includes those with number of infected>19 when school or workplace closures are enacted, 53 countries. ET denotes extensive testing NPI; SWC denotes schools and/or workplaces closures NPI. "ET * " and "SWC * " indicate interactions of NPIs with the country characteristics as specified in the heading each column. Coefficients presented, standard errors in parenthesis. Statistical significance is denoted as *10%, **5%, and ***1% levels.

We test for robustness of the finding using an alternative measure of government response. The OxCGRT data provides a Government Response Stringency Index (Stringency Index, SI), the index ranges from 0 to 100 and each additional government response leads to a higher index value. Hale, Petherick, Phillips and Webster (2020) provide an extensive description of how this index is constructed and how it varies across time and countries. We estimate how the relationship between SI and transmission rate varies with country-specific characteristics using the following specification,

$$\log \beta_{jt} = \beta_0 + \beta_1 SI_{jt} + \mathbb{Z}_j \beta_2 SI_{jt} + \varepsilon_{jt}. \tag{8}$$

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Table 4: Estimated NPI impact on COVID-19 transmission rate, with country characteristics interactions, fixed effects, selected countries, N=3534

	(1)	(2)	(3)	(4)	(5)	(6)
ET	0.3623***	2.3782***	0.1814	0.061	-1.5558	-0.2339
	(0.0641)	(0.7322)	(1.0855)	(1.0839)	(1.2243)	(1.2527)
SWC	0.2498***	-0.9482**	2.8001***	2.9250***	3.6446***	3.9805***
	(0.0412)	(0.4302)	(0.7912)	(0.7903)	(0.8203)	(0.8527)
ET * ln GDP per capita		-0.2021***	-0.0787	-0.1922**	0.1317	-0.4483***
		(0.0730)	(0.0840)	(0.0901)	(0.1298)	(0.1553)
SWC * ln GDP per capita		0.1200***	-0.0149	0.0725	-0.1443*	-0.0501
		(0.0428)	(0.0543)	(0.0592)	(0.0860)	(0.0990)
ET * Pop density			0.0145*	0.0134*	0.0104	0.0255***
			(0.0076)	(0.0076)	(0.0077)	(0.0080)
SWC * Pop density			-0.0285***	-0.0281***	-0.0247***	-0.0271***
			(0.0048)	(0.0048)	(0.0049)	(0.0049)
ET * ln surface area			0.0576*	0.054	0.1027***	0.1013**
			(0.0333)	(0.0335)	(0.0379)	(0.0398)
SWC * ln surface area			-0.1760***	-0.1800***	-0.2011***	-0.2196***
			(0.0263)	(0.0263)	(0.0273)	(0.0274)
ET * PM2.5			0.0080**	0.0024	-0.0022	0.0161***
			(0.0038)	(0.0043)	(0.0046)	(0.0051)
SWC * PM2.5			-0.0035	-0.0009	0.002	-0.0046
			(0.0025)	(0.0026)	(0.0027)	(0.0029)
ET * Employment rate				0.0244***	0.0071	0.0363***
				(0.0077)	(0.0090)	(0.0100)
SWC * Employment rate				-0.0172***	-0.0019	-0.0104
				(0.0046)	(0.0064)	(0.0068)
ET * Health expenditure, % GDP					-0.1438***	-0.1164***
					(0.0411)	(0.0435)
SWC * Health expenditure, % GDP					0.0988***	0.1392***
					(0.0284)	(0.0306)
ET * Physicians per 1000 people						0.2444***
						(0.0944)
SWC * Physicians per 1000 people						0.0117
						(0.0552)
ET * % 65 yo +						0.1033***
						(0.0202)
SWC * % 65 yo +						-0.0525***
						(0.0105)
R2	0.042	0.045	0.066	0.07	0.074	0.095

Note: The subset of selected countries includes those with number of infected>19 when school or workplace closures are enacted, 53 countries. ET denotes extensive testing NPI; SWC denotes schools and workplaces closures NPI. Coefficients presented, standard errors in parenthesis. Statistical significance is denoted as *10%, **5%, and ***1% levels.

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Table 5 reports the results. Column (1) shows that there is a negative correlation between SI and COVID-19 transmission rate, more stringent policy response leads to a reduction in transmission rate. Columns (2)-(6) gradually introduce aggregate country-specific controls. The effectiveness of government policies, summarized by the SI, shows similar patterns as the effectiveness of schools and workplace closures. The effectiveness of policies is declining with GDP per capita, population density and surface area; and increasing with health expenditure and proportion of physicians in population.

Table 5: Estimated impact government response on COVID-19 transmission rate, with country characteristics interactions, fixed effects, selected countries, N=3522

	(1)	(2)	(3)	(4)	(5)	(6)
SI	-0.0067***	0.0032	-0.0356***	-0.0357***	-0.0481***	-0.0558***
	(0.0004)	(0.0043)	(0.0077)	(0.0077)	(0.0082)	(0.0087)
SI * ln GDP per capita		-0.0010**	0.0008	0.0002	0.0024***	0.0036***
		(0.0004)	(0.0006)	(0.0006)	(0.0008)	(0.0009)
SI * Pop density			0.0003***	0.0003***	0.0003***	0.0002***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
SI * ln surface area			0.0015***	0.0015***	0.0020***	0.0020***
			(0.0002)	(0.0002)	(0.0003)	(0.0003)
SI * PM2.5			0.0001***	0.0001***	0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
SI * Employment rate				0.0001**	0.0000	0.0000
				(0.0000)	(0.0001)	(0.0001)
SI * Health expenditure,					-0.0010***	-0.0011***
% GDP					(0.0002)	(0.0003)
SI * Physicians						-0.0018***
per 1000 people						(0.0006)
SI * % 65 yo +						0.0002
						(0.0001)
R2	0.069	0.07	0.082	0.083	0.087	0.089

Note: The subset of selected countries includes those with number of infected>19 when school or workplace closures are enacted, 53 countries. SI denotes the OxCGRT data provides a Government Response Stringency Index. Coefficients presented, standard errors in paranthesis. Statistical significance is denoted as *10%, **5%, and ***1% levels.

We further test for the robustness of the findings by reducing the assumption that the impact of the stringency index is linear. We construct a set of 5 dummy variables to allow for a nonlinearity in the effect of the stringency of government response. The lowest group indicates no response (i.e., $SI = 0$), the remaining groups indicate wether the index in the first, second, third or fourth quartile.

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$$\beta_{jt} = \gamma_0 + \gamma_1 \sum_{s=1}^{5} \mathbb{I}_{jst} + \mathbb{Z}_j \gamma_2 \sum_{s=1}^{5} \mathbb{I}_{jst} + \zeta_{ct}. \quad (9)$$

Results in Appendix Table 3 show similar patterns to those in Tables 4 and 5. However, the impact of policies is more pronounced when stringency index reaches 75%, i.e., when the final measures or government response, such as closures of schools and workplaces, are initiated. The effectiveness of policies is declining with GDP per capita, surface area; and increasing with employment rate, health expenditure and proportion of physicians in population.

4 Discussion and conclusion

Governments around the world have responded to the COVID-19 crisis with a range of NPIs aiming to flatten the spread of the virus, relieve the pressure on hospital systems, and save lives. These policies constrain social interactions, minimize arrivals of infected individuals from overseas as well as establish practices of testing and tracing infected individuals. Recent studies show that such policies are effective in reducing the spread of the virus. However, it is not determined whether the same combination of NPIs is optimal for each country, or whether country specific characteristics should dictate which policies should be implemented or how they should be implemented. This paper aims to fill this gap by studying the interactions between the effectiveness of NPIs at a country-level and country-specific characteristics.

We embed NPIs in a dynamic epidemiological SIR model and show empirically how the effectiveness of NPIs varies with country-specific characteristics. The effectiveness of lockdown policies is declining with GDP per capita, population density and surface area; and increasing with health expenditure and proportion of physicians in population.

The findings can be explained by incentives driven behaviors and public resource constraints. Higher population density, larger geographical area, and higher employment rate may demand more resources from the government to promote compliance. On the other

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hand, access to better public health system may slow down voluntary social distancing due to decreased risks and lockdown policies are more effective in flattening the spread of the virus in such communities. The latter explanation is also consistent with the lower effectiveness of policies in communities with higher proportion of elderly, who are in higher risk group in terms of becoming severely ill if infected and therefore have more incentive to voluntary observe social distancing.

Our results complement earlier epidemiological research which shows a substantial degree of heterogeneity in individual infectiousness rates in epidemics. This analysis also complements recent literature on socio-economic inequalities associated with the COVID-19 crisis. Our findings emphasize that the effectiveness of a given NPI policy varies with the socio-economic and geographic characteristics of a given community and highlight that targeted policies may improve the outcomes of government response policies.

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Appendix Table 1: Summary of available NPIs

	Number of countries with given NPI	Average starting date
Gov information campaign	132	24-Feb-20
Movement restrictions	133	26-Feb-20
Contact tracing	59	4-Mar-20
International travel restrictions	132	5-Mar-20
Public events cancellations	134	11-Mar-20
School closures	135	13-Mar-20
Extensive testing	68	14-Mar-20
Workplace closures	121	18-Mar-20
Public transport closures	97	22-Mar-20

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Appendix Table 2: Selected countries, summary statistics

	Total cases as of 15/04/20	ln GDP per capita ($US)	Pop density, (people per sq. km)	surface area (sq. km)	PM2.5 air pollution (mg per m3)	ln Empl. to pop. ratio	Health expend., % GDP	Physicians per 1000 people	% 65 yo. + in pop.
Algeria	2160	8.47	0.18	14.68	38.88	36.91	6.65	1.52	6.10
Argentina	2443	9.21	0.16	14.84	13.31	54.10	7.55	3.69	10.92
Australia	6440	10.95	0.03	15.86	8.55	62.15	9.25	3.41	15.26
Austria	14336	10.82	1.07	11.34	12.48	58.39	10.44	4.94	18.93
Bahrain	1671	9.97	20.17	6.65	70.82	70.93	4.87	0.95	2.37
Belgium	33573	10.76	3.77	10.33	12.89	50.96	10.04	3.01	18.47
Brazil	28320	9.31	0.25	15.96	12.71	54.57	11.77	1.96	8.46
Canada	28208	10.85	0.04	16.12	6.43	61.60	10.53	2.44	16.65
Chile	8273	9.62	0.25	13.54	21.04	55.51	8.53	1.08	11.05
China	83356	8.96	1.48	16.07	52.66	67.66	4.98	1.60	10.10
Colombia	3105	8.95	0.45	13.95	16.53	62.16	5.91	1.83	8.08
Costa Rica	626	9.20	0.98	10.84	15.73	54.43	7.56	1.15	9.11
Croatia	1741	9.67	0.73	10.94	17.90	46.87	7.18	2.97	19.83
Czechia	6216	10.06	1.38	11.28	16.07	59.20	7.15	3.76	18.73
Denmark	6681	11.06	1.38	10.67	10.03	59.38	10.35	3.75	19.49
Egypt	2505	7.97	0.99	13.82	87.00	39.73	4.64	1.21	5.17
Estonia	1400	9.90	0.30	10.72	6.73	60.38	6.68	3.33	19.20
Finland	3237	10.79	0.18	12.73	5.86	55.07	9.49	3.20	21.01
France	133470	10.68	1.22	13.22	11.81	50.74	11.54	3.20	19.47
Germany	134753	10.77	2.37	12.79	12.03	59.21	11.14	3.99	21.34
Greece	2192	10.07	0.83	11.79	16.22	41.88	8.45	5.83	21.25
Iceland	1727	10.86	0.04	11.54	6.48	79.63	8.29	3.67	14.25
Indonesia	5136	8.36	1.48	14.46	16.50	64.66	3.12	0.28	5.61
Iran	76389	8.85	0.50	14.37	38.98	39.14	8.10	1.17	5.99
Ireland	12547	11.25	0.70	11.16	8.21	58.60	7.38	2.79	13.33
Israel	12501	10.46	4.11	10.00	21.38	61.37	7.31	3.30	11.60
Italy	165155	10.48	2.05	12.62	16.75	44.62	8.94	3.97	22.36
Japan	8100	10.80	3.47	12.84	11.70	60.03	10.93	2.32	26.82
Kuwait	1405	10.41	2.32	9.79	60.75	72.24	3.90	2.49	2.32
Luxembourg	3373	11.61	2.50	7.86	10.36	56.54	6.16	2.85	14.08
Malaysia	5072	9.40	0.96	12.71	16.04	66.37	3.80	1.32	6.32
Mexico	5399	9.25	0.65	14.49	20.92	57.60	5.47	2.14	6.97
Morocco	2024	8.12	0.81	13.01	32.59	42.22	5.84	0.65	6.67
Netherlands	28153	10.92	5.11	10.63	12.03	61.82	10.36	3.29	18.57
New Zealand	1386	10.55	0.19	12.50	5.96	67.69	9.22	2.79	15.16
Norway	6740	11.43	0.15	13.21	6.96	61.68	10.50	4.35	16.70
Oman	910	9.67	0.16	12.64	41.12	66.59	4.29	2.04	2.33
Philippines	5453	8.01	3.58	12.61	18.07	57.60	4.39	1.28	4.86
Poland	7582	9.72	1.24	12.65	20.88	54.17	6.52	2.26	16.63
Portugal	18091	10.09	1.12	11.43	8.16	54.98	9.08	3.97	21.36
Qatar	3711	11.06	2.40	9.36	91.19	87.95	3.08	2.12	1.18
Romania	7216	9.35	0.85	12.38	14.61	52.68	4.98	2.50	17.65
Russia	24490	9.37	0.09	16.65	16.16	59.82	5.27	3.83	14.09
Serbia	4873	8.84	0.80	11.39	24.73	47.55	9.14	2.59	17.66
Singapore	3699	10.97	79.53	6.58	19.08	65.08	4.47	1.93	10.21
Slovenia	1248	10.19	1.03	9.93	16.02	55.81	8.47	2.66	18.78
South Africa	2506	8.91	0.48	14.01	25.10	40.32	8.11	0.77	5.17
Spain	177644	10.40	0.94	13.13	9.70	49.08	8.97	3.84	19.02
Switzerland	26336	11.28	2.16	10.63	10.30	65.26	12.25	4.01	18.32
Thailand	2643	8.76	1.36	13.15	26.26	67.28	3.71	0.53	11.24
UAE	5365	10.62	1.36	11.33	40.92	79.20	3.52	1.84	1.01
UK	98476	10.68	2.75	12.40	10.47	60.56	9.76	2.75	18.20
USA	636350	10.91	0.36	16.10	7.41	60.42	17.07	2.53	15.23

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Appendix Table 3: Estimated impact government response on COVID-19 transmission rate, with country characteristics interactions, fixed effects, selected countries, N=3381

	(1)	(2)	(3)	(4)	(5)	(6)
SI <25%	0.1801***	-0.431	1.4239	1.6452	0.1162	-1.1792
	(0.0614)	(0.5972)	(1.1740)	(1.2375)	(1.4664)	(1.5686)
25% ≤SI <50%	0.2400***	-0.6297	-2.7202**	-2.3548*	-4.1136***	-5.9358***
	(0.0665)	(0.6369)	(1.1971)	(1.2629)	(1.4681)	(1.5788)
50% ≤SI <75%	-0.0615	-0.489	0.3124	0.5892	-1.7946	-3.3259**
	(0.0651)	(0.6320)	(1.1999)	(1.2630)	(1.4735)	(1.5846)
SI >75%	-0.3631***	0.2849	-1.2472	-1.0732	-3.4569**	-4.7744***
	(0.0587)	(0.5348)	(1.1125)	(1.1846)	(1.3996)	(1.5046)
ln GDP per capita *						
SI <25%		0.0606	0.0013	0.012	0.1656	0.3313**
		(0.0599)	(0.0950)	(0.0973)	(0.1341)	(0.1652)
25% ≤SI <50%		0.0875	0.2007**	0.2143**	0.3987***	0.6038***
		(0.0642)	(0.0960)	(0.0974)	(0.1374)	(0.1731)
50% ≤SI <75%		0.0437	-0.007	0.0002	0.3242**	0.5187***
		(0.0640)	(0.0975)	(0.0997)	(0.1401)	(0.1735)
SI >75%		-0.065	0.0217	0.0052	0.2981**	0.5115***
		(0.0542)	(0.0908)	(0.0913)	(0.1264)	(0.1573)
Pop density *						
SI <25%			-0.1119*	-0.097	-0.0553	-0.0471
			(0.0571)	(0.0612)	(0.0625)	(0.0629)
25% ≤SI <50%			-0.1123**	-0.0975	-0.0553	-0.0482
			(0.0570)	(0.0611)	(0.0624)	(0.0628)
50% ≤SI <75%			-0.1047*	-0.0898	-0.0494	-0.0421
			(0.0571)	(0.0612)	(0.0625)	(0.0628)
SI >75%			-0.0980*	-0.0836	-0.0412	-0.0345
			(0.0570)	(0.0611)	(0.0624)	(0.0628)
ln surface area *						
SI <25%			-0.0751**	-0.0683*	0.0069	0.036
			(0.0360)	(0.0370)	(0.0498)	(0.0507)
25% ≤SI <50%			0.0933**	0.0984**	0.1822***	0.2199***
			(0.0390)	(0.0400)	(0.0512)	(0.0521)
50% ≤SI <75%			0.0061	0.0124	0.1150**	0.1475***
			(0.0375)	(0.0387)	(0.0505)	(0.0513)
SI >75%			0.056	0.0615*	0.1676***	0.1937***
			(0.0350)	(0.0359)	(0.0488)	(0.0494)
PM2.5 *						
SI <25%			-0.0071	-0.0073	-0.0099*	-0.0061
			(0.0048)	(0.0053)	(0.0054)	(0.0057)
25% ≤SI <50%			-0.0014	-0.0008	-0.0043	0.0017
			(0.0047)	(0.0052)	(0.0054)	(0.0057)
50% ≤SI <75%			-0.0110**	-0.0111**	-0.0166***	-0.0121**
			(0.0047)	(0.0051)	(0.0054)	(0.0056)
SI >75%			0.0035	0.0018	-0.0027	-0.0007
			(0.0042)	(0.0047)	(0.0048)	(0.0050)

Continued on next page

Appendix Table 3: Estimated impact government response on COVID-19 transmission rate, with country characteristics interactions, fixed effects, selected countries, N=3381

Employment rate *						
SI <25%				-0.0076	-0.0154*	-0.0318***
				(0.0081)	(0.0092)	(0.0103)
25% ≤SI <50%				-0.0102	-0.0194**	-0.0341***
				(0.0084)	(0.0097)	(0.0110)
50% ≤SI <75%				-0.0078	-0.0248***	-0.0415***
				(0.0081)	(0.0095)	(0.0105)
SI >75%				-0.0012	-0.0163*	-0.0356***
				(0.0078)	(0.0089)	(0.0099)
Health expenditure, % GDP *						
SI <25%					-0.0592*	-0.0639*
					(0.0349)	(0.0355)
25% ≤SI <50%					-0.0702*	-0.0967**
					(0.0395)	(0.0403)
50% ≤SI <75%					-0.1361***	-0.1527***
					(0.0402)	(0.0411)
SI >75%					-0.1190***	-0.1249***
					(0.0345)	(0.0349)
Physicians per 1000 people *						
SI <25%						-0.3339***
						(0.0995)
25% ≤SI <50%						-0.4739***
						(0.1068)
50% ≤SI <75%						-0.3975***
						(0.1016)
SI >75%						-0.3732***
						(0.0982)
% 65 yo + *						
SI <25%						0.0665**
						(0.0269)
25% ≤SI <50%						0.0978***
						(0.0281)
50% ≤SI <75%						0.0785***
						(0.0273)
SI >75%						0.0593**
						(0.0263)
R2	0.073	0.077	0.108	0.109	0.115	0.122

Note: The subset of selected countries includes those with number of infected>19 when school or workplace closures are enacted, 53 countries. SI denotes the OxCGRT data provides a Government Response Stringency Index. The omitted category of the SI index is 0, i.e., no government response. Coefficients presented, standard errors in parenthesis. Statistical significance is denoted as *10%, **5%, and ***1% levels.

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Working from home under Covid-19: Who is affected? Evidence from Latin American and Caribbean countries[1]

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Millions of individuals are required to work from home as part of national efforts to fight COVID-19. To evaluate the employment impact of the pandemic, an important point is whether individuals are able to work from home. This paper estimates the share of jobs that can be performed at home in 23 Latin American and Caribbean (LAC) countries as well as examines the workers' characteristics associated with such jobs. To carry out this analysis, this paper uses rich harmonised household surveys and presents two measures of teleworkability. The first measure of the feasibility of working from home is borrowed from Dingel and Neiman (2020), while the second closely follows the methodology of Saltiel (2020). We use the second measure as our benchmark, as it is based on a more representative task content of occupations for LAC countries. We find that the share of individuals who are able to work from home varies from 7% in Guatemala to 16% in the Bahamas. We document considerable variation in the potential to work from home across occupations, industries, regions and workers' socioeconomic characteristics. Our results show that some individuals are better positioned to cope with the current situation than others. This highlights the need to assist the most vulnerable workers in the context of the global pandemic.

1 We thank the Inter-American Development Bank for giving us a limited and stricly academic access to the Harmonized Household Surveys of Latin America and the Caribbean. We also thank Juan Barrios, Julia Escobar and Pablo Slon-Montero for their comments on an earlier draft. All possible errors remain ours.
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1 Introduction

Millions of individuals are required to work from home as part of national efforts to fight COVID-19. This could become a long-term shift if we consider the possibility of a prolonged or recurring outbreak. To evaluate the employment impact of the pandemic, an important point is whether individuals are able to work from home. This strongly depends on the task content of their occupation. Recent research shows that occupations can be classified according to their feasibility of being conducted at home. Using task-content information from the O*NET, Dingel and Neiman (2020) estimate that 34% of U.S. jobs can be performed at home. Although this measure is computed for other countries, a valid concern is that the task content of occupations may differ substantially between developed and developing economies. Taking these differences into consideration, Saltiel (2020) uses information on workers' tasks in the World Bank's Skills Toward Employability and Productivity (STEP) surveys and estimates the share of jobs that can be done from home in ten developing economies. The author finds that few jobs can be done at home, ranging from 6% in Ghana to 23% in Yunnan (China).

This paper contributes to this line of research by estimating the share of jobs that can be performed at home in 23 Latin American and Caribbean countries. It examines the workers' socioeconomic characteristics associated with such jobs as well as country-level indicators linked with higher shares of teleworkability. To carry out the analysis, this study uses rich household surveys harmonised by the Inter-American Development Bank (IADB). The harmonised household surveys cover 23 countries, including one North American country, ten South American countries, seven Central American countries and five Caribbean countries.[1] The surveys contain harmonised individual-level data on demographic, educational, labour, income and housing conditions. More specifically, we have information on workers' occupations, employment status and other labour market outcomes. The richness of the data gives us a unique opportunity to investigate how the feasibility to work from home varies across occupations and to explore the characteristics of individuals able to work from home.

Our first measure of the likelihood that the occupation can be performed at home is borrowed from Dingel and Neiman (2020) while our second measure of teleworkability is calculated by closely following the methodology of Saltiel (2020). In particular, for the second measure, we use the average share of Bolivia and Colombia by occupation and apply country-specific occupational weights. We compare the share of jobs that can be done from home based on these two measures. We find that the proportion of individuals who are able to work from home based on Saltiel (2020)'s measure is constantly lower than the proportion using Dingel and Neiman (2020)'s measure. This is not surprising since our second measure relies on information provided in Bolivia and Colombia while the first measure is based on the task content of occupations in the US. Therefore, we choose to

[1]The list of countries is as follows: Argentina, the Bahamas, Belize, Bolivia, Brazil, Barbados, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, El Salvador, Trinidad and Tobago, Uruguay and Venezuela.

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use the second measure as our benchmark, as it is more likely to be representative of the LAC region. We find that the percentage of individuals able to work from home varies from 7% to 16%. The countries with the lowest share of teleworkability in our sample are Guatemala and Honduras while the countries with the highest share are Costa Rica and the Bahamas.

We examine the share of individuals who are able to work from home by occupation and economic activity in each LAC country included in our sample. The feasibility to work from home is positively correlated with higher skilled occupations. Indeed, the share of teleworkability is much higher for managers and professionals (25% and 32% respectively). A high share of teleworkability is found as well for clerical workers (45%). On the opposite, individuals who work in elementary occupations are not likely to be able to work from home. Besides, we find important differences across countries in the feasibility of working from home in high-paying occupations. Among the different economic activities, the highest share of individuals able to work from home is in finance, insurance and the real estate sector. On the opposite, individuals working in agriculture or in the construction sector are significantly less able to work from home.

We also explore the socioeconomic characteristics of individuals who are able to work from home. The results show that the individuals who are the most educated, who live in urban areas, who have a formal job and who work in a large firm, as well as the individuals who are in the top quintile of the total labour income distribution are the most likely to be able to work from home. Women are also more likely than men to be able to work from home, a result that might be related to pre-established gender roles.

Lastly, we document the relationship between the national share of teleworkability and country-level indicators such as GDP per capita and the Human Development Index. We also look at how the proportion of individuals who have access to internet is associated with the share of teleworkability at the country level. Overall, we find a clear positive correlation between the country's level of development and the share of individuals who are able to work from home. We also investigate how the feasibility to work from home varies across regions in each country. The results obtained are important from a policy perspective, as they highlight the most vulnerable regions in each country - the ones with a low share of teleworkability. This information might help policy makers on designing policies that aim at easing the lockdown.

This study contributes to the literature on the feasibility to work from home in a number of ways. First, we closely follow two recent studies by Dingel and Neiman (2020) and Saltiel (2020) by examining the share of jobs that can be done from home in the context of Latin America and the Caribbean.[2] Therefore, our contribution is empirical rather than methodological. Our results show considerable variation in the potential to work from home across countries, and within each country, across occupations, industries and regions. Second, the richness of the harmonised data set allows us to conduct an extensive

[2]Our empirical question focuses on estimating how many jobs can be perfomed from home. This differs from estimating the actual number of individuals that are working from home.

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and comparable analysis on the characteristics of workers who are able to work from home. In this respect, this study is in line with recent work by Mongey and Weinberg (2020). The results provide important insights about the potential negative employment impacts arising from COVID-19 and contribute to the discussion on how the pandemic exacerbates inequalities (Adams-Prassl et al. 2020). More generally, our results also contribute to the discussion on alternative work arrangements (Mas and Pallais 2017) by providing evidence on the feasibility to work from home in Latin America and the Caribbean.

This paper proceeds as follows. Section 2 presents the data and explains how the measures of teleworkability were constructed. Section 3 presents evidence on the share of jobs that can be done from home, along with the worker characteristics associated with the capacity to work from home, and country-levels indicators linked with high shares of teleworkability. Lastly, Section 4 concludes.

2 Data and Measurement

This paper relies on rich household surveys harmonised by the IADB: the Harmonized Household Surveys of Latin America and the Caribbean (CMAEH).[3] This source of data is unique as it contains a set of harmonised databases corresponding to 23 countries in the region. The surveys collect information on demographic, educational, labour, income and housing conditions at the individual level. More specifically, we have information on workers' employment status, occupation, labour income and other labour market outcomes. We also have detailed information on individual sociodemographic characteristics, including gender, age, educational attainment and other indicators. This gives us a unique opportunity to study the share of individuals who are able to work from home in Latin America and the Caribbean.

The databases already include a harmonised variable for individuals' occupation. This variable has been codified by the IADB following the one-digit ISCO for all the 23 countries. In addition, we construct a variable which maps the two-digit ISCOs. We do so by following the general guidelines of the 2008 edition of the international standard classification of occupation from ILO. This exercise was feasible for 20 countries in our sample. We construct this variable in order to estimate the share of jobs than can be performed at home for each ISCO at the one-digit level. However, our preferred measure for occupation is the one-digit ISCO harmonised by the IADB. We then construct two measures of teleworkability, capturing the feasibility for each occupation to be performed from home. The first one is borrowed from Dingel and Neiman (2020) while the second closely follows Saltiel (2020).

Measuring the feasibility of teleworking following Dingel and Neiman (2020). First, the authors construct the index of teleworkability, capturing the likelihood that the occupation can be performed at home. To construct this measure, Dingel and Neiman

[3]The year of the survey differs for each country. We report this information in Table 1.

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(2020) use the responses to two O*NET surveys. O*NET provides occupation-level data for the US. It contains information on work activities by occupation, where occupations are defined based on the standard occupational classification (SOC). The measure of teleworkability is computed based on responses covering "Work Context" and "Generalized Work Activities".[4] For instance, if the occupation requires to perform general physical activities, Dingel and Neiman (2020) conclude that the occupation cannot be performed at home. If any of these statements are true, then they code the occupation as one that cannot be performed from home.

Once the measure is constructed, the authors map the six-digit SOCs to the 2008 edition of the ISCO at the two-digit level. However, each SOC do not map to a unique ISCO and vice versa. To circumvent this issue, Dingel and Neiman (2020) allocate the SOC's U.S. employment counts as weights across the ISCOs in proportion to the ISCO's employment shares in their set of countries. We replicate this exercise by using the ISCO's employment shares using the household surveys for the LAC countries. Once we apply the weights, we obtain for each country the share of jobs that can be done from home in each two-digit ISCO.

Measuring the feasibility of teleworking following Saltiel (2020). We closely follow the methodology of Saltiel (2020) to construct the second measure of teleworkability. More specifically, the author classifies workers as unable to work from home if they either do not use a computer at work, lift heavy objects, repair electronic equipment, operate heavy machinery or report that customer interaction is very important. The share of individuals who are able to work from home can then be computed by occupation and by country. Among the ten developing economies sampled by the STEP survey, there are two LAC countries: Bolivia and Colombia. The information provided in these two countries regarding the task content of occupations is likely to be representative for the all region.[5]

Therefore, we follow the methodology of Saltiel (2020) to obtain the share of individuals who are able to work from home in Bolivia and Colombia and construct an average share for each occupation. This gives us a share for all 2-digit ISCOs. The fact that the two countries have different levels of development reinforces the representativeness of this average for the LAC region. We can then merge this information to our individual-level data using our two-digit ISCO variable and the one-digit ISCO variable harmonised by

[4]The statements from the "Work Context" are the following: 1) average respondent says they use email less than once per month; 2) majority of respondents say they work outdoors every day; 3) average respondent says they deal with violent people at least once a week; 4) average respondent says they spent majority of time wearing common or specialized protective or safety equipment; 5) average respondent says they spent majority of time walking or running; 6) average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week; and 7) average respondent says they are exposed to diseases or infection at least once a week. The statements from the "Generalized Work Activities" are the following: 1) performing general physical activities is very important; 2) handling and moving objects is very important; 3) controlling machines and processes [not computers nor vehicles] is very important; 4) operating vehicles, mechanized devices, or equipment is very important; 5) performing for or working directly with the public is very important; 6) repairing and maintaining mechanical equipment is very important; 7) repairing and maintaining electronic equipment is very important; 8) inspecting equipment, structures, or materials is very important.

[5]One limitation of the STEP surveys used for Colombia and Bolivia for the year 2012 is that they only collect information on urban areas. In this respect, our share of teleworkability might be overestimated.

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the IADB. We apply weights using the country-specific ISCO's employment shares. As previously mentioned, the share of individuals who are able to work from home differs across countries since the ISCO employment shares vary across countries.

Summary statistics. Table 1 presents summary statistics for the sample used. The first column provides the summary statistics for the whole sample. It includes 23 countries and more than 1,385,000 individuals. For the purpose of the analysis, we have excluded individuals who are younger than 16 years old. Therefore, we use sample weights to make the results representative of the population older than 16 in each country.

A bit less than half of the individuals are men. The average individual is 41 years old. Around 57% of the individuals in the sample are with a partner. There are important cross-country differences in terms of educational attainment. However, the average individual in the full sample has completed 8.9 years of education. On average, about 79% of the individuals live in urban areas. In terms of employment outcomes, informality is common in Latin America and the Caribbean. On average, 54% of the workers in the full sample are informal. Furthermore, the majority of the individuals work in small firms. Around 43% of the individuals live with children. The rest of the measures such as access to basic infrastructure and "dwelling overcrowded" provide an idea of the wealthiness of the population.[6]

[6]On a side note, the proportion of individuals who have more than one occupation remains low on average (7%). However, for some countries, it reaches more than 20%. Not taking into account individuals' secondary occupations might underestimate the share of workers who are able to work from home. Further research should investigate this. However, for the sake of simplicity, we focus on the individuals' main occupation.

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Table 1. Summary Statistics, by Country

	All (1)	*ARG* (2)	*BHS* (3)	*BLZ* (4)	*BOL* (5)	*BRA* (6)	*BRB* (7)	*CHL* (8)	*COL* (9)	*CRI* (10)	*DOM* (11)	*ECU* (12)
Sociodemographic Characteristics												
Male	0.48	0.47	0.46	0.49	0.49	0.48	0.48	0.46	0.48	0.48	0.49	0.48
Age	41	42.3	41.7	37.6	39.4	41.9	46.9	43.5	40.6	41.9	40.5	39.5
With partner	0.57	0.54			0.60	0.57	0.28	0.51	0.54	0.51	0.50	0.59
Years of education	8.9	11.1		8.3	9.4	8.3	11.3	10.6	8.7	9	8.8	9.2
Urban	0.79			0.50	0.70	0.86		0.87	0.79	0.74	0.68	0.70
Employment Outcomes												
More than one occupation	0.07	0.08		0.03	0.08	0.04	0.02	0.04	0.09	0.05	0.08	0.05
Informal	0.54	0.48			0.82	0.38		0.31	0.64	0.31	0.61	0.54
Public sector	0.11	0.18	0.20	0.11	0.34	0.12	0.20	0.11	0.04		0.14	0.10
Underemployment	0.07	0.09		0.02	0.02		0.03	0.09	0.07	0.14	0.11	0.10
Hours worked per week		37.8		43.4	43.4	38.6	40.8	41.9	43.3	42.9	41.4	38.5
Size firm - Small	0.53	0.44			0.73	0.45		0.38	0.62	0.47	0.52	0.62
Size firm - Medium	0.17	0.29			0.21	0.09		0.30	0.14	0.16	0.16	0.15
Size firm - Large	0.29	0.26			0.06	0.46		0.32	0.25	0.37	0.32	0.23
Environment at home												
Household size	3.4	3.2	2.6	4.2	3.6	2.9	2.3	3.3	3.4	3.3	3.4	3.7
Living with children	0.43	0.37		0.55	0.49	0.34		0.37	0.46	0.36	0.41	0.52
Dwelling overcrowded	0.05	0.07			0.20	0.002		0.006	0.05	0.008	0.03	0.07
Access to water pipe	0.88	0.90		0.87	0.67	0.85		0.95	0.89	0.99	0.75	0.88
Access to electricity	0.97			0.92	0.92	1		1	0.98	0.99	0.97	0.99
Access to phone	0.89			0.42	0.90	0.94		0.98	0.95	0.98	0.85	0.92
Access to computer	0.41			0.19	0.24	0.49		0.58	0.37	0.46	0.22	0.41
Access to internet	0.34				0.15	0.42		0.53	0.36	0.65		0.33
Sample size	1,385,992	90,273	4,998	5,550	24,895	275,615	13,450	168,834	145,537	28,147	18,854	75,499
Survey year		2015	2012	2007	2015	2014	2015	2013	2015	2016	2015	2015

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table 1 presents the summary statistics by country for individuals aged 16 and above. The "Environment at home" category indicates the share of households in each country who belong to each category. "Underemployment" is equal to 1 if the person works less than 30 hours per week but desires to work more, and is equal to 0 otherwise. "Dwelling overcrowded" is equal to 1 if there is more than 2.5 persons per room in the dwelling, 0 otherwise. Argentina and the Bahamas only have information from urban areas. When the information was not available, we leave the cells as empty.

Table 1. Summary Statistics, by Country (Continued)

	GTM (13)	*HND* (14)	*JAM* (15)	*MEX* (16)	*NIC* (17)	*PAN* (18)	*PER* (19)	*PRY* (20)	*SLV* (21)	*TTO* (22)	*URY* (23)	*VEN* (24)
Sociodemographic Characteristics												
Male	0.47	0.46	0.48	0.48	0.48	0.49	0.48	0.49	0.46	0.49	0.47	0.50
Age	36.8	38.1	40	40.1	37.4	42.4	42.1	39.7	40.2	43.5	44.7	39.6
With partner	0.59	0.53		0.60	0.56		0.54	0.56	0.51	0.46	0.57	
Years of education		6.7	9.8	9.1	7.2	10.3	9.4	9.2	7.6		9.2	9.9
Urban	0.53	0.56	0.53	0.79	0.60	0.71	0.78	0.62	0.62		0.84	
Employment Outcomes												
More than one occupation	0.18	0.27	0.04	0.08	0.12	0.07	0.22	0.08	0.05	0.01	0.10	0.02
Informal	0.81	0.84		0.68	0.77	0.48	0.80	0.78	0.72		0.25	0.58
Public sector	0.06	0.06	0.13	0.10		0.16	0.09	0.11	0.07	0.24	0.15	0.21
Underemployment		0.13	0.04				0.04	0.10	0.08	0.03	0.07	0.02
Hours worked per week		36.6		42.1	41.3	37.5	38.8	40.8	42.1	39.4	38.6	38.9
Size firm - Small	0.61	0.96	0.57	0.54		0.44	0.65	0.66	0.49	0.14	0.40	0.53
Size firm - Medium	0.22	0.04	0.27	0.29		0.16	0.14	0.22	0.20	0.06	0.22	0.14
Size firm - Large	0.17	0.005	0.16	0.17		0.41	0.20	0.12	0.32	0.79	0.37	0.32
Environment at home												
Household size	4.8	4.3	3	3.8	5.4	3.5	3.9	4	3.6	3.1		3.9
Living with children	0.66	0.61	0.39	0.49	0.74	0.41	0.47	0.50	0.47	0.30		0.48
Dwelling overcrowded	0.41	0.11		0.05	0.30	0.07	0.10	0.10	0.20	0.03		0.06
Access to water pipe		0.88		0.97	0.65	0.94	0.84	0.81	0.79		0.94	0.94
Access to electricity	0.81	0.88		0.99	0.80	0.92	0.93	0.99	0.97		0.99	1
Access to phone	0.83	0.90		0.86	0.90	0.91	0.87	0.96	0.94		0.98	0.41
Access to computer		0.17		0.30		0.38	0.31	0.29	0.16		0.66	0.40
Access to internet	0.08	0.26		0.28	0.02	0.64	0.23	0.23	0.17		0.53	0.29
Sample size	33,677	15,481	14,104	51,094	19,909	30,596	85,090	21,661	53,895	24,970	99,252	84,611
Survey year	2014	2017	2012	2014	2014	2017	2014	2015	2017	2013	2013	2015

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table 1 presents the summary statistics by country for individuals aged 16 and above. The "Environment at home" category indicates the share of households in each country who belong to each category. "Underemployment" is equal to 1 if the person works less than 30 hours per week but desires to work more, and is equal to 0 otherwise. "Dwelling overcrowded" is equal to 1 if there is more than 2.5 persons per room in the dwelling, 0 otherwise. When the information was not available, we leave the cells as empty.

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3 Results

In this section, we provide empirical evidence on the share of workers who are able to work from home. We compute the national share for all LAC countries in our sample. We also look at the variation in the share of teleworkability across occupations and economic activities within each country. Second, we examine the socioeconomic characteristics of the workers who are able to work from home. Finally, we document the relationships between countries' share of teleworkability and a number of country-specific measures. We investigate the share of individuals who are able to work from home at the regional level for most of the countries in our sample.

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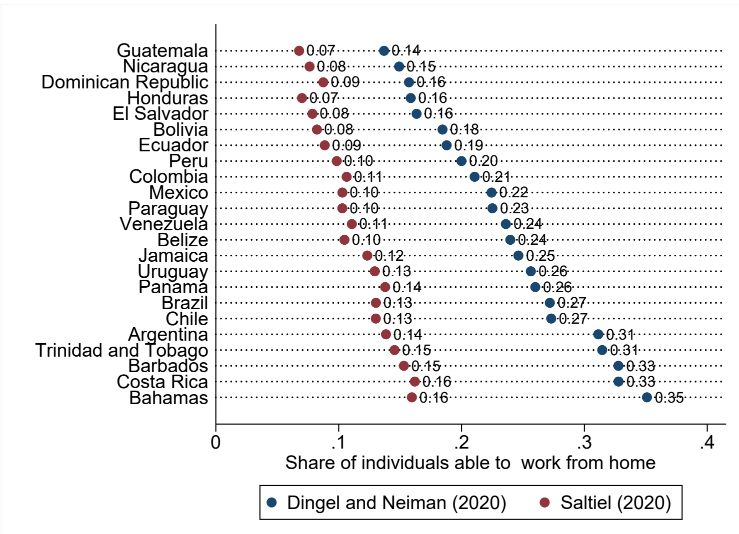
3.1 Share of Individuals Who Can Work From Home

Figure 1 shows the share of jobs which can be done from home in each country.[7] We report two shares per country: the first one based on Dingel and Neiman (2020)'s measure of teleworkability and the second, based on Saltiel (2020)'s methodology. The share of individuals who are able to work from home is much lower when we use the method of Saltiel (2020). This is not surprising since the second measure has been calculated based on the task content of occupations for developing countries. For the rest of the analysis, we report the shares obtained by using the index of Saltiel (2020) since it is more likely to be representative of Latin America and the Caribbean. Therefore, the share of individuals who are able to work from home varies between 7 and 16%. The countries with the lowest shares of teleworkability in our sample are Guatemala and Honduras while the countries with the highest shares are Costa Rica and the Bahamas.

Figure 1. Share of Jobs Which Can Be Done from Home, by Country



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure 1 shows the proportion of individuals who are able to work from home by country. This proportion varies across countries, from 7% in Guatemala to 16% in the Bahamas.

The share of individuals who can work from home differs across occupations. Table 2 reports the shares by one-digit occupation and country. The results show that the feasibility of working from home is positively correlated with occupation-level wages. Indeed, the share of teleworkability is much higher for managers and professionals (25% and 32% respectively). A high share of teleworkability is found as well for clerical workers (45%). On the opposite, individuals who work in skilled agricultural jobs and in elementary occupations are not likely to be able to work from home. There are important differences

[7] Alternatively, Figure A.1 in the appendix provides a map of Latin America where the share of jobs that can be done at home is reported by country. The shares are based on Saltiel (2020)'s measure, which is our preferred measure as it gives a better approximation for developing countries in the LAC region.

across countries in the feasibility of working from home in high-paying occupations. For instance, 55% of the managers in Brazil are able to work from home, compared to only 13% of their peers in Paraguay. There is much less variation across countries for lower-skilled occupations.

Table 2. Share of Individuals Who Can Work from Home, by One-digit Occupation and Country

	All (1)	*ARG* (2)	*BHS* (3)	*BLZ* (4)	*BOL* (5)	*BRA* (6)	*BRB* (7)	*CHL* (8)	*COL* (9)	*CRI* (10)	*DOM* (11)	*ECU* (12)
1 Manager	0.25	0.24	0.22	0.46	0.24	0.55	0.25	0.29			0.35	0.31
2 Professional	0.32	0.24	0.31	0.28	0.31	0.32	0.37	0.39			0.29	0.30
3 Technician	0.20	0.24	0.29	0.26	0.24	0.24	0.26	0.25			0.28	0.28
4 Clerical	0.45	0.42	0.45	0.43	0.44	0.42	0.45	0.45			0.47	0.45
5 Services/Sales	0.07	0.08	0.10	0.09	0.07	0.07	0.04	0.05			0.07	0.08
6 Agricultural	0	0	0	0	0	0	0	0			0	0
7 Craft/Trades	0.02	0.02	0.01	0.02	0.02	0.01	0.008	0.008			0.03	0.03
8 Machine Operators	0.002	0.003	0.001	0.001	0.002	0.002	0.0003	0.0008			0.002	0.002
9 Elementary Occupations	0.01	0.006	0.02	0.01	0.02	0.01	0.008	0.004			0.01	0.01

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Table 2 reports the share of workers who can work from home by one-digit occupation and by country. The share has been calculated as a weighted average of all the shares of the two-digit occupations within the one-digit occupation. Besides, the share is based on Saltiel (2020)'s measure of teleworkability. When the information was not available, we leave the cells as empty.

Table 2. Share of Individuals Who Can Work from Home by One-digit Occupation and Country (Continued)

	GTM (13)	*HND* (14)	*JAM* (15)	*MEX* (16)	*NIC* (17)	*PAN* (18)	*PER* (19)	*PRY* (20)	*SLV* (21)	*TTO* (22)	*URY* (23)	*VEN* (24)
1 Manager	0.19	0.25	0.29	0.23	0.22	0.24	0.26	0.13	0.30	0.26	0.31	
2 Professional	0.26	0.30	0.36	0.32	0.36	0.32	0.38	0.31	0.32	0.41	0.30	
3 Technician	0.22	0.28	0.29	0.10	0.30	0.29	0.13	0.27	0.23	0.27	0.24	
4 Clerical	0.44	0.44	0.48	0.50	0.47	0.42	0.39	0.47	0.44	0.44	0.41	
5 Services/Sales	0.08	0.08	0.05	0.05	0.05	0.15	0.02	0.06	0.08	0.05	0.08	
6 Agricultural	0	0	0	0	0	0	0	0	0	0	0	
7 Craft/Trades	0.03	0.03	0.006	0.06	0.02	0.03	0.001	0.02	0.03	0.008	0.02	
8 Machine Operators	0.002	0.003	0.0005	0.002	0.001	0.001	0.0001	0.0006	0.003	0.001	0.002	
9 Elementary Occupations	0.008	0.007	0.006	0.02	0.004	0.01	0.001	0.005	0.009	0.007	0.01	

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Table 2 reports the share of workers who can work from home by one-digit occupation and by country. The share has been calculated as a weighted average of all the shares of the two-digit occupations within the one-digit occupation. Besides, the share is based on Saltiel (2020)'s measure of teleworkability. When the information was not available, we leave the cells as empty.

Table 3 presents the share of individuals who can work from home across countries and across economic activities. The highest share of teleworkability is found in finance, insurance and the real estate sector (24% for the full sample). It varies however considerably across countries, from 17% in Colombia and in Jamaica to 36% in Peru. A significant share of individuals are able to work from home as well in social and community services (19% for the full sample). On the opposite, individuals are much less likely to be able to work from home when they work in agriculture and in the construction sector (0.007% and 0.04% respectively).

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Table 3. Share of Individuals Who Can Work from Home by Economic Activity and Country

	All (1)	*ARG* (2)	*BHS* (3)	*BLZ* (4)	*BOL* (5)	*BRA* (6)	*BRB* (7)	*CHL* (8)	*COL* (9)	*CRI* (10)	*DOM* (11)	*ECU* (12)
Agriculture, hunting, forestry and fishing	0.007	0.10	0.05	0.01	0.003	0.006		0.03	0.006	0.05	0.006	0.009
Mining and quarrying	0.09	0.15	0.09	0.06	0.06	0.11		0.09	0.08	0.08	0.08	0.10
Manufacturing industries	0.09	0.09	0.09	0.07	0.05	0.11		0.08	0.09	0.12	0.09	0.07
Electricity, gas and water	0.14	0.13	0.18	0.11	0.12	0.19		0.15	0.21	0.22	0.18	0.15
Construction	0.04	0.05	0.07	0.05	0.04	0.04		0.06	0.05	0.12	0.05	0.04
Wholesale and retail trade	0.11	0.11	0.12	0.12	0.08	0.13		0.13	0.09	0.13	0.11	0.09
Transport and storage	0.09	0.20	0.17	0.13	0.04	0.10		0.12	0.11	0.10	0.09	0.08
Financial, insurance and real estate	0.24	0.23	0.29	0.21	0.30	0.28		0.25	0.17	0.31	0.33	0.20
Social and community services	0.19	0.21	0.19	0.16	0.20	0.20		0.19	0.18	0.22	0.23	0.18

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table 3 reports the share of workers who can work from home by economic activity and by country. The share is based on Saltiel (2020)'s measure of teleworkability. When the information was not available, we leave the cells as empty.

Table 3. Share of Individuals Who Can Work from Home by Economic Activity and Country (Continued)

	GTM (13)	*HND* (14)	*JAM* (15)	*MEX* (16)	*NIC* (17)	*PAN* (18)	*PER* (19)	*PRY* (20)	*SLV* (21)	*TTO* (22)	*URY* (23)	*VEN* (24)
Agriculture, hunting, forestry and fishing	0.003		0.002	0.006	0.02	0.02	0.004	0.005	0.007	0.02	0.03	0.008
Mining and quarrying	0.04		0.10	0.11	0.07	0.09	0.10	0.02	0.02	0.14	0.08	0.12
Manufacturing industries	0.05		0.08	0.07	0.06	0.17	0.08	0.06	0.05	0.11	0.08	0.07
Electricity, gas and water	0.02		0.17	0.15	0.12	0.23	0.23	0.18	0.16	0.18	0.17	0.16
Construction	0.05		0.03	0.05	0.04	0.22	0.06	0.04	0.03	0.07	0.04	0.04
Wholesale and retail trade	0.13		0.11	0.10	0.09	0.14	0.09	0.10	0.07	0.16	0.11	0.10
Transport and storage	0.34		0.15	0.08	0.11	0.08	0.07	0.12	0.08	0.11	0.13	0.06
Financial, insurance and real estate	0.30		0.17	0.22	0.31	0.28	0.36	0.30	0.21	0.22	0.23	0.20
Social and community services	0.17		0.18	0.16	0.23	0.23	0.21	0.18	0.14	0.18	0.18	0.17

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table 3 reports the share of workers who can work from home by economic activity and by country. The share is based on Saltiel (2020)'s measure of teleworkability. When the information was not available, we leave the cells as empty.

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3.2 Characteristics of Individuals Who Can Work From Home

We now examine the characteristics of the workers who can perform their job from home. To examine which observed characteristics are associated with occupations that are more feasible to do from home, we estimate the following OLS regression:

$$WFH_{ijc} = \beta_0 + \beta_1 X_{ij} + \epsilon_{ij} \tag{1}$$

where the dependent variable WFH_{ij} is a binary variable which equals 1 if the share of teleworkability at the one-digit occupational level is above the median, and 0 otherwise. In other words, this variable is equal to 1 if the individual is working in an occupation that is relatively more feasible to be performed from home, and 0 otherwise. X_{ij} is a vector of characteristics including gender, age, being with a partner, educational attainment, whether the individual lives in a urban area, informality, the size of the firm where the individual works, and lastly, the quintiles in terms of the total labour income distribution.

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Table 4. Characteristics of Individuals Able to Work from Home

	All	*ARG*	*BHS*	*BLZ*	*BOL*	*BRA*	*BRB*	*CHL*	*COL*	*CRI*	*DOM*	*ECU*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Male	-0.114***	-0.173***	-0.227***	-0.126***	-0.087***	-0.160***	-0.237***	-0.193***	-0.048***	-0.095***	-0.166***	-0.108***
	(0.002)	(0.007)	(0.016)	(0.020)	(0.006)	(0.003)	(0.010)	(0.007)	(0.004)	(0.008)	(0.016)	(0.005)
Aged 41 and above	0.010***	0.071***	-0.030*	0.100***	0.021***	-0.019***	-0.080***	-0.035***	-0.004	-0.006	0.013	0.016***
	(0.002)	(0.007)	(0.016)	(0.017)	(0.006)	(0.003)	(0.011)	(0.007)	(0.004)	(0.008)	(0.014)	(0.005)
With partner	-0.041***	-0.003			-0.036***	-0.060***	0.033***	-0.022***	-0.037***	-0.031***	-0.024*	-0.037***
	(0.002)	(0.007)			(0.007)	(0.003)	(0.012)	(0.007)	(0.004)	(0.008)	(0.014)	(0.005)
Above 9 years education	0.258***	0.326***		0.398***	0.186***	0.262***	0.156***	0.177***	0.185***	0.307***	0.239***	0.188***
	(0.002)	(0.007)		(0.020)	(0.007)	(0.003)	(0.017)	(0.007)	(0.005)	(0.010)	(0.017)	(0.005)
Urban	0.019***			0.051***	0.030***	0.046***		0.048***	0.026***	0.024***	0.026*	0.046***
	(0.002)			(0.018)	(0.007)	(0.004)		(0.006)	(0.005)	(0.009)	(0.013)	(0.005)
Informal	-0.063***	0.022**			-0.345***	-0.038***		-0.041***	-0.064***	-0.019*	-0.144***	-0.079***
	(0.003)	(0.010)			(0.012)	(0.004)		(0.008)	(0.008)	(0.010)	(0.031)	(0.006)
Ref group: small firm												
Firm Size - Medium	0.099***	0.085***			0.158***	0.045***		0.111***	0.142***	0.138***	0.191***	0.134***
	(0.003)	(0.010)			(0.010)	(0.005)		(0.008)	(0.008)	(0.012)	(0.030)	(0.008)
Firm Size - Large	0.110***	0.149***			0.075***	0.084***		0.116***	0.196***	0.196***	0.184***	0.209***
	(0.003)	(0.011)			(0.017)	(0.004)		(0.008)	(0.009)	(0.011)	(0.033)	(0.009)
Ref group: first quintile												
Second quintile	0.003**	0.058***	0.116***	-0.015	-0.011	-0.010**	0.078***	-0.005***	0.001	0.032***	0.011	0.013**
	(0.003)	(0.010)	(0.023)	(0.026)	(0.009)	(0.004)	(0.015)	(0.009)	(0.005)	(0.012)	(0.018)	(0.005)
Third quintile	0.027***	0.090***	0.310***	-0.056**	0.005	0.029***	0.225***	0.114***	-0.021***	0.090***	0.024	0.007
	(0.003)	(0.011)	(0.024)	(0.024)	(0.009)	(0.004)	(0.015)	(0.011)	(0.006)	(0.013)	(0.018)	(0.007)
Fourth quintile	0.102***	0.181***	0.512***	-0.025	0.046***	0.106***	0.438***	0.260***	0.006	0.280***	0.086***	0.037***
	(0.003)	(0.012)	(0.023)	(0.028)	(0.010)	(0.004)	(0.017)	(0.011)	(0.007)	(0.014)	(0.021)	(0.008)
Fifth quintile	0.317***	0.331***	0.695***	0.010	0.101***	0.339***	0.670***	0.512***	0.240***	0.430***	0.231***	0.291***
	(0.003)	(0.013)	(0.023)	(0.027)	(0.010)	(0.005)	(0.014)	(0.011)	(0.008)	(0.015)	(0.023)	(0.010)
R-squared	0.3069	0.2784	0.2968	0.2502	0.3796	0.2629	0.3207	0.3016	0.3140	0.4391	0.4057	0.4050
Observations	549,505	35,629	2,877	2,056	13,835	113,620	6,565	73,927	84,429	11,194	7,671	40,535
Region fixed effects	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table 4 presents the estimated coefficients from equation (1) for the full sample in column 1 and separately for each country in the sample from column 2 to column 24. The results are weighted using sample weights to represent the population aged 16 and above. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Table 4. Characteristics of Individuals Able to Work from Home (Continued)

	GTM	*HND*	*JAM*	*MEX*	*NIC*	*PAN*	*PER*	*PRY*	*SLV*	*TTO*	*URY*	*VEN*
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Male	-0.105***	0.003	-0.098***	-0.071***	-0.049***	-0.154***	-0.076***	-0.118***	-0.065***	-0.350***	-0.114***	-0.176***
	(0.009)	(0.008)	(0.022)	(0.006)	(0.010)	(0.009)	(0.003)	(0.010)	(0.008)	(0.009)	(0.003)	(0.006)
Aged 41 and above	-0.015**	0.020***	0.107***	0.024***	0.043***	0.024***	0.024***	0.040***	0.018***	-0.079***	0.025***	0.024***
	(0.007)	(0.008)	(0.024)	(0.006)	(0.010)	(0.009)	(0.003)	(0.010)	(0.007)	(0.009)	(0.003)	(0.005)
With partner	-0.028***	0.0005		-0.032***	-0.029***		-0.041***	-0.028***	-0.024***	-0.007	-0.004	
	(0.008)	(0.007)		(0.006)	(0.011)		(0.003)	(0.010)	(0.007)	(0.009)	(0.003)	
Above 9 years education		0.170***	0.144***	0.276***	0.316***	0.262***	0.162***	0.267***	0.238***		0.364***	0.208***
		(0.016)	(0.024)	(0.007)	(0.013)	(0.012)	(0.003)	(0.012)	(0.008)		(0.004)	(0.005)
Urban	0.053***	0.036***	0.020	0.019***	-0.015	0.038***	0.052***	0.010	0.032***		0.037***	
	(0.007)	(0.008)	(0.026)	(0.006)	(0.014)	(0.011)	(0.003)	(0.011)	(0.006)		(0.004)	
Informal	-0.220***	-0.270***		-0.065***	-0.303***	-0.063***	-0.171***	-0.177***	0.016**		-0.005	-0.140***
	(0.017)	(0.058)		(0.009)	(0.014)	(0.017)	(0.008)	(0.018)	(0.012)		(0.004)	(0.009)
Ref group: small firm												
Firm Size - Medium	0.111***	0.128***	0.118***	0.088***		0.187***	0.132***	0.136***	0.144***	-0.021	0.066***	0.070***
	(0.009)	(0.036)	(0.025)	(0.008)		(0.019)	(0.005)	(0.014)	(0.010)	(0.019)	(0.005)	(0.009)
Firm Size - Large	0.042***	0.020	0.102***	0.031***		0.223***	0.319***	0.146***	0.184***	-0.064***	0.163***	0.210***
	(0.016)	(0.093)	(0.034)	(0.011)		(0.018)	(0.008)	(0.021)	(0.012)	(0.013)	(0.005)	(0.010)
Ref group: first quintile												
Second quintile	0.006	-0.001	0.016	0.026***	-0.034**	0.036**	0.017***	0.004	0.006	0.160***	-0.001	0.038***
	(0.006)	(0.006)	(0.028)	(0.007)	(0.015)	(0.014)	(0.003)	(0.011)	(0.008)	(0.012)	(0.005)	(0.008)
Third quintile	0.016**	0.004	0.126***	0.049***	-0.009	0.165***	0.014***	0.020	-0.036***	0.343***	0.059***	0.072***
	(0.007)	(0.008)	(0.032)	(0.008)	(0.018)	(0.019)	(0.004)	(0.014)	(0.010)	(0.015)	(0.005)	(0.007)
Fourth quintile	0.072***	0.009	0.025	0.143***	0.070***	0.296***	0.043***	0.081***	0.022*	0.476***	0.139***	0.129***
	(0.011)	(0.012)	(0.52)	(0.010)	(0.017)	(0.019)	(0.005)	(0.015)	(0.012)	(0.016)	(0.006)	(0.009)
Fifth quintile	0.256***	0.168***	0.500***	0.361***	0.154***	0.392***	0.149***	0.239***	0.282***	0.668***	0.290***	0.148***
	(0.013)	(0.022)	(0.040)	(0.011)	(0.017)	(0.018)	(0.006)	(0.017)	(0.013)	(0.014)	(0.006)	(0.008)
R-squared	0.2966	0.2485	0.3073	0.3432	0.3890	0.4213	0.4226	0.3821	0.3549	0.3192	0.3965	0.3296
Observations	16,064	6,103	1,511	28,867	8,162	11,044	51,227	5,834	18,672	8,803	57,232	38,322
Region fixed effects	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table 4 presents the estimated coefficients from equation (1) for the full sample in column 1 and separately for each country in the sample from column 2 to column 24. The results are weighted using sample weights to represent the population aged 16 and above. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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We include, when the information is available, region fixed effects. Lastly, we estimate equation (1) for the full sample and then separately by country. We apply sample weigths for the results to be representative of the all population above 16 years old.

Table 4 presents the results of the OLS regressions.[8] The results for the all sample indicate that men are less likely to be able to work from home compared to women. This might be due to pre-established gender roles, where women have had to ask for more flexible working arrangements to be able to take care of children. A higher educational attainment as well as living in a urban area increases the likelihood to work in an occupation which involves tasks that can be done from home. Informality is associated with a lower probability of being able to work from home. Among other reasons, this is likely related to the fact that informality often involves businesses where a lot of interactions with others are required. As for the effect of working in large firms, the probability of being able to work from home increases. Lastly, being in the top quintile of the total labour income distribution increases the likelihood to be able to work from home. The coefficients differ across countries in terms of magnitude. However, the direction of the effects remains in general the same. Overall, our results are in line with recent works by Saltiel (2020) and Mongey and Weinberg (2020).

3.3 Share of Teleworkability and Level of Development

We also want to examine the relationship between the country's share of teleworkability and some country-level indicators. A first important indicator that is susceptible to be highly correlated with the share of jobs that can be done from home is the level of development of the country. Figure 2 shows a clear positive relationship between the share of individuals able to work from home and the level of development. Countries with higher levels of GDP per capita such as the Bahamas or Trinidad and Tobago are clearly countries where more individuals have the potential to work from home. On the opposite, countries characterised by low levels of GDP per capita, such as Honduras and Nicaragua, have lower shares of teleworkability. Similarly, Figure 3 documents a positive relationship between the share of jobs that can be performed from home and the Human Development Index. Our results echo the findings of previous research by Dingel and Neiman (2020) and Gottlieb, Grobovšek and Poschke (2020).

Another way to look at this relationship is to examine the proportion of individuals using internet and to see how this connects with the share of teleworkability. Figure 4 illustrates this relationship. The connection is the same: countries where a higher proportion of individuals use internet also have higher shares of teleworkability.

[8] Alternatively, Table A.2 in the Appendix reports the share of individuals who are able to work from home along several characteristics.

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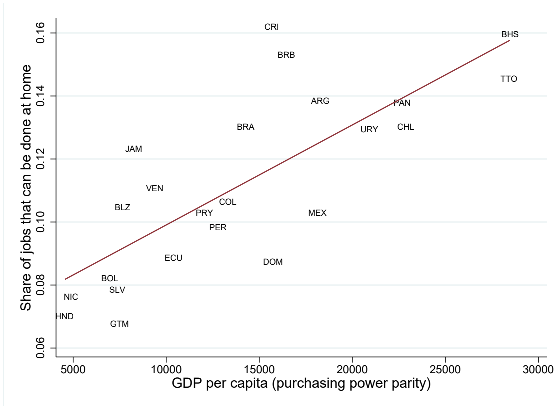
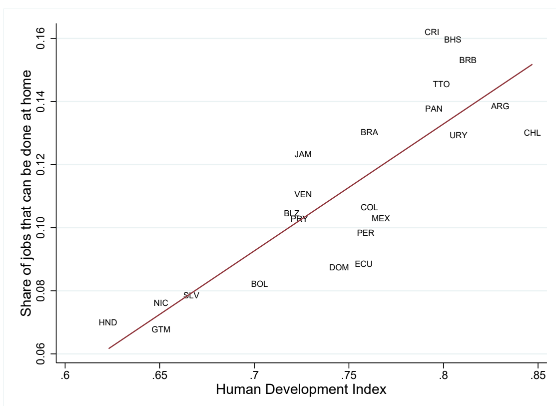
Figure 2. Share of Jobs Which Can Be Done from Home, by GDP (PPP) per capita



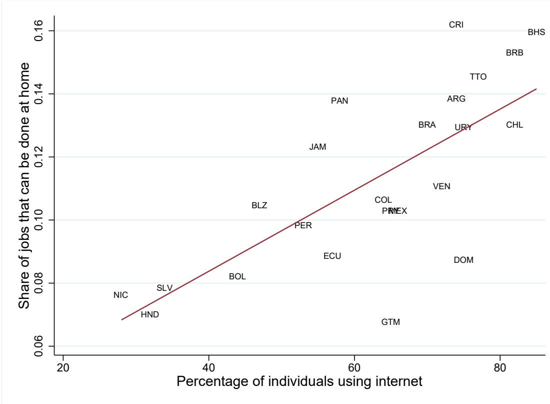
Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure 2 illustrates a positive relationship between the share of teleworkability and GDP per capita (2018). The measures for GDP per capita were taken from World Bank (2020).

Figure 3. Share of Jobs Which Can Be Done from Home, by HDI



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure 3 illustrates a positive relationship between the share of teleworkability and the Human Development Index (2018). The measures for HDI were taken from United Nations (2019).

Figure 4. Share of Jobs Which Can Be Done from Home, by Internet Usage



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure 4 illustrates a positive relationship between the share of teleworkability and the proportion of individuals using internet. Guatemala and the Dominican Republic are outliers in the World Bank data. The proportions were taken from World Bank (2020).

Lastly, we explore within-country heterogeneity by examining the variation in the feasibility to work from home at the regional level.[9] This might be informative given the fact that some countries in Latin America and the Caribeean have implemented social distancing policies recently to contain the virus.[10] We find significant differences across regions. The capitals are often in areas in which the share of teleworkability is high. However, for other regions, the share of individuals who are able to work from home might be far below the national average share. The results obtained are important from a policy perspective, as they highlight the most vulnerable regions in each country - the ones with a low share of teleworkability. This information might help policy makers on designing policies that aim at easing the lockdown.

4 Conclusion

To stop the spread of COVID-19, countries around the world have started to put in place broad social distancing policies. One of the implications is that individuals have to work from home. The employment effect of such policy is likely to vary depending on the feasibility of the job to be performed from home. Indeed, some individuals might be more affected than others due to the impossibility to carry certain tasks from home. In order to identify the individuals who are able to work from home, we construct two measures of teleworkability: the first one follows the methodology of Dingel and Neiman (2020) while the second measure closely follows Saltiel (2020). We use as our benchmark the second measure, as it better reflects the task content of occupations in Latin America and the Caribbean.

[9]The maps for each country are reported in the Appendix from Figure A.2 to A.18.
[10]Information about the level of the lockdown in each country is provided in Table A.1 in the Appendix.

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We find that the percentage of individuals able to work from home varies from 7% to 16%. The countries with the lowest share of teleworkability are Guatemala and Honduras while the countries with the highest share are Costa Rica and the Bahamas. We examine the share of individuals who are able to work from home by occupation and economic activity in each LAC country included in our sample. The feasibility to work from home is positively correlated with higher skilled occupations. Besides, we find considerable variation across occupations and across countries. Among the different economic activities, the highest share of individuals able to work from home is in finance, insurance and the real estate sector. On the opposite, individuals working in agriculture or in the construction sector are significantly less able to work from home.

We also explore the socioeconomic characteristics of individuals who are able to work from home. The results show that the individuals who are the most educated, who live in urban areas, who have a formal job and who work in a large firm, as well as the individuals who are in the top quintile of the total labour income distribution are the most likely to be able to work from home. Women are also more likely than men to be able to work from home, a result that might be related to pre-established gender roles.

Lastly, we explore the relationship between the national share of teleworkability and country-level indicators such as GDP per capita and the Human Development Index. We find a clear positive correlation between the country's level of development and the share of individuals who are able to work from home. Furthermore, we also investigate how the feasibility to work from home varies across regions in each country. The results obtained are important from a policy perspective, as they highlight the most vulnerable regions in each country - the ones with a low share of teleworkability. The results obtained provide important insights about the potential negative employment impacts arising from COVID-19 and highlight the need to assist the most vulnerable workers in the context of the global pandemic.

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Appendix

Table A.1. Situation Under COVID-19, by Country

Country	Country code	Lockdown	Valid up to
Argentina	ARG	Total	15-Apr
Bahamas	BHS	Total	15-Apr
Belize	BLZ	Partial	15-Apr
Bolivia	BOL	Total	16-Apr
Brazil	BRA	Partial	16-Apr
Barbados	BRB	Partial	16-Apr
Chile	CHL	Partial	16-Apr
Colombia	COL	Total	16-Apr
Costa Rica	CRI	Partial	8-Apr
Dominican Republic	DOM	Partial	16-Apr
Ecuador	ECU	Total	17-Apr
Guatemala	GTM	Total	19-Apr
Honduras	HND	Total	19-Apr
Jamaica	JAM	Partial	16-Apr
Mexico	MEX	Partial	16-Apr
Nicaragua	NIC	Partial	9-Apr
Panama	PAN	Total	16-Apr
Peru	PER	Total	15-Apr
Paraguay	PRY	Total	15-Apr
El Salvador	SLV	Total	15-Apr
Trinidad & Tobago	TTO	Partial	15-Apr
Uruguay	URY	Partial	16-Apr
Venezuela	VEN	Total	25-Mar

Source: Information from Inter-American Development Bank (2020) and International Monetary Fund (2020).

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Table A.2. Share of Individuals Who Can Work from Home by Individual Characteristics and by Country

	All (1)	*ARG* (2)	*BHS* (3)	*BLZ* (4)	*BOL* (5)	*BRA* (6)	*BRB* (7)	*CHL* (8)	*COL* (9)	*CRI* (10)	*DOM* (11)	*ECU* (12)
Dingel and Neiman National level	0.24	0.31	0.35	0.24	0.18	0.27	0.33	0.27	0.21	0.33	0.16	0.19
Saltiel National level	0.12	0.14	0.16	0.10	0.08	0.13	0.15	0.13	0.11	0.16	0.09	0.09
Male	0.09	0.13	0.12	0.07	0.07	0.10	0.11	0.10	0.09	0.14	0.10	0.07
Female	0.15	0.19	0.20	0.17	0.11	0.17	0.20	0.17	0.13	0.19	0.19	0.12
Aged 16-40	0.13	0.15	0.15	0.11	0.09	0.14	0.16	0.15	0.12	0.18	0.15	0.10
Age 41 and above	0.10	0.16	0.17	0.10	0.07	0.11	0.15	0.11	0.09	0.14	0.11	0.08
Not with partner	0.13	0.16			0.10	0.15	0.15	0.14	0.12	0.18	0.15	0.10
With partner	0.11	0.15			0.07	0.12	0.17	0.12	0.10	0.15	0.12	0.08
Below 9 years of education	0.05	0.07		0.05	0.03	0.06	0.06	0.05	0.04	0.08	0.06	0.03
Above 9 years of education	0.17	0.19		0.18	0.12	0.19	0.16	0.16	0.15	0.22	0.19	0.14
Rural	0.04			0.07	0.03	0.05		0.06	0.03	0.11	0.09	0.04
Urban	0.13			0.14	0.10	0.14		0.14	0.12	0.17	0.15	0.11
Informal	0.07	0.11			0.05	0.07		0.09	0.06	0.09	0.08	0.04
Formal	0.17	0.20			0.19	0.16		0.15	0.17	0.18	0.21	0.14
Size firm - Small	0.07	0.11			0.05	0.10		0.10	0.06	0.10	0.07	0.05
Size firm - Medium	0.14	0.17			0.16	0.15		0.14	0.14	0.18	0.19	0.10
Size firm - Large	0.17	0.22			0.17	0.16		0.16	0.19	0.22	0.21	0.17
Quintile total labour income - First	0.07	0.09	0.08	0.10	0.03	0.09	0.10	0.08	0.05	0.8	0.09	0.04
Quintile total labour income - Second	0.09	0.12	0.12	0.11	0.07	0.12	0.12	0.10	0.06	0.12	0.12	0.04
Quintile total labour income - Third	0.11	0.15	0.17	0.10	0.08	0.13	0.15	0.12	0.10	0.16	0.14	0.08
Quintile total labour income - Fourth	0.13	0.19	0.20	0.11	0.10	0.14	0.21	0.15	0.13	0.22	0.13	0.10
Quintile total labour income - Fifth	0.19	0.23	0.22	0.09	0.13	0.20	0.24	0.20	0.19	0.24	0.18	0.18

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table A.2 presents the share of individuals able to work from home along individuals' characteristics. Argentina and the Bahamas only have information for urban areas. This might lead to an overestimation of the share of jobs that can be done from home. When the information was not available, we leave the cells as empty.

Table A.2. Share of Individuals Who Can Work from Home by Individual Characteristics and by Country (Continued)

	GTM (13)	*HND* (14)	*JAM* (15)	*MEX* (16)	*NIC* (17)	*PAN* (18)	*PER* (19)	*PRY* (20)	*SLV* (21)	*TTO* (22)	*URY* (23)	*VEN* (24)
Dingel and Neiman National level	0.14	0.16	0.25	0.22	0.15	0.26	0.20	0.23	0.16	0.31	0.26	0.24
Saltiel National level	0.07	0.07	0.12	0.10	0.08	0.14	0.10	0.10	0.08	0.15	0.13	0.11
Male	0.05	0.05	0.08	0.09	0.08	0.13	0.08	0.08	0.07	0.10	0.10	0.08
Female	0.11	0.10	0.14	0.13	0.14	0.21	0.12	0.13	0.10	0.21	0.17	0.17
Aged 16-40	0.08	0.08	0.11	0.11	0.11	0.18	0.11	0.12	0.08	0.16	0.13	0.12
Age 41 and above	0.05	0.06	0.10	0.10	0.09	0.15	0.08	0.08	0.07	0.13	0.13	0.10
Not with partner	0.09	0.08		0.12	0.12		0.12	0.12	0.09	0.15	0.13	
With partner	0.06	0.06		0.10	0.09		0.08	0.09	0.07	0.14	0.13	
Below 9 years of education	0.04	0.03	0.05	0.05	0.04	0.06	0.03	0.04	0.04		0.06	0.05
Above 9 years of education	0.22	0.17	0.14	0.17	0.17	0.21	0.14	0.16	0.14		0.21	0.15
Rural	0.03	0.03	0.07	0.05	0.05	0.09	0.03	0.06	0.04		0.06	
Urban	0.10	0.11	0.13	0.12	0.13	0.19	0.12	0.13	0.10		0.14	
Informal	0.04	0.05		0.07	0.06	0.08	0.06	0.07	0.05		0.06	0.06
Formal	0.16	0.17		0.16	0.19	0.22	0.22	0.19	0.14		0.15	0.17
Size firm - Small	0.04	0.04	0.06	0.07		0.07	0.05	0.06	0.04	0.13	0.08	0.06
Size firm - Medium	0.10	0.11	0.15	0.14		0.19	0.12	0.15	0.10	0.12	0.13	0.11
Size firm - Large	0.12	0.19	0.17	0.14		0.23	0.22	0.18	0.15	0.17	0.19	0.18
Quintile total labour income - First	0.02	0.02	0.07	0.05	0.04	0.06	0.04	0.04	0.04	0.10	0.07	0.08
Quintile total labour income - Second	0.03	0.03	0.10	0.07	0.06	0.16	0.06	0.07	0.05	0.11	0.10	0.12
Quintile total labour income - Third	0.04	0.05	0.14	0.09	0.11	0.20	0.10	0.11	0.06	0.15	0.13	0.12
Quintile total labour income - Fourth	0.09	0.08	0.08	0.12	0.14	0.22	0.12	0.12	0.10	0.17	0.16	0.13
Quintile total labour income - Fifth	0.15	0.17	0.21	0.19	0.15	0.23	0.17	0.17	0.17	0.20	0.20	0.12

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.

Notes: Table A.2 presents the share of individuals able to work from home along individuals' characteristics. When the information was not available, we leave the cells as empty.

Figure A.1. Share of Jobs Which Can Be Done from Home, by Country

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.1 provides the share of individuals who are able to work from home by country in Latin America and the Caribbean. The red shaded countries have the lowest share of teleworkability (between 6.8 and 8.5%) while the green shaded countries have the highest share (between 13 and 16.2%). The white shaded areas represent regions where no data was available.

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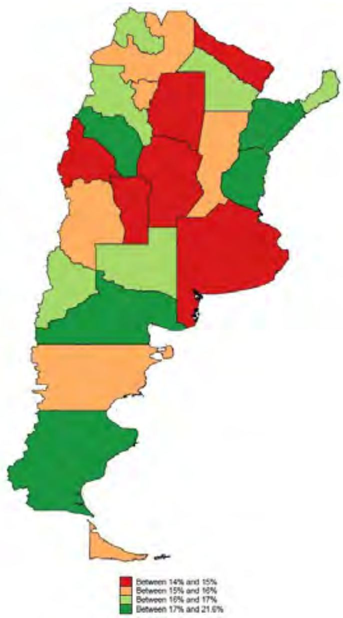
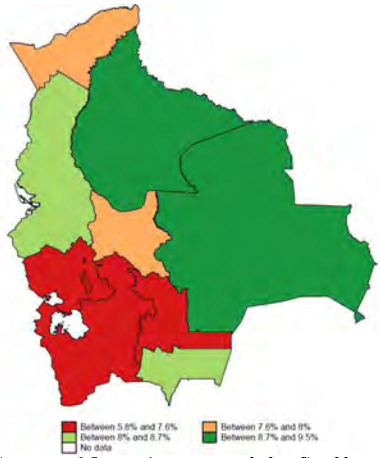
Figure A.2. Share of Jobs Which Can Be Done from Home in Argentina



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.2 presents the share of individuals who are able to work from home by regions in Argentina. The red shaded regions have the lowest share of teleworkability (between 14 and 15%) while the green shaded regions have the highest share (between 17 and 21.6%). Even though the percentage is low in Buenos Aires (14%), it should be noted that the percentage is much higher for Ciudad de Buenos Aires which is within the region of Buenos Aires (22%).

Figure A.3. Share of Jobs Which Can Be Done from Home in Bolivia



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.3 presents the share of individuals who are able to work from home by regions in Bolivia. The red shaded regions have the lowest share of teleworkability (between 5.8 and 7.6%) while the green shaded regions have the highest share (between 8.7 and 9.5%). The white shaded areas represent regions where no data was available.

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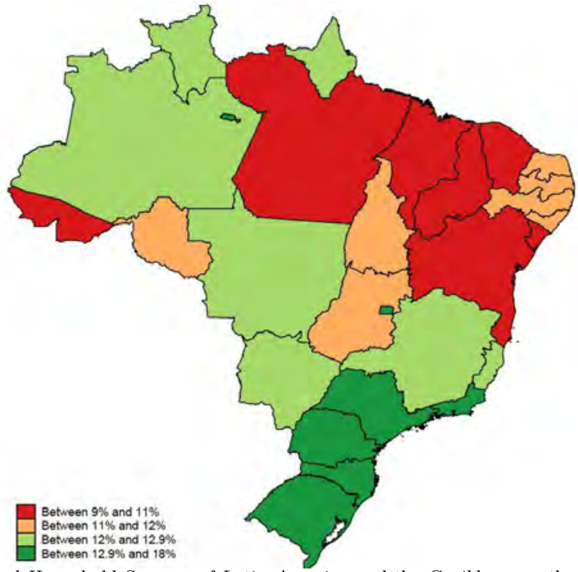
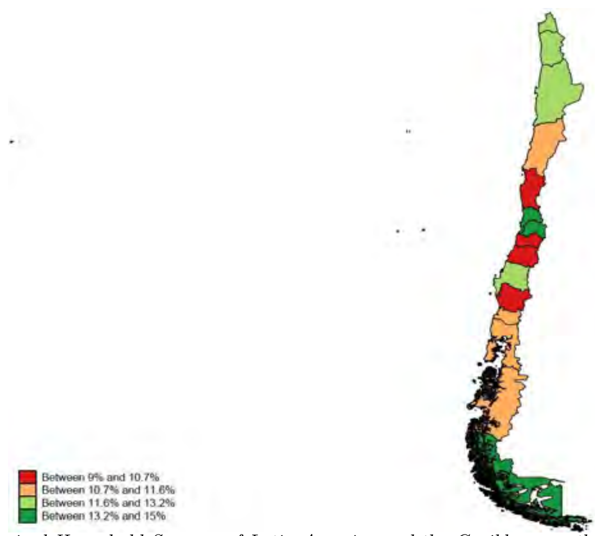
Figure A.4. Share of Jobs Which Can Be Done from Home in Brazil



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.4 presents the share of individuals who are able to work from home by regions in Brazil. The red shaded regions have the lowest share of teleworkability (between 9 and 11%) while the green shaded regions have the highest share (between 12.9 and 18%).

Figure A.5. Share of Jobs Which Can Be Done from Home in Chile



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.5 presents the share of individuals who are able to work from home by regions in Chile. The red shaded regions have the lowest share of teleworkability (between 9 and 10.7%) while the green shaded regions have the highest share (between 13.2 and 15%).

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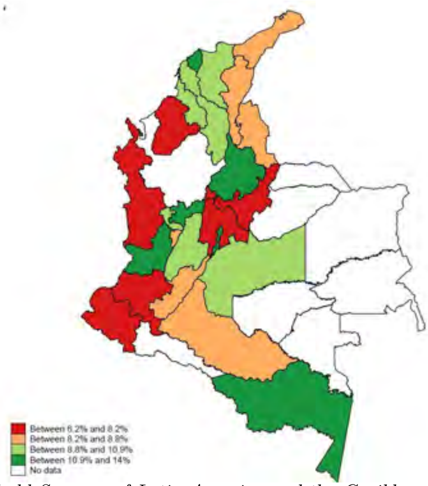
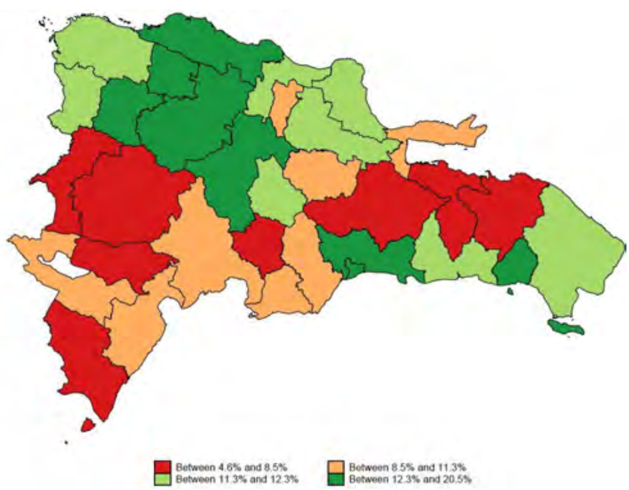
Figure A.6. Share of Jobs Which Can Be Done from Home in Colombia



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.6 presents the share of individuals who are able to work from home by regions in Colombia. The red shaded regions have the lowest share of teleworkability (between 6.2 and 8.2%) while the green shaded regions have the highest share (between 10.9 and 14%). The white shaded areas represent regions where no data was available.

Figure A.7. Share of Jobs Which Can Be Done from Home in the Dominican Republic



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.7 presents the share of individuals who are able to work from home by regions in the Dominican Republic. The red shaded regions have the lowest share of teleworkability (between 4.6 and 8.5%) while the green shaded regions have the highest share (between 12.3 and 20.5%).

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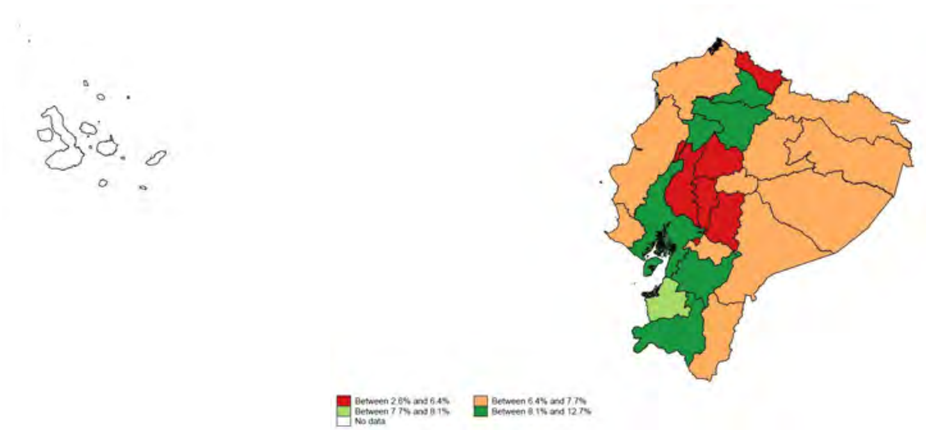
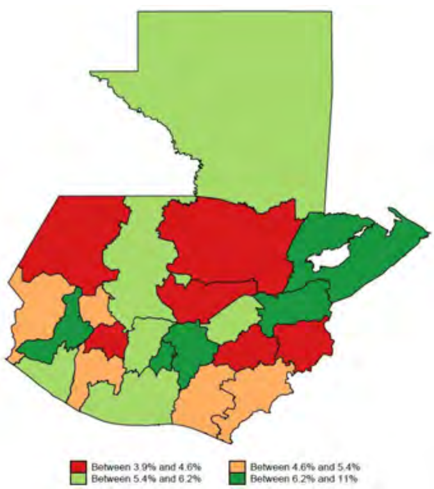
Figure A.8. Share of Jobs Which Can Be Done from Home in Ecuador



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.8 presents the share of individuals who are able to work from home by regions in Ecuador. The red shaded regions have the lowest share of teleworkability (between 2.6 and 6.4%) while the green shaded regions have the highest share (between 8.1 and 12.7%). The white shaded areas represent regions where no data was available.

Figure A.9. Share of Jobs Which Can Be Done from Home in Guatemala



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.9 presents the share of individuals who are able to work from home by regions in Guatemala. The red shaded regions have the lowest share of teleworkability (between 3.9 and 4.6%) while the green shaded regions have the highest share (between 6.2 and 11%).

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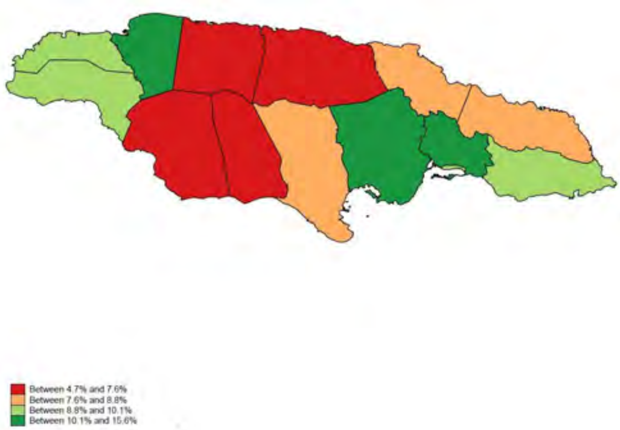
Figure A.10. Share of Jobs Which Can Be Done from Home in Honduras

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.10 presents the share of individuals who are able to work from home by regions in Honduras. The red shaded regions have the lowest share of teleworkability (between 3.9 and 4.5%) while the green shaded regions have the highest share (between 6 and 11%). The white shaded areas represent regions where no data was available.

Figure A.11. Share of Jobs Which Can Be Done from Home in Jamaica



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.11 presents the share of individuals who are able to work from home by regions in Jamaica. The red shaded regions have the lowest share of teleworkability (between 4.7 and 7.6%) while the green shaded regions have the highest share (between 10.1 and 15.6%).

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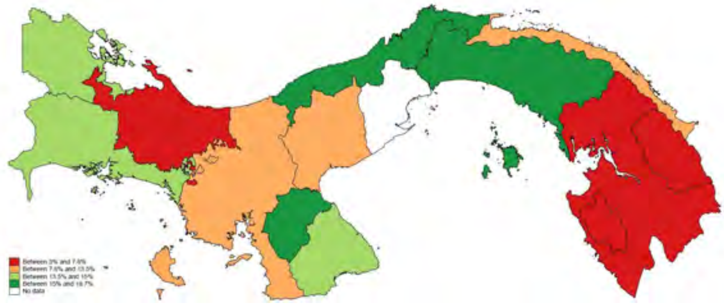
Figure A.12. Share of Jobs Which Can Be Done from Home in Mexico

Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.12 presents the share of individuals who are able to work from home by regions in Mexico. The red shaded regions have the lowest share of teleworkability (between 6.6 and 8.4%) while the green shaded regions have the highest share (between 11 and 15.7%).

Figure A.13. Share of Jobs Which Can Be Done from Home in Panama



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.13 presents the share of individuals who are able to work from home by regions in Panama. The red shaded regions have the lowest share of teleworkability (between 3 and 7.6%) while the green shaded regions have the highest share (between 15 and 18.7%). The white shaded areas represent regions where no data was available.

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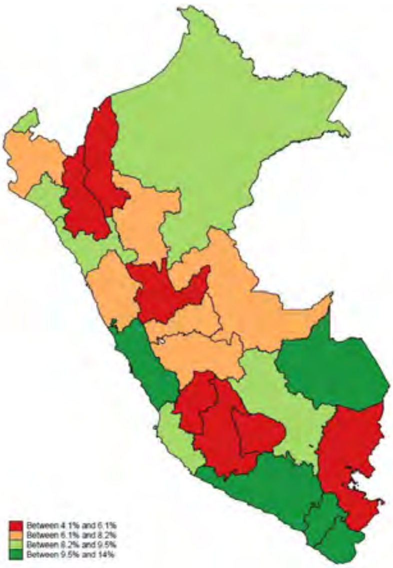
Figure A.14. Share of Jobs Which Can Be Done from Home in Peru

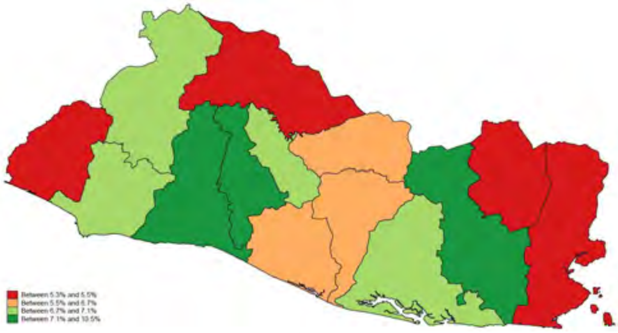


Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.14 presents the share of individuals who are able to work from home by regions in Peru. The red shaded regions have the lowest share of teleworkability (between 4.1 and 6.1%) while the green shaded regions have the highest share (between 9.5 and 14%).

Figure A.15. Share of Jobs Which Can Be Done from Home in Paraguay

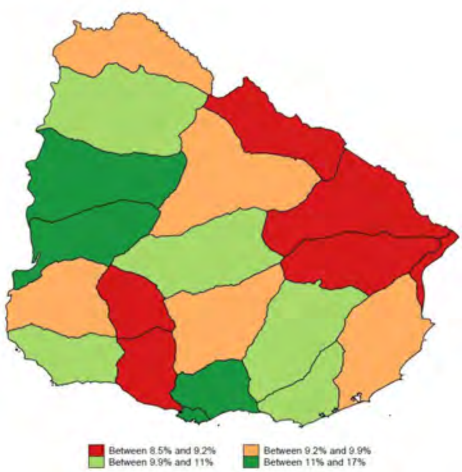
Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.15 presents the share of individuals who are able to work from home by regions in Paraguay. The red shaded regions have the lowest share of teleworkability (between 5.9 and 6.7%) while the green shaded regions have the highest share (between 12.4 and 16.6%). The white shaded areas represent regions where no data was available.

Figure A.16. Share of Jobs Which Can Be Done from Home in El Salvador



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.16 presents the share of individuals who are able to work from home by regions in El Salvador. The red shaded regions have the lowest share of teleworkability (between 5.3 and 5.5%) while the green shaded regions have the highest share (between 7.1 and 10.5%).

Figure A.17. Share of Jobs Which Can Be Done from Home in Uruguay



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.17 presents the share of individuals who are able to work from home by regions in Uruguay. The red shaded regions have the lowest share of teleworkability (between 8.5 and 9.2%) while the green shaded regions have the highest share (between 11 and 17%).

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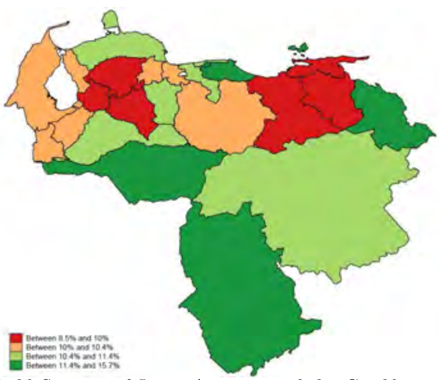
Figure A.18. Share of Jobs Which Can Be Done from Home in Venezuela



Source: Harmonized Household Surveys of Latin America and the Caribbean, authors' own calculations.
Notes: Figure A.18 presents the share of individuals who are able to work from home by regions in Venezuela. The red shaded regions have the lowest share of teleworkability (between 8.5 and 10%) while the green shaded regions have the highest share (between 11.4 and 15.7%).