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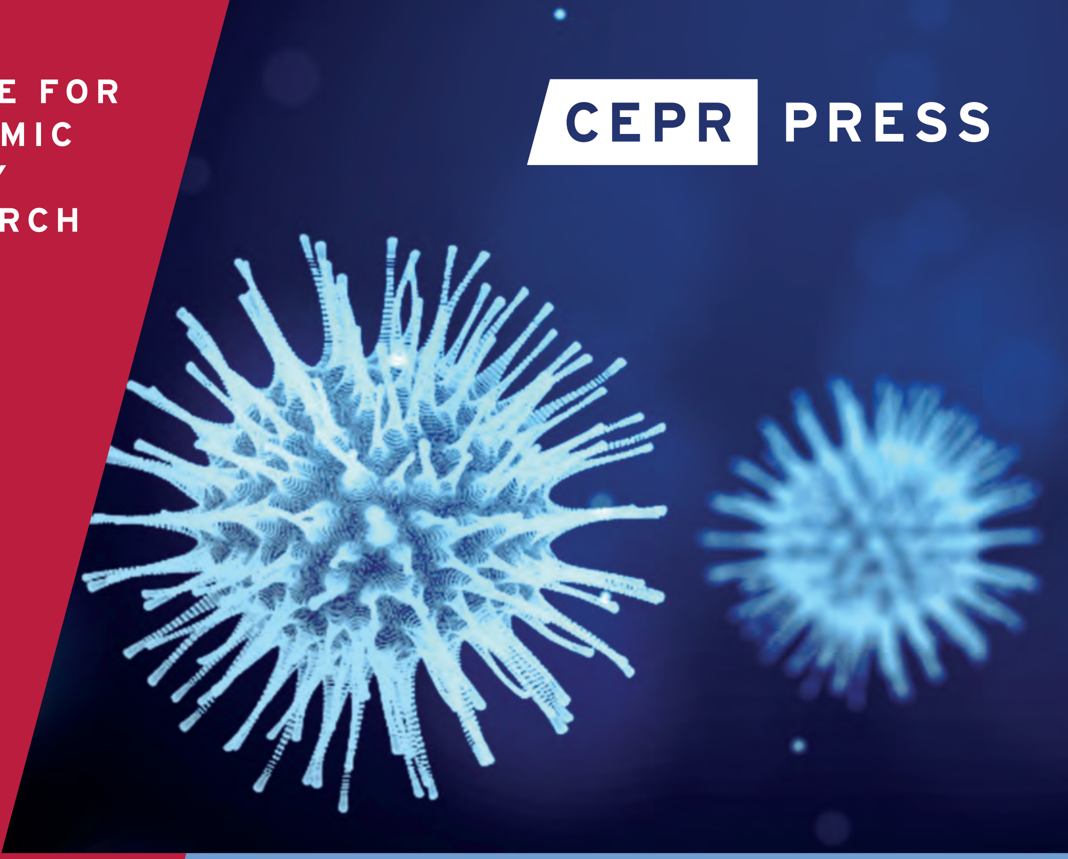

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 11
29 APRIL 2020

Covid Economics
Vetted and Real-Time Papers

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COVID-19 infection externalities: Pursuing herd immunity or containment?[1]

Zachary Bethune[2] and Anton Korinek[3]

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We analyze the externalities that arise when social and economic interactions transmit infectious diseases such as COVID-19. Public health measures are essential because individually rational agents do not internalize that they impose infection externalities upon others. In an SIR model calibrated to capture the main features of COVID-19 in the US economy, we show that private agents perceive the cost of an additional infection to be around $80k whereas the social cost including infection externalities is more than three times higher, around $286k. This misvaluation has stark implications for how society ultimately overcomes the disease: individually rational susceptible agents act cautiously to atten the curve of infections, but the disease is not overcome until herd immunity is acquired, with a deep recession and slow recovery lasting several years. By contrast, the socially optimal approach in our model isolates the infected and quickly contains the disease, producing a much milder recession. If the infected and susceptible cannot be targeted independently, then containment is far costlier: it remains optimal for standard statistical values of life but not if only the economic losses from lost lives are counted.

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2 Assistant Professor, University of Virginia.
3 Associate Professor, University of Virginia and CEPR Research Fellow.

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1 Introduction

The ongoing coronavirus pandemic has presented policymakers with a pivotal challenge: to choose between either an uncontrolled spread of the virus, that may cost millions of lives in worst-case scenarios, or the imposition of non-pharmaceutical public health interventions, such as social distancing that harm economic and social activity and may undermine the livelihoods of far larger numbers of people. Containing epidemics falls into the realm of public policy because infectious diseases by their very nature involve externalities: when infected individuals engage in social or economic activity, they impose significant externalities on those with whom they interact and whom they put at risk of infection. The objective of this paper is to characterize the infection externalities of COVID-19 and compare individually rational behavior with what is socially optimal.

The novel coronavirus was first identified in Wuhan, China, in December 2019. It jumped from bats via an intermediate host to humans. The virus has officially been named "SARS-CoV-2," and the disease that it causes has been named "coronavirus disease 2019" (abbreviated "COVID-19"). It spreads among humans via respiratory droplets and aerosols as well as by touching infected surfaces. In an uncontrolled outbreak, the disease burden grows exponentially, with cases doubling approximately every six days. The incubation period, i.e. the time between when one is exposed to the virus and when one develops symptoms of disease, is from two to 14 days, with an average of five days. Those infected usually present with a fever, a dry cough and general fatigue, frequently involving a mild form of pneumonia. About 15 percent of cases develop more severe pneumonia that requires hospitalization, intensive care, and in many cases, mechanical ventilation. Verity et al. (2020) estimate the infection fatality rate to be around 0.67% – as long as the healthcare capacity of a country is not overwhelmed.

This paper analyzes the externalities that arise when economic interactions transmit infectious diseases such as COVID-19. We embed rationally optimizing individual agents into epidemiological models to study and quantify the trade-off between economic costs and epidemiological control.[1] We start out by building on the simplest epidemiological model, the SIS model, which splits the population into two

[1]See Anderson and May (1991) for a comprehensive textbook treatment of models of epidemiology. A good overview is also available at
https://en.wikipedia.org/wiki/Compartmental_models_in_epidemiology

compartments – susceptible S and infected I – and assumes that susceptible agents can acquire an infection by interacting with infected agents at a given rate. Infected agents I in turn recover at a given rate and return to the pool of susceptible agents S. In section 2 we embed optimizing individual agents into this model who choose the level of an economic activity that may transmit infections and analyze the externalities arising from individual choices. In section 3 we include an epidemiological compartment R of recovered & resistant agents in our analysis, delivering the SIR model in the spirit of the epidemiological model first laid out by Kermack and McKendrick (1927).

We start by analyzing a model economy in which we introduce a disease that imposes a utility cost on infected agents and that follows the dynamics of an SIS model. We contrast the behavior of individually rational optimizing agents with what would be chosen by a social planner who has the power to coordinate the decisions of individual agents. Individual agents who are susceptible to a disease rationally reduce the level of their economic activity so as to reduce the risk of infection. However, individually rational infected agents recognize that they have nothing to lose from further social interaction and do not internalize that their economic activities impose externalities upon others by exposing them to the risk of infection. We show in a proposition that this induces the social planner to value the cost of an extra infection more highly than decentralized agents. The decentralized SIS economy converges to an equilibrium in which the disease is endemic. By contrast, a social planner who internalizes the infection externalities induces infected agents to significantly reduce their economic activity so as to lower the spread of the disease. In our simulations, we find that for a wide range of parameter values, the social planner does this to a sufficient extent to contain and eradicate the disease from the population. Only if the social cost of a disease is extremely low, akin to the common cold, will the planner allow the disease to become endemic.

We expand our analysis to an SIR model that is calibrated to capture the epidemiological parameters of COVID-19 and the US economy. Again, we find and prove that infected individuals who behave individually rationally engage in excessive levels of economic activity because they disregard the infection externalities that they impose upon the susceptible. In our numerical simulations based on standard statistical value of life considerations, we show that private agents perceive the cost of an additional infection to be around \$80k whereas the true social cost in-

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cluding infection externalities is more than three times higher, around \$286k, when the fraction of infected agents is 1%.

Focusing on dynamics, this mis-valuation has stark implications for how society ultimately overcomes the disease: for a population of individually rational agents, the main focus is precautionary behavior by the susceptible, which flattens the curve of infections. However, in the decentralized setting, the disease is not overcome until herd immunity is acquired. The resulting economic cost is high: an initial sharp decline in aggregate output by about 8% is followed by a slow recovery that takes several years. By contrast, the socially optimal approach in our model focuses public policy measures on the infected in order to contain and eradicate the disease. Since the infected make up a smaller fraction of the population, this produces a much milder recession.

A natural concern is that targeting the infected is difficult since many countries, including the US, have suffered from shortages in testing kits, and because COVID-19 has a long incubation period and a significant fraction of infected individuals are asymptomatic. To capture this situation, we analyze a version of our model in which the epidemiological status of individuals is hidden so the planner has to choose a uniform level of economic activity for all agents. Even in that case, the social planner aggressively contains the disease for our baseline parameterization. However this must now be achieved through a reduction in the level of activity of all agents, generating a decline in aggregate output that is much more severe - about 15% - and permanent since the planner needs to keep activity low even when only a small measure of the population is infected to prevent the re-emergence of the disease. If the planner assigns a lower value to lives, e.g. if he only counts the economic losses from losing workers rather than the statistical value of life as in our baseline parameterization, then the planner finds it optimal to let the disease spread and go for herd immunity. In either case, when the planner cannot distinguish the epidemiological status of agents, the social cost of an extra infection is larger than when the planner can target infected individuals, about \$300k for a fraction infected of 1%.

In an extension of our model, we compare the private and social gains from vaccination. Individually rational susceptible agents find vaccines useful for two reasons: first, they no longer face the risk of costly infection and second they no longer need to incur the cost of social distancing to avoid becoming infected. Vaccines are most

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useful in a society in which social distancing is determined by individually rational behavior. When no one in such a population has immunity, the private gain from an individual vaccination is $26k. By contrast, a planner would perceive the social gain from vaccination nearly 17 times larger, at $430k when there is no existing immunity in the population.

Literature In the economics literature, our work is most closely related to Goldman and Lightwood (2002), Gersovitz and Hammer (2003, 2004) and Gersovitz (2011) who study externalities of health interventions for infectious diseases in SIS and SIR models. Georgiy et al. (2011) show cross-country externalities in responding to flu pandemics. Our addition to this strand of literature is (i) to analyze the economic effects of the specific non-pharmaceutical interventions relevant for COVID-19 – social distancing – and (ii) to contribute a quantitative analysis to the evaluation of COVID-19 infection externalities to better inform the policy debate.

Our work is also related to recent papers who analyze optimal non-pharmaceutical controls in SIR models calibrated to COVID-19, that feature a tradeoff of economic activity and disease transmission. Alvarez et al. (2020) and Eichenbaum et al. (2020) characterize optimal disease control in SIR models in which the transmission of disease depends on economic choices. We complement these papers by providing analytic results on the externalities that arise in both SIS and SIR models and by quantifying by how much individually rational agents undervalue the cost of infection. Our findings also highlight the crucial role of testing, as suggested in Berger et al. (2020) and Piguillem and Shi (2020). We also provide quantitative estimates of the magnitude of the externalities imposed by COVID-19 and formulate policy as a function of the measure of infected and susceptible agents. We rely on various estimates of the rate of COVID-19 transmission, death rates, and hospital capacity provided by Atkeson (2020), Verity et al. (2020), and others. Our work complements the collection of recent economics papers that analyze the role of fiscal policy (e.g. Faria-e-Castro, 2020) or spillover effects caused by COVID-19 (e.g. Guerrieri et al., 2020).

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2 First Step: An SIS Economy

2.1 Model Setup

In this section, we develop a simple SIS model that introduces a role for economic decision-making, an analysis of welfare and an expression of the externalities that arise. Although the SIS model omits important characteristics of diseases such as COVID-19, it illustrates the basic structure of the problem and allows us to analyze the interactions between economics and epidemiology in utmost clarity. We will build on this setting below to provide a richer description of externalities in the SIR model.

Epidemiology Let us denote the mass of susceptible individuals by S and the mass of infected individuals by I, and normalize the total population to $N = S+I = 1\forall t$. By assumption, all individuals in a given category are identical. Time is continuous and goes on forever. We follow the convention in the epidemiological literature of dropping the time subscript of S and I but remind the reader that they are, of course, time-dependent. Changes are denoted by $\dot{S}$ and $\dot{I}$. The evolution of S and I follows the standard epidemiological laws

$$\dot{S} = -\beta(\cdot) IS + \gamma I \tag{1}$$

$$\dot{I} = \beta(\cdot) IS - \gamma I \tag{2}$$

The term $\beta(\cdot) IS$ captures the flow of susceptible individuals that become infected, where $\beta(\cdot)$ is the meeting intensity at which individuals interact with each other, $\frac{I}{N} = I$ is the probability that an individual's interaction partner is infected conditional on meeting, and S normalizes the term by the measure of susceptible individuals in the population. In the economic model block below, we will specify how exactly $\beta(\cdot)$ depends on individual behavior. The term $+\gamma I$ captures that infected individuals recover at rate γ and return to the pool of susceptible individuals. The expression for $\dot{I}$ is the mirror image of $\dot{S}$ since the population is constant. Thus it is sufficient to keep track of only one of the two variables – an epidemiological version of Walras' Law.

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Individual Behavior The utility of an individual agent depends on her epidemiological status $i = \mathcal{S}, \mathcal{I}$ as well as on the level of activity $a_i \in [0,1]$ that she chooses to take.[2] This may be interpreted as the extent of social activity and the portion of economic activity in which physical interaction is required. Activity level $a_i = 0$ reflects complete isolation whereas $a_i = 1$ captures normal activity. We parameterize the probability of infection $\beta(a_S, a_I) = \beta_0 a_S a_I$ in the spirit of the epidemiological relationships described above, where β_0 reflects the spread at the maximum level of activity for both types of agents.

In the analysis of individual behavior, we denote by $I = Pr(i = \mathcal{I})$ the probability of an agent being infected. We observe that each atomistic agent takes as given the activity level of other agents and the fraction of infected in the population and denote these by $\bar{a}_I$, $\bar{a}_S$, and $\bar{I}$, where the latter evolves according to the law (2). The individual's epidemiological status thus satisfies[3]

$$\dot{I} = \beta(a_S, \bar{a}_I)\,\bar{I}(1-I) - \gamma I \tag{3}$$

In equilibrium it will be the case that $\bar{a}_I = a_I$, $\bar{a}_S = a_S$, and $\bar{I} = I$.

For an individual with initial epidemiological status $I(0)$, the utility maximization problem is to choose a path of activity levels $\{a_S, a_I\}$ so as to

$$\max_{\{a_S, a_I\}} U = \int_t E_i\left[e^{-rt} u_i(a_i)\right] \tag{4}$$

subject to (3), where the flow utility of the agent in a given period is $E_i[u_i(a_i)]$. For now, we capture the utility derived from social activity in reduced form. In our full model below we will describe how activity a interacts with the economic functions of agents in more detail. We assume that the flow utility of susceptible agents $u_S(a) = u(a)$ is increasing and concave $u''(a) < 0 < u'(a)$ up to its maximum level at which it becomes flat so $u'(1) = 0$.[4] For now, the flow utility of infected agents is $u_I(a) = u(a) - c(\bar{I})$ where $c(\bar{I})$ captures the additional utility loss from being sick and satisfies $c(0) > 0$ and $c'(\bar{I}) \geq 0$. The latter may reflect congestion effects

[2] Note that an individual's epidemiological status $i = \mathcal{S}, \mathcal{I}$ differs from the aggregate measures $\bar{S}$ and $\bar{I}$.

[3] An alternative interpretation is that the decision maker is a household with a fraction I of members infected.

[4] We could also consider a vector a instead of a scalar a to capture that there is a multi-dimensional set of choice variables affecting disease transmission.

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in the healthcare system, which are of critical importance during the COVID-19 pandemic.

We reformulate the individual's optimization problem in terms of the current-value Hamiltonian

$$\mathcal{H} = I\left[u\left(a_I\right) - c\left(\bar{I}\right)\right] + \left(1 - I\right)u\left(a_S\right) - V_I\left[\beta\left(a_S, \bar{a}_I\right)\bar{I}\left(1 - I\right) - \gamma I\right]$$

together with the transversality condition $\lim_{T\to\infty} e^{-rT}V_I = 0$, where V_I is the current-value shadow cost of an agent being infected. Each agent internalizes that her infection status depends on her choice of interactions with other agents but rationally takes as given the overall fraction of the population infected $\bar{I}$, which determines both the risk of infection for susceptible individuals and the congestion effects in the healthcare system. This generates rich externalities, as we will explore subsequently.

In addition to the transversality condition, the individual's optimality conditions are

$$u'\left(a_S\right) = V_I \cdot \beta_0 \bar{a}_I \bar{I} \tag{5}$$

$$u'\left(a_I\right) = 0 \tag{6}$$

$$rV_I = u\left(a_S\right) - u\left(a_I\right) + c\left(\bar{I}\right) - V_I \beta\left(\cdot\right)\bar{I} - V_I\gamma + \dot{V}_I \tag{7}$$

The first optimality condition reflects that the agent equates the marginal utility of activity a_S to the marginal expected cost of becoming infected, which consists of the lifetime utility loss of infection V_I times the marginal probability of infection $\beta_S\left(\cdot\right)\bar{I} = \beta_0\bar{a}_I\bar{I}$. Ceteris paribus, a larger number of infected agents increases the infection probability $\beta\bar{I}$ and induces the agent to scale back her economic activity, i.e. to behave in a more cautious manner. The second optimality condition implies that it is individually rational for the infected agent to pick the maximum level of activity $a_I = 1$ that maximizes her utility, not taking into account the epidemiological effects of her behavior. The third optimality condition reflects the flow shadow cost of being infected versus susceptible: the agent obtains different flow utility and experiences the cost $c\left(\bar{I}\right)$; moreover, the agent no longer faces the risk of infection, captured by the term $-V_I\beta\left(\cdot\right)\bar{I}$ and faces the potential prospect of recovery $-V_I\gamma$; finally, the shadow cost of being infected changes through time as I changes.

In equilibrium, the probability of infection of an individual agent equals the

aggregate fraction of infected agents $I = \bar{I}$.

Definition 1 (Decentralized SIS Economy)**.** For given initial $I(0)$, a decentralized equilibrium of the described SIS system is given by a path of the epidemiological variable I that follows the epidemiological law (2) as well as paths of action variables (a_S, a_I) and the shadow cost V_I that satisfy the optimization problem of individual agents.

Steady State In steady state, we set $\dot{I} = 0$ in equation (2), obtaining a non-degenerate infection rate of $I = 1 - \gamma/\beta(a_S, a_I)$, and set $\dot{V}_I = 0$ in (7). The optimality condition (6) implies $a_I = 1$. The three variables I, a_S, V_I are jointly pinned down by equation (5) as well as the two laws-of-motion set to zero.

2.2 Social Planner

Let us now contrast the outcome in a decentralized setting with what would be socially optimal if a planner who must obey the epidemiological laws can determine the path of individual actions $\{a_S, a_I\}$. The planner would maximize overall social welfare, consisting of the integral over the utility (4) of the unit mass of agents $j \in [0, 1]$,

$$W = \int U dj$$

where the epidemiological status of individuals follows the epidemiological law (2).

For a given value of inital infections $I(0)$, the problem of the planner can be captured by the current-value Hamiltonian

$$\mathcal{H} = I[u(a_I) - c(I)] + (1 - I)u(a_S) - W_I[\beta(a_I, a_S)I(1 - I) - \gamma I]$$

plus the transversality condition $\lim_{T\to\infty} e^{-rT} W_I = 0$, where W_I is the current-value shadow cost of an agent being infected. The resulting optimality conditions are

$$u'(a_S^*) = W_I \cdot \beta_0 a_I^* I \tag{8}$$

$$u'(a_I^*) = W_I \cdot \beta_0 a_S^* (1 - I) \tag{9}$$

$$rW_I = u(a_S^*) - u(a_I^*) + c(I) + Ic'(I) + W_I \cdot \beta(\cdot)(1 - 2I) - W_I\gamma + \dot{W}_I \tag{10}$$

where we denote by an asterisk the planner's choices.

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Definition 2 (Planner's Allocation in SIS Economy)**.** For given $I(0)$, the planner's allocation in the described SIS system is given by a path of the epidemiological variable I that follows the epidemiological law (2) as well as paths of action variables (a_S^*, a_I^*) and the shadow cost W_I that satisfy the planner's optimization problem.

The optimality condition for a_S^* mirrors the equivalent expression (5) in the decentralized equilibrium – individual agents and the planner both account for the risk of infection of susceptible agents in a similar manner. However, the planner's shadow price of infection W_I differs from that of decentralized agents, which we describe below. In our simulations we found that generally $V_I < W_I$ so the planner values the cost of acquiring the infection more highly than private agents and will act in a more precautionary manner than private agents for given parameter values. The second optimality condition for a_I^* differs from the optimality condition of private agents: the planner captures that the activity of infected agents increases the infection risk of the susceptible, which individual agents disregard.

The third optimality condition captures the law of motion of the planner's shadow price of infection. In addition to the costs captured by individual agents in the decentralized equilibrium, the term $Ic'(I)$ reflects that at the aggregate level, the cost of infections is convex, and the extra term $W_I\beta(\cdot)(1-I)$ reflects that the planner internalizes that additional infections will transmit to the current population of susceptible agents. We summarize our results as follows:

Proposition 1 (Infection Externalities in SIS Economy)**.** *The planner internalizes the infection externalities of the infected and would choose a lower level of activity for infected agents, $a_I^* < a_I$. For given actions, the planner experiences a higher social cost of infection than private agents, $W_I > V_I$.*

Proof. See discussion above. □

Whether the planner will induce more or less activity for susceptible agents than in the decentralized equilibrium for given I depends on two competing forces: since the infected engage in less activity, the risk of infection for susceptible agents is lower, generating a force toward greater activity; however, for given actions, the planner recognizes a greater social loss from one more individual becoming infected, $W_I > V_I$, generating a force toward lower levels of activity. By implication, for given a_I, she would choose a lower level $a_S^* < a_S$ than decentralized agents.

Corollary 1 (Decentralizing the SIS Economy)**.** *The planner can implement her allocation in a decentralized setting in the following ways:*

1. *by imposing taxes on the activities of susceptible and infected agents a_S and a_I such that*

$$\tau_I = W_I \cdot \beta_0 a_S^* (1 - I) > 0 \tag{11}$$
$$\tau_S = (W_I - V_I)\, \beta_0 a_I^* \bar{I} > 0 \tag{12}$$

2. *by imposing a tax (11) on the activity of infected a_I, and a utility penalty on becoming infected of*

$$\tau_V = W_I - V_I > 0 \tag{13}$$

3. *by imposing a tax (11) on the activity of infected a_I, and a utility penalty or equivalent tax on being infected such that*

$$\tau_C = Ic'(I) + W_I \cdot \beta(\cdot)(1 - I) > 0 \tag{14}$$

as well as any appropriate combination of the three instruments τ_S, τ_V, τ_C.

Formulating the different ways of decentralizing the SIS economy is not necessarily meant to provide hands-on policy guidance (especially for points 2. and 3.) Instead, we describe the three options because they offer three complementary ways to understand the infection externalities in our framework. Clearly, as captured by point 1., it is the actions of the susceptible and infected that ultimately need to change to implement the socially optimal allocation. However, the sole reason why the behavior of the susceptible is distorted is that they misperceive the social cost of being infected. As point 2. illustrates, this implies that correcting the shadow price of becoming infected by imposing an extra penalty would induce the socially optimal level of activity among the susceptible. Moreover, as clarified in point 3., the undervaluation of the shadow price of infection arises simply because infected individuals – even once we have induced them to engage in the socially optimal level of activity – do not internalize the potential cost that they impose on others, captured by the right-hand side of (14), which consists both of the increase in the cost $C(I)$ for all agents and the term reflecting the infection externality.

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Proof. The current-value Hamiltonian of individuals who face taxes τ_S and τ_I on consuming goods that are produced by actions a_S and a_I of susceptible or infected individuals and a tax on being infected τ_C is

$$\mathcal{H} = I\left[u\left(a_I\right) - \tau_I a_I - c\left(\bar{I}\right) - \tau_C\right] + (1-I)\left[u\left(a_S\right) - \tau_S a_S\right] - V_I\left[\beta\left(a_S, \bar{a}_I\right)\bar{I}\left(1-I\right) - \gamma I\right]$$

Given a utility penalty τ_V of becoming infected, the resulting optimality conditions are

$$u'\left(a_S\right) = \tau_S + \left(V_I + \tau_V\right)\beta_0 \bar{a}_I \cdot \bar{I} \tag{15}$$

$$u'\left(a_I\right) = \tau_I \tag{16}$$

$$rV_I = u\left(a_S\right) - u\left(a_I\right) + c\left(\bar{I}\right) + \tau_C - V_I\beta\left(\cdot\right)\bar{I} - V_I\gamma + \dot{V}_I \tag{17}$$

By setting τ_I to the value given in (11) and one of the three instruments τ_S, τ_V, τ_C to the values given in (12) to (14), the optimality conditions of decentralized agents who face the taxes will replicate the optimality conditions (8) and (9) of the planner. $\square$

Steady State The steady state of the system is obtained by setting $\dot{I} = 0$ and $\dot{W}_I = 0$ in equations (2) and (10). For given (I, W_I), optimality conditions (8) and (9) jointly pin down a_S^* and a_I^*.

2.3 Calibration

The time units in our calibration are weeks. We set the epidemiological parameters to $\gamma = 1/3$ to reflect an average duration of the disease of three weeks and $\beta_0 = 2.5/3$ to capture a parameter $R_0 = \beta_0/\gamma$ of 2.5, reflecting best available estimates on the spread of the disease without precautionary measures.[5] We set the economic parameter ρ to reflect a typical annual discount rate of 4%.

To capture the effects of the level of activity a on the economy and ultimately on welfare, we assume that there is a unit mass $h \in [0,1]$ of goods c_h, of which a fraction ϕ requires physical contact. Examples for goods that do not require physical contact are real estate services, information services, etc. Conversely, examples of

[5] See the discussion in Atkeson (2020) and references therein. Current evidence suggests that covid-19 has an R_0 between 2.0 to 3.25.

goods that do require physical contact include personal services such as haircuts, hospitality, medical treatments, transportation, etc. Although it is difficult to draw a sharp delineation, we set $\phi = .25$, in line with estimates reported in Mitchell (2020) on the fraction of the economy that is paralyzed by a severe physical lockdown of economic activity. (We note that demand multiplier effects such as those discussed in Guerrieri et al. (2020) may lead to additional negative spillovers from physical lockdowns to other sectors of the economy that do not intrinsically rely on physical contact. At present, we still lack data on the magnitude of these effects.)

Producing and consuming c_h units of good h generates disutility $d(c_h)$ and provides consumption utility $\tilde{u}(c_h)$. All the goods together provide the agent with overall flow utility of

$$u = \int [\tilde{u}(c_h) - d(c_h)]\, dh$$

For any good that does not depend on physical contact, it is optimal to choose the first-best level of output and consumption c^*, which satisfies $\tilde{u}'(c^*) = d'(c^*)$. By contrast, for the fraction ϕ of goods that do require physical interaction, output and consumption is scaled by the activity variable a so that $c_h = ac^*$. The resulting flow utility of activity level a is

$$u(a) = \phi [\tilde{u}(ac^*) - d(ac^*)] + (1-\phi)[\tilde{u}(c^*) - d(c^*)]$$

In our numerical application below, we assume log consumption utility $\tilde{u}(c) = \log c$ and linear disutility $d(c) = c$, implying that overall flow utility is $u(a) = \phi [\log a - a]$, omitting a constant term. Observe that this specification satisfies our earlier assumptions $\lim_{a \to 0} u'(a) = \infty$ and $u'(1) = 0$. Note that we have implicitly assumed that the utility of all individuals of a given epidemiological status is affected equally by a reduction in activity a. This is valid if individuals are well-insured, including if they receive social insurance against idiosyncratic shocks. By contrast, if some individuals lose their jobs and incomes whereas others can continue to work, additional welfare costs arise (see e.g. Guerrieri et al., 2020).

The cost of disease captures both the disutility of being sick and, in reduced form, the potential risk of death. In the analysis of public policies, e.g. safety regulations or environmental policies, economists routinely have to weigh decisions that compare economic benefits and health costs. Estimates of the implied cost of adverse health events are obtained by evaluating how much individuals are willing

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to spend to avoid a given risk of an adverse event. Based on guidance from the US Department of Transportation (2012) on the value of a statistical life by consumer price inflation, a current estimate in the US is around \$10.3m at the age of the median worker of approximately 40 years. By comparison, before the pandemic, the weekly level of economic activity in the US as measured by GDP was approximately \$1200/capita. In our model, we assume that this corresponds to the first-best level $c^* = 1$ and observe that the marginal utility of consumption at that level satisfies $\tilde{u}'(c^*) = 1$. For a median worker, a risk of death of $\delta = 0.66\%$ for a disease that lasts on average for $1/\gamma$ weeks can thus be expressed in terms of a weekly flow utility cost of $\$10.3\text{m}/\$1200 \cdot 0.0066 \cdot \gamma \approx 19$.

However, a striking feature of COVID-19 is that the case fatality rate depends strongly on age (Verity et al., 2020), ranging from virtually zero for children and teenagers to 7.8% for patients of age≥80. Combining Verity et al (2020)'s case fatality rates with life expectancy data from the SSA, Table A1 shows that the expected statistical loss of life years for an average infected individual in the US is 0.136 years. Using the procedure described by Atkins and Bradford (2020) and a discount rate of 4%, we translate the \$10.3m statistical value of life into a \$498k value of a statistical life year. Calculating the present discounted value of this figure across different age cohorts, Table A1 shows that this delivers an expected statistical loss of life valued at \$50.0k, which amounts to a weekly flow utility cost of $\$50.0\text{k}/\$1200 \cdot \gamma \approx 14$.

We parameterize the cost of disease as $c(I) = c_0 \cdot (1 + \kappa I)$ where the base cost of disease is given by $c_0 = 14$. One of the concerns about COVID-19 is its potential to overwhelm the capacity of our healthcare system since about 15% of cases require hospitalization and about 5% of cases require mechanical ventilators. (Given the early stage of medical research, there is still considerable uncertainty about these parameter values.) The US currently has only about 200,000 ventilators available. Assuming the best available distribution to the places where they are needed and no other demand for ventilators by chronically sick patients, this implies that at most .06% of the population can be served at a given time. If the infection rate rises above $I = .06\%/5\% = .012$, mortality will rise significantly, as experienced in earlier hotspots such as Wuhan or Northern Italy. We set $\kappa = 1/.012/2 \approx 40$ to reflect that the cost of disease is an increasing function of the fraction of the population that is infected. In summary, the parameters for our baseline calibration of the cost

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of disease are $(c_0, \kappa) = (14, 40)$.

To explore the full range of outcomes in the SIS model, we also consider a low-cost disease for which individuals experience just a minor reduction in utility, akin to e.g. the common cold. Without appealing to any specific disease, we set $r = 5\%$ so a unit of time corresponds to longer time periods and $(c_0, \kappa) = (0.05, 0)$ for this low-cost scenario. As we will show in the numerical analysis below, these parameter choices induce the planner to prefer an endemic equilibrium over eradication for sufficiently high values of $I(0)$.

Computational Procedure Computationally, we solve a system of two non-linear differential equations with boundary conditions using a shooting algorithm. In the decentralized equilibrium, the system is given by (I, V_I) described in (2) and (7), subject to $I(0)$ and the transversality condition. The system features two steady states: an unstable one at $I = 0$ and a stable one at $I \in (0, 1-\frac{\gamma}{\beta_0})$. Starting from any $I(0) > 0$, the system is saddle-path stable leading to the non-degenerate equilibrium. Similarly, the planner's allocation is given by a path of (I, W_I) described in 2 and 10, subject to $I(0)$ and the transversality condition. However, unlike the decentralized equilibrium, the planner's allocation may feature multiple steady states and dynamic paths that satisfy the transversality condition, so the shooting algorithm for each steady state must be complemented by a comparison of the global optimum across multiple different $W_I(0)$'s.

2.4 SIS Results

Figure 1 depicts the law of motion for the fraction of infected agents in the population for our baseline calibration (left) and the low cost-of-disease scenario (right).[6] The decentralized SIS economy converges to a unique steady state for any positive initial $I(0) > 0$, which occurs where the law of motion intersects with the 45-degree line.[7] This occurs around $I = 0.2$ in the baseline scenario, and around $I = 0.6$ in the low-cost scenario. The left-hand side of Figure 2 shows the policy functions for a_I and a_S as a function of I in the decentralized equilibrium: infected agents disregard the infection externalities and engage in full activity $a_I = 1$, whereas susceptible

[6] For illustration, we compute the law of motion from the continuous-time system on a discrete time grid with step size one, equivlent to a week in our calibration.

[7] There is, of course, also a locally unstable steady state at $I = 0$, at which the population is wholly disease-free.

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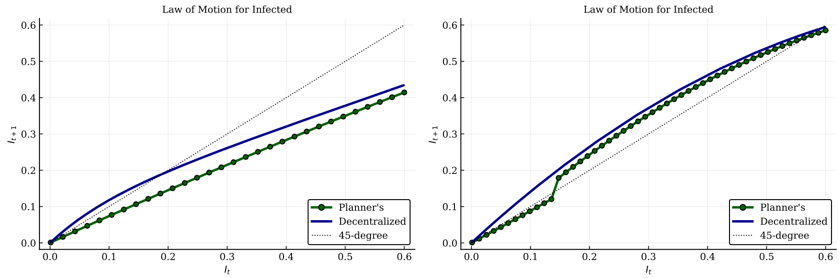
Figure 1: Law of motion for I, in baseline (left) and low cost-of-disease scenario (right)



agents reduce their activity the greater the fraction of infected in the population. By contrast, susceptible agents scale down their activity level in proportion to the cost and risk of infection they face, which is proportional to I.

The social planner, by contrast, chooses to eradicate the disease in the baseline scenario (right panel of Figure 1) by reducing the activity level of both susceptible and infected agents, ensuring that $I \to 0$ asymptotically. For low I, she focuses her risk mitigation on infected individuals. As I grows, the planner shifts her mitigation efforts from infected agents to susceptible agents. Intuitively, the planner relents on the activity reduction of the infected since there are fewer and fewer agents left to whom they could pass on the infection. In the low-cost scenario (lower panels of Figure 2), there is a discontinuity around $I(0) = 0.16$: when the initial fraction of the population is sufficiently low, the planner chooses to eradicate the disease as in the baseline scenario. However, when the initial disease burden is higher, it is no longer optimal to incur the cost of eradication, and the planner instead chooses a steady state with a positive disease burden that is slightly below the steady state of decentralized agents, internalizing the infection externalities.

The upper panels of Figure 3 simulate the paths of the SIS economy for initial $I(0) = 10\%$ in the baseline parameterization. The solutions in the decentralized economy and under the planner diverge – the disease remains endemic in the decentralized economy, with the fraction of infected converging to an interior steady state, whereas the planner eradicates the disease. The middle panel shows that the lives of susceptible agents quickly return to normal under the planner's solution, whereas decentralized agents find it optimal to progressively reduce their activity as I rises.

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Figure 2: Activity as a function of the measure of infected agents, in baseline (top panels) and low cost scenario (bottom panels)

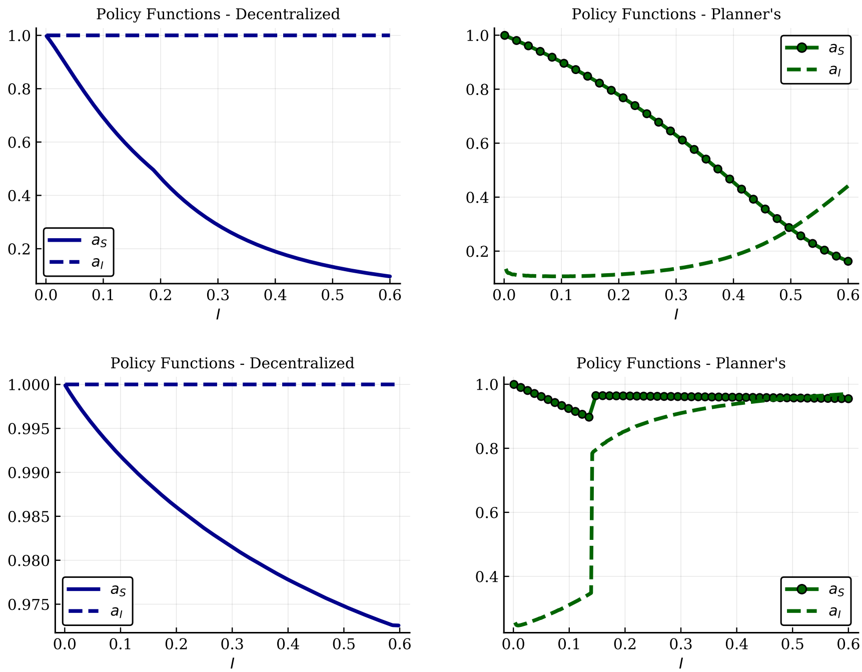

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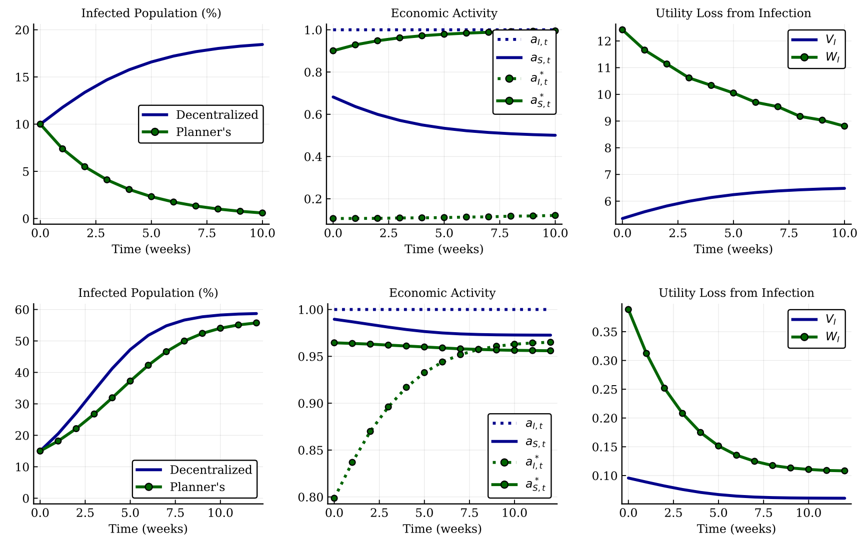
Figure 3: Dynamic paths starting from $I(0) = 0.10$ in the baseline (top panels) and $I(0) = 0.15$ in the low-cost scenario (bottom panels)



To accomplish a rapid eradication, the planner isolates infected agents by reducing their economic activity to near zero, which mitigates the harm to the susceptible. The efficient solution relies on the planner's ability to identify and isolate the the sick, highlighting the role of testing which we explore in later sections.

What is particularly interesting is that the shadow cost of an additional infection as perceived by the planner is significantly greater than what decentralized agents perceive. Private agents disregard the infection externalities, whereas the planner recognizes that additional infections cost not only the affected agents but also pose a risk to others. In the baseline scenario, the cost of infection is an increasing function of I for both the decentralized and the planner's allocation because more infections imply greater risk for the susceptible as well as more externalities and (for the planner) a higher cost of reducing the activity of infected agents.

The lower panels of Figure 3 show the paths of the economy for an initial level of infection $I(0)$ that is above the planner's eradication threshold under a low cost-of-disease scenario. In that case, the planner focuses on slowing down the rate of infection to preserve the higher utility of uninfected agents, and then converges to a steady state I that is slightly below the decentralized steady state. The right-hand

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panel shows that the planner recognizes the utility loss from infection to be a multiple of what decentralized agents perceive – because she internalizes the infection externalities generated by an additional infected agent. Moreover, the marginal cost of an additional infection is now decreasing over time as the economy approaches the steady state.

3 SIR Model

3.1 Model Setup

We expand the SIS model from above to account for the observation that individuals recovered from COVID-19 acquire resistance to future infection.

Epidemiology We denote the fraction of recovered/resistant individuals by R and normalize the population to $S + I + R = 1$. The epidemiological laws of motion in our SIR model are

$$\dot{S} = -\beta(\cdot) IS \tag{18}$$
$$\dot{I} = \beta(\cdot) IS - \gamma I \tag{19}$$
$$\dot{R} = \gamma I \tag{20}$$

where the last compartment reflects that infected individuals recover at rate γ. Recovered/resistant is an absorbing state. In our derivations below, we will keep track of the state variables I and R and note that $S = 1 - I - R$.

Individual Behavior The optimal activity level of resistant individuals R is $a_R = 1$ since they can no longer become infected, generating flow utility $u_R = u(1)$. Given that this is constant, there is no change in the endogenous economic decision variables of agents, and the individual optimization problem continues to be given by equation 4.

The current-value Hamiltonian of individuals in the SIR model is

$$\begin{aligned} \mathcal{H} =& I\left[u(a_I) - c\left(\bar{I}\right)\right] + Ru_R + (1 - I - R)\,u(a_S) \\ & - V_I\left[\beta(\bar{a}_I, a_S)\,\bar{I}\,(1 - I - R) - \gamma I\right] + V_R[\gamma I], \end{aligned} \tag{21}$$

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where $R = Pr(i = \mathcal{R})$ is the individual's probability of being resistant, plus the two transversality conditions $\lim_{T\to\infty} e^{-rT} V_I = 0$ and $\lim_{T\to\infty} e^{-rT} V_R = 0$ on the current-value shadow cost of being infected and shadow value of becoming resistant, respectively. The optimality conditions from the Hamiltonian are[8]

$$u'(a_S) = V_I \cdot \beta_0 \bar{a}_I \bar{I} \tag{22}$$

$$u'(a_I) = 0 \tag{23}$$

$$rV_I = u(a_S) - u(a_I) + c\left(\bar{I}\right) - V_I \beta(\cdot)\,\bar{I} - (V_I + V_R)\,\gamma + \dot{V}_I \tag{24}$$

$$rV_R = u_R - u(a_S) + V_I \beta(\cdot)\,\bar{I} + \dot{V}_R \tag{25}$$

Definition 3 (Decentralized SIR Economy)**.** For given $I(0)$ and $R(0)$, a decentralized equilibrium of the described system is given by a path of the epidemiological variables I and R that follow the epidemiological laws as well as paths of (a_S, a_I) and V_I, V_R that satisfy the optimization problem of individual agents.

3.2 Social Planner

Social welfare in the economy continues to be given by expression (4), where the expected flow utility $E_i[u_i(a_i)]$ is now calculated over the fractions of the three types of agents $i = \mathcal{S}, \mathcal{I}, \mathcal{R}$. The planner's Hamiltonian is given by the equivalent to the decentralized Hamiltonian (21) with $\bar{I} = I$, $\bar{R} = R$ and $\bar{a}_I = a_I$, where we denote the shadow prices on the laws of motion for I and R by W_I and W_R. The planner's optimality conditions for a_S^* and a_I^* are equivalent to (8) and (9) with $S = 1 - I - R$. The optimality conditions describing the evolution of shadow prices are

$$rW_I = u(a_S^*) - u(a_I^*) + c(I) + Ic'(I) \tag{26}$$

$$+ W_I \cdot \beta(\cdot)(1 - 2I - R) - (W_I + W_R)\gamma + \dot{W}_I \tag{27}$$

$$rW_R = u_R - u(a_S^*) + W_I \beta(\cdot)\, I + \dot{W}_R \tag{28}$$

Definition 4 (Planner's Allocation in SIR Economy)**.** For given $I(0)$ and $R(0)$, the planner's allocation in the described SIR system is given by a path of the epidemiological variables I and R that follow the epidemiological laws as well as paths

[8] Note that we define V_I as a shadow cost but V_R as a shadow value in the Hamiltonian; therefore the optimality conditions for the two are $rV_I = -\mathcal{H}_I + \dot{V}_I$ but $rV_R = +\mathcal{H}_R + V_R$.

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of (a_S, a_I) and V_I, V_R that satisfy the planner's optimization problem.

Comparing the allocations of decentralized agents and the planner, we arrive at similar results on the differences in behavior as in the SIS model:

Proposition 2 (Infection Externalities in SIR Model)**.** *The planner internalizes the infection externalities of the infected and would choose a lower level of activity for infected agents, $a_I^* < a_I$, but the same (full) level of activity for recovered agent, $a_R^* = a_R = 1$. For given actions, the planner perceives a higher social cost of infection than private agents, $W_I > V_I$, but the same social value of being recovered as private agents.*

Proof. See discussion above. □

As in our discussion follow Proposition 1, the planner's effects on the activity level of susceptible agents depends on the two competing forces: since the infected engage in less activity, the risk of infection for susceptible agents is lower, generating a force toward greater activity; however, for given actions, the planner recognizes a greater social loss from one more individual becoming infected, $W_I > V_I$, generating a force toward lower levels of activity.

The social planner's allocation can be decentralized in a similar fashion to what we discussed in Corollary 1 for the SIS economy:

Corollary 2 (Decentralizing the SIR Economy)**.** *The planner can implement her allocation in a decentralized setting in the three ways discussed in Corollary 1.*

3.3 SIR Results

We keep the parameterization from the baseline scenario of Section 2.3 but now account for the fact that recovered individuals are resistant to re-infection. Computationally, we solve a non-linear four-dimensional boundary value problem in (I, R, V_I, V_R) with conditions $I(0) > 0$, $R(0) = 0$ and the two transversality conditions. The boundary conditions for the planner's solution are equivalent in the corresponding system in (I, R, W_I, W_R), where again the algorithm must check for a global optimum across potentially multiple paths that satisfy the system given by equations (19), (20), (26),(28), and the boundary conditions.

Figure 4 illustrates the path of the disease in the decentralized and planner's allocation starting from an initial infection rate of $I\,(0)\ =1\%$, which is close to

estimates of the true number of COVID-19 cases in the US in the first half of April, given that the fraction of undiagnosed cases is significant (Verity et al., 2020), and setting $R(0) = 0$. In the decentralized economy, susceptible agents reduce their economic activity but infections continue to rise for the first 12 weeks. As the higher fraction of infected increases the risk for susceptible agents, they continue to reduce their economic activity until infection activity peaks. Subsequently, the rising number of recovered agents in the population together with still very cautious behavior by the susceptible leads to a decline in the fraction of infected, allowing susceptible agents to increase economic activity again. One striking observation is that even after two years, the epidemic is still ongoing: the fraction of infected in the population is still 0.5%, whereas close to half of the population has recovered and acquired resistance (middle panel).

Taken together, once could say that the extremely cautious behavior of the susceptible has "flattened the curve," but ultimately the mechanism that overcomes the epidemic is to acquire herd immunity, i.e. to acquire sufficient resistance in the population so that the epidemic dies out. Given the externalities, infected agents simply do not find it individually rational to engage in the severe measures that would be necessary to contain the disease.

The planner, by contrast, aims to eradicate the disease as quickly as possible by reducing activity by the infected to close to zero, even though this imposes a stark utility cost on infected agents given the Inada condition $\lim_{a \to 0} u_I'(a) = \infty$. After eight weeks, the fraction of infected is sufficiently close to zero that the planner allows infected individuals to raise their economic activity. However, observe that all throughout, the planner allows susceptible agents – who make up the majority of the population – to engage in almost full activity. In short, one could say that the planner's strategy to overcome the epidemic is containment and eradication, i.e. to drive down the number of infected sufficiently so that it no longer poses a risk to the susceptible, even though they never acquire herd immunity. This illustrates the stark difference in how the disease is overcome by decentralized agents versus the planner.

These results crucially hinge on the assumption that the epidemiological status of individuals is observable. In practice, widespread shortages in testing capacity as well as the considerable number of asymptomatic cases that are still potentially able to spread the disease currently make it difficult to implement what we have

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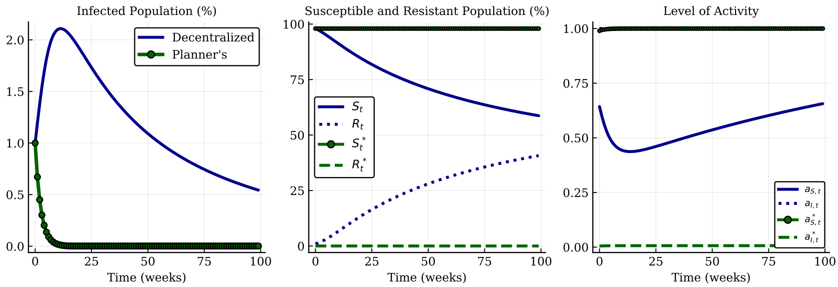
Figure 4: Dynamic paths starting from $I(0) = 0.01$ under the baseline scenario.



characterized as the planner's optimal strategy. For comparison, we consider the case in which the epidemiological status of individuals is unobservable in Section 3.4.

To provide additional intuition on the differences between the decentralized outcome and the planner's solution, the left-hand panel of Figure 5 illustrates how private agents and the planner perceive the marginal cost of an additional infection V_I versus W_I. The first observation is that the planner's W_I is significantly higher than private agents' V_I, for two reasons: first, she internalizes that infected agents spread the disease, and secondly she induces infected agents to starkly reduce their level of economic activity. At the initial level of infected $I(0) = 1\%$, private agents perceive the cost of infection to be around \$80k (using the same conversion mechanism as discussed in Section 2.3 when we converted the statistical value of life years into utils). The social cost of an additional infection as perceived by the planner, by contrast, is much larger and corresponds to approximately \$286k – about three-and-a-half times higher than what decentralized agents perceive. Furthermore, the social cost of infection rises in I as the planner internalizes that the rising case load risks overwhelming the capacity of the healthcare system, raising the social cost of disease $C(I)$.

The right-hand panel of Figure 5 illustrates the policy functions for economic activity $a_S(I, R)$ and $a_I(I, R)$ for varying I while holding $R = 0$. Since an increase in I exposes susceptible agents to higher infection risk, they strongly scale back their economic activity in the decentralized equilibrium. For an infection rate of I =1%, susceptible agents cut back physical activity from a normal level of 1.00 to $a_S = 0.65$; for I =5%, they cut activity to a_S =0.25. By contrast, the planner

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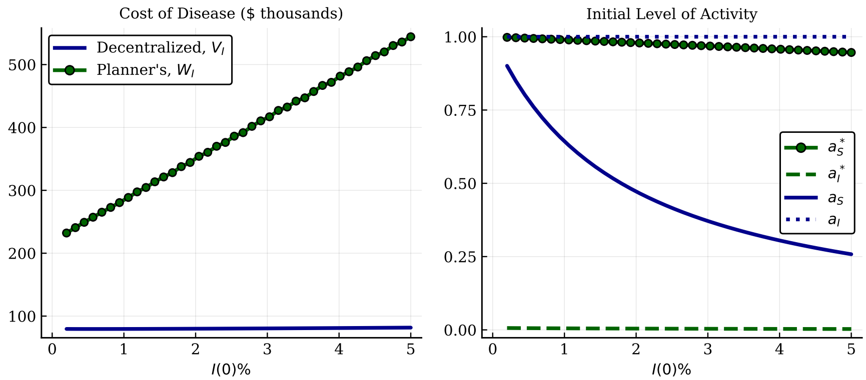
Figure 5: Cost of disease and initial economic activity (for $R = 0$) as a function of I.



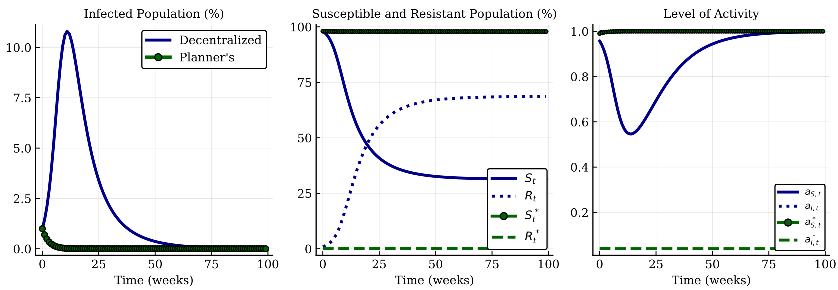
reduces the economic activity of the infected to near zero while maintaining activity for the susceptible near normal levels.

To verify the robustness of our findings, Figure 6 illustrates an alternative scenario in which we only consider the purely economic cost of the disease with $c(I) = c_0 = 1.7$ – this is 88% less than the cost in our baseline scenario that was derived from the statistical value of life calculation in Section 2.3. The planner's solution is nearly identical, with rapid containment and elimination of the disease. By contrast, the disease spreads more rapidly in the decentralized economy since susceptible agents engage in less precautionary behavior when the cost of disease is lower. They cut back on activity in proportion to the fraction I, which drives their risk of infection. In the long-run, over 70% of the population experiences an infection (middle-panel) compared to 50% in the baseline. There continues to be a discrepancy between the private and social shadow cost of an infection V_I and W_I – the two differ by a factor of almost six as private agents do not internalize the infection externalities that are now greater, given less precautionary behavior of the susceptible population.

3.4 Hidden Epidemiological Status

Following a containment and elimination strategy that focuses on the infected, as we found optimal in our analysis above, requires that the epidemiological status

Figure 6: Dynamic paths starting from $I(0) = 0.01$ under $c_0 = 1.7$ and $\kappa = 0$.



of individuals is readily identifiable. This has been a challenge, not only because COVID-19 has a long incubation period, up to 14 days, and a significant fraction of infected individuals are asymptomatic (Verity et al., 2020), but also because many countries, including the US, have suffered from shortages in testing kits. Whereas our baseline model assumed that individuals and the planner can easily target their chosen actions to whether a given individual is susceptible or infected, the reality is that many are unaware of their epidemiological status. To analyze the implications of this lack of information, we now consider the extreme case that the epidemiological status i of an individual is hidden so that the planner needs to chose a uniform level of activity $\hat{a}$ that does not depend on epidemiological status.

This modifies the Hamiltonian (21) of the planner so that there is just a single decision variable $\hat{a}$ that replaces a_S, a_I and a_R,

$$\mathcal{H} = u(\hat{a}) - Ic\left(\bar{I}\right) - V_I\left[\beta\left(\bar{\hat{a}}, \hat{a}\right)\bar{I}(1 - I - R) - \gamma I\right] + V_R[\gamma I]$$

The optimality condition for individual agents with respect to $\hat{a}$ is

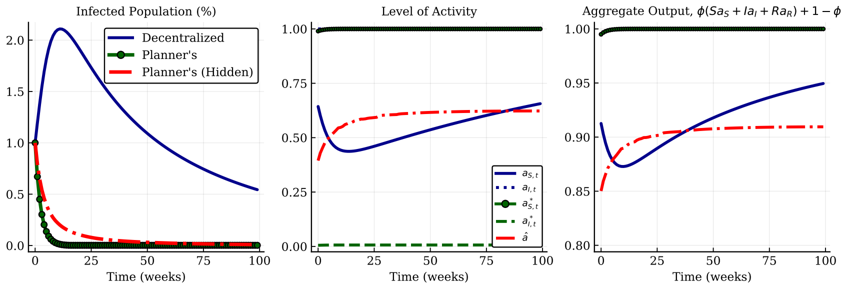
$$u'(\hat{a}) = V_I \cdot \beta_0 \bar{\hat{a}} \bar{I}(1 - I - R)$$

By contrast, the planner's optimality condition becomes

$$u'(\hat{a}) = 2W_I \cdot \beta_0 \hat{a} I (1 - I - R)$$

Comparing the the two conditions, we find:

Figure 7: Dynamic paths starting from $I(0) = 0.01$ under the baseline scenario, including optimal policy under hidden status



Proposition 3 (Infection Externalities with Hidden Status)**.** *In the model with hidden epidemiological status, the planner internalizes twice the infection risk perceived by decentralized agents for a given cost of infection. Furthermore, for given actions, the planner perceives a higher social cost of infection than private agents, $W_I > V_I$.*

Proof. See discussion above. □

The reason why the planner internalizes twice the expected cost of infection is that she recognizes that it is not only the actions of the susceptible that matter but also the actions of the infected agents.

Figure 7 illustrates the dynamic path of the disease starting from an infection rate of 1%. The left and middle panels reproduce the paths of infections and levels of activity from Figure 4 and add (red dash-dotted) lines for the planner who cannot distinguish the epidemiological status of individuals. The planner still contains and quickly eliminates the virus, but the path of infections is slightly higher compared to the optimal planning scenario. Containment must now be achieved through a reduction in the level of activity of all agents. The middle panel shows that the level of activity of all agents is initially reduced to 40% of the normal level, increasing back to 55% over the span of 11 weeks, but never rising above 63% over the first two years.

The reason is that the planner must choose an activity level at which the infection rate is non-increasing, even if the fraction infected is close to zero. The fraction

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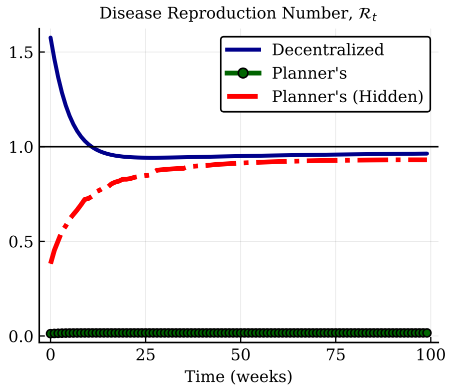
Figure 8: The dynamic path of the disease reproduction number, $\mathcal{R}_t = \beta(\cdot)S\gamma^{-1}$, starting from $I(0) = 0.01$ under the baseline scenario, including optimal policy under hidden status



infected is non-increasing if the disease reproduction number satisfies $\mathcal{R}_t \leq 1$, where

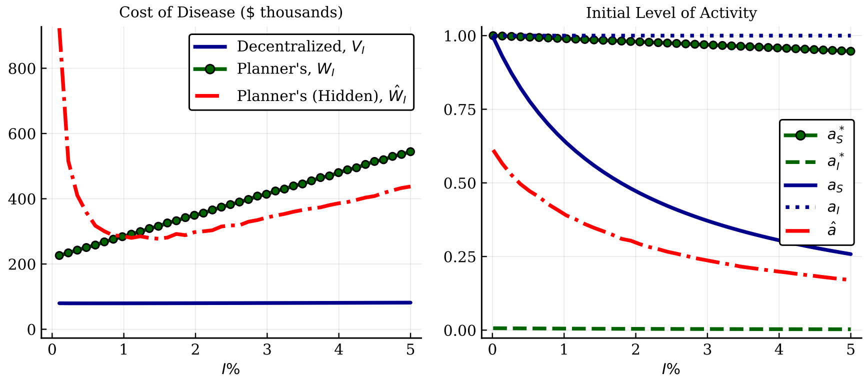
$$\mathcal{R}_t = \frac{\beta(\hat{a}, \hat{a})S}{\gamma} = \frac{\beta_0 \hat{a}^2 S}{\gamma}$$

Transforming the inequality above, the planner must set activity below $\hat{a} \leq \sqrt{\gamma/\beta_0 S}$ in order to keep the disease contained. Since, under the planner's allocation, the susceptible population remains close to one, this implies $\hat{a} \leq \sqrt{\gamma/\beta_0} \approx 0.63$. Figure 8 illustrates the disease reproduction number $\mathcal{R}_t$ along the dynamic paths of the three allocations.

The right panel of Figure 7 illustrates the impact on aggregate output (which includes the fraction $1 - \phi$ of output that does not require physical/social interaction). When the planner must resort to blunt measures that are independent of epidemiological status, she induces a recession that is larger than in the decentralized economy. Aggregate output is initially reduced by 15% and returns to 10% below normal after 20 weeks. The long-term prospects are grim since the planner never allows the level of physical activity to go above 63%.

If the planner assigns a lower value to lives, e.g. if he only counts the economic losses from losing workers rather than the statistical value of life as in our baseline parameterization, then she finds it optimal to let the disease spread and go for herd

Figure 9: Cost of disease and economic activity as a function of I under hidden status (for $R = 0$)



immunity, albeit at a slower rate than in the decentralized equilibrium. Once herd immunity is acquired, then the planner can relax restrictions on activity.

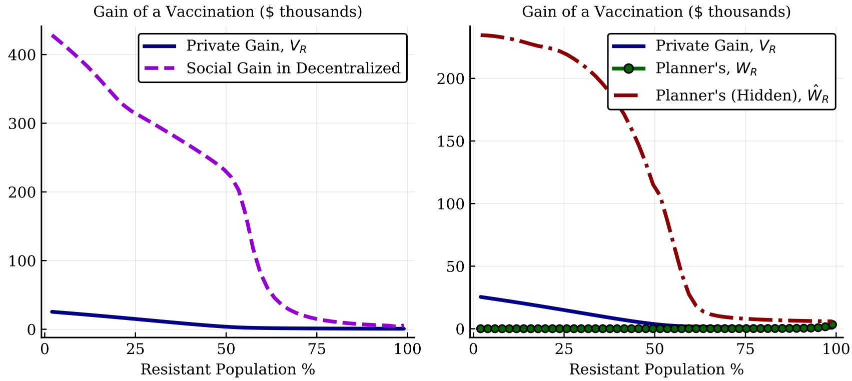
The hidden epidemiological status also raises the social cost of an additional infection, as shown in the left-panel of Figure 9. At an initial infection rate of 1%, the social cost is \$300k, slightly higher compared to when the planner can separately reduce the activity of the infected but more than seven times as high as what is perceived by decentralized agents who know their epidemiological status. For a lower infection rate of 0.5%, the social cost under hidden status increases to \$345k compared to a social cost of \$250k when status is observable.

The planner internalizes that even for a small initial outbreak, she must impose economic costs across all agents, which leads to large social costs. The right panel of Figure 9 shows that the planner, under hidden epidemiological status (red dash-dotted line), reduces economic activity by 60% at an infection rate of 1% and by up to 80% if the fraction infected is 5%.

3.5 Private versus Social Gains from Vaccination

The future economic damage imposed by the virus will depend heavily on how soon a vaccine is developed. Individually rational susceptible agents have incentives to become vaccinated in order to avoid the risk of infection. In our SIR model, the benefit of moving from susceptible to resistant is reflected by V_R in equation (25).

Figure 10: Private versus social gains from vaccination, given $I = 1\%$



The flow gains over time are captured by two terms. The first term, $u_R - u(a_S)$, captures that recovered agents do not have to distance themselves in order to avoid becoming infected. The second term, $V_I \beta(\cdot) I$, captures the expected gain from avoiding the infection entirely.

The left panel of Figure 10 illustrates the private gain from a vaccination (solid-blue line) when 1% of the population is infected, for $R \in [0, 0.99]$. Initially if no one has immunity, the private gain from becoming vaccinated is equivalent to \$26k. The gain falls as more of the population becomes resistant/recovered as this reduces the risk of infection. Around $R = 0.6$ the population acquires herd immunity, and the private gain to an additional vaccination declines to \$1.8k as the infection risk of susceptible individuals becomes negligible.

However, since private agents do not internalize the infection externality, the social gain of an additional vaccination in the decentralized economy is many times larger, shown as the dashed-purple line in the left panel of 10, which reflects W_R, the planner's willingness to pay to transition an agent from susceptible to resistant/recovered, taking as given the private actions of agents. At zero immunity the social gain from an additional vaccination is \$430k, nearly 17 times larger than what private agents are willing to pay. As more of the population becomes resistant the social gains from additional vaccinations fall. Around the level of herd immunity, W_R declines sharply: from to \$67k at $R = 0.6$ to merely \$14k. at $R = 0.75$.

The right panel of Figure 10 illustrates that the social gains from vaccination depend crucially on what strategy society adopts to contain the disease. The green

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line marked with circles plots the social benefit of an extra vaccination, W_R, under the assumption that the planner employs the optimal containment strategy described in section 3.2. Since the disease is quickly eradicated in that scenario, the social gain from moving an agent from susceptible to recovered is rather small – only \$40 (without "k"). This illustrates that eradication and vaccination are substitutes. However, when the epidemiological status of individuals is hidden and the planner is forced to reduce activity across all individuals to contain the disease, the social gain from an extra vaccination $\hat{W}_R$ is significantly larger, around \$235k at zero immunity, and remaining positive even once herd immunity is reached.

4 Conclusions

We integrate macroeconomic activity into epidemiological SIS and SIR models in order to analyze and quantify the externalities that arise. Our main finding is that agents who behave individually rationally generate large externalities because they do not internalize the effects of their economic and social activities on the infection risk of others and therefore engage in inadequate social distancing. Infected agents rationally choose to engage in full economic activity, while susceptible agents reduce activity which flattens the spread of the virus. However full recovery only occurs after herd immunity is reached across several years.

We find in a model calibrated to capture the main features of COVID-19 and the US economy that private agents perceive the cost of an additional infection to be around \$80k whereas the true social cost is more than three times higher, around \$286k. Facing an initial outbreak in which 1% of the population is infected, the planner optimally isolates the infected by reducing their social activity close to zero while only slightly reducing the activity of the susceptible. This leads to a sharp reduction in the number of infected agents and an overall mild impact on aggregate output.

Alternatively, if the planner cannot make policy contingent on the epidemiological status of individuals, for instance either because of the asymptomatic nature of COVID-19 or the lack of sufficient testing, then optimal policy still sharply reduces the number of infections but at significantly larger initial economic cost but that is short lived. The social cost of an additional infection in this scenario is around \$300k.

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We leave several possible extensions for future work: First, it would be useful to refine our epidemiological models to account for additional nuances of the SARS-CoV-2 virus. For example, including a separate compartments for exposed agents E would make it possible to explicitly account for the long incubation period of COVID-19 and for the possibility that exposed agents recover without ever displaying symptoms of the disease. Accounting for spatial heterogeneity would make it possible to better capture the dynamics of the disease in a large country such as the US and to analyze the benefits of travel restrictions. Moreover, since the case fatality rate of COVID-19 differs so strongly for patients of different age, accounting for different age groups would make it possible to analyze how the externalities by age group differ.

Secondly, it would be useful to refine the analysis of the macroeconomic feedback effects of the reductions in social and economic activity that we analyze. For example, Guerrieri et al. (2020) show that feedback effects in a multi-sector economy with financial market imperfections may lead to an amplification of the initial shock generated by social distancing. This provides valuable insights for macroeconomic policymakers.

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Table A1: Calculation of population-weighted expected loss of VSLYs (Value of Statistical Life Years) in US given infection

Age group	Population		Life Expectancy		Value of statistical life*		Infection fatality rate	E[loss] given infection*	
	Men	Women	Men	Women	Men	Women		Men	Women
0–9	20.45	19.56	72.0	76.9	$ 12,171	$ 12,305	0.002%	$ 0.2	$ 0.2
10–19	21.43	20.54	62.2	67.1	$ 11,810	$ 12,006	0.007%	$ 0.8	$ 0.8
20–29	23.22	22.21	52.8	57.3	$ 11,304	$ 11,571	0.031%	$ 3.5	$ 3.6
30–39	21.98	21.71	43.6	47.7	$ 10,598	$ 10,947	0.084%	$ 8.9	$ 9.2
40–49	20.06	20.40	34.5	38.3	$ 9,600	$ 10,058	0.161%	$ 15.5	$ 16.2
50–59	20.95	21.88	26.0	29.3	$ 8,266	$ 8,839	0.595%	$ 49.2	$ 52.6
60–69	17.76	19.65	18.3	20.9	$ 6,628	$ 7,243	1.930%	$ 127.9	$ 139.8
70–79	10.35	12.31	11.6	13.4	$ 4,713	$ 5,280	4.280%	$ 201.7	$ 226.0
≥80	4.92	7.76	6.2	7.4	$ 2,810	$ 3,240	7.800%	$ 219.2	$ 252.7
	Total:	327.14						Wgt. Average:	$ 50.0

* in thousands of USD

Sources:
Population numbers: US Census Bureau (2018)
Life Expectancy: US Social Security Administration, Period Life Table (2016): https://www.ssa.gov/oact/STATS/table4c6.html
Case fatality rate: Verity et al. (2020), Table 1

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Love in the time of COVID-19: The resiliency of environmental and social stocks

Rui Albuquerque,[1] Yrjo Koskinen,[2] Shuai Yang[3] and Chendi Zhan[4]

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The COVID-19 pandemic and the subsequent lockdown brought about a massive slowdown of the economy and an unparalleled stock market crash. Using US data, this paper explores how firms with high Environmental and Social (ES) ratings fare during the first quarter of 2020 compared to other firms. We show that stocks with high ES ratings have significantly higher returns, lower return volatilities, and higher trading volumes than other stocks. Firms with high ES ratings and high advertising expenditures perform especially well during the crash. This paper highlights the importance of ES policies in making firms more resilient during a time of crisis.

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1 Professor of Finance, Boston College and CEPR Research Fellow.
2 Professor of Finance, University of Calgary.
3 Finance PhD Student, University of Calgary.
4 Professor of Finance, University of Exeter.

“Life would still present them with other moral trials, of course, but that no longer mattered: they were on the other shore.”
- Gabriel Garcia Marquez, *Love in the Time of Cholera*

The magnitude and the speed of the stock market crash in the U.S. and around the world caused by the COVID-19 pandemic and the subsequent economic lockdown took everyone by surprise. The stock market in the U.S. peaked on February 19, and a mere month later prices had declined by almost 30%. Yet, in this rampant stock market sell out, investors were not indiscriminate. This paper documents and compares the relative performance of stocks with high Environmental and Social (ES) ratings to other stocks and studies why these stocks have turned out to be so resilient during the roller-coaster first quarter of 2020.

Many previous studies show that ES policies provide cash flow and discount rate benefits to firms. In particular, Lins, Servaes, and Tamayo (2017) show that U.S. non-financial firms with high ES ratings had better financial performance than other firms during the Great Recession of 2008-2009. The current crisis is a major economic shock to the economy, like the Great Recession was. However, the COVID-19 pandemic is very different from the Great Recession as the speed and severity of the economic meltdown are unprecedented. Whereas in the Great Recession the unemployment rate in the U.S. climbed to nearly 10% by the end of the recession, in the current crisis, initial claims for jobless benefits reached 11% of the U.S. labor force in just three weeks. Do ES policies that preceded the COVID-19 crisis help firms mitigate the stock market sell out? Is the relative performance of high ES rated stocks better than other stocks, akin to the situation in the Great Recession? Why do ES policies ease the way to “the other shore” - help firms to survive the unprecedented stock market crash? We address these questions in this paper.

Our first result is that first quarter abnormal returns are significantly correlated with ES ratings in the cross-section, even after controlling for the usual firm characteristics including size, cash to assets, Tobin's Q, and leverage. An increase in ES ratings equal to one standard deviation is associated with an increase in quarterly returns of 2.1%. There is evidence (see, e.g. Berg, Koelbel, and Rigobon, 2020) of ESG ratings disagreements between different rating agencies. We use ES ratings from Thomson Reuters Refinitiv for our main results, but we find similar results using MSCI ES scores.

Next, we inspect more closely the relation between the returns for firms with high ES ratings and the COVID-19 pandemic. We estimate a difference-in-difference regression of firm-level daily abnormal returns with two treatment dates, February 24,[5] when the stock market

[5] The S&P 500 peaked on February 19, 2020. On Friday, February 21, several municipalities in Northern Italy went into lockdown and subsequently the decline in the S&P 500 accelerated.

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decline started, and March 18, when President Trump signed the second Coronavirus Emergency Aid Package. We include the second treatment date because we wish to identify the effect the COVID-19 pandemic has on stocks. The second treatment date is the start of an aggressive fiscal policy response to the pandemic, which may affect the results from the previous treatment. We find that firms with high ES ratings earned an extra daily return of 0.41% from February 24 until the end of the 1st quarter relative to firms with low ES ratings.

We complement the difference-in-difference regressions with a less parametric look into the relation between the returns to ES ratings and the COVID-19 pandemic. Following Ramelli and Wagner (2020), we estimate daily cross-sectional regressions of cumulative abnormal returns of U.S. listed firms and inspect the evolution of the loading on ES ratings over time. We find that the loading on ES ratings is flat from January 1, 2020 till the end of February and then increases consistently afterwards until it plateaus around mid-March. These results are consistent with ES stocks being more resilient during the COVID-19 market crash.

We consider two mechanisms that can potentially explain the resilience of high ES firms. Albuquerque, Koskinen, and Zhang (2019) present a model where firms with credible ES policies have more loyal customer base and face less price-elastic demands for their products. This in turn leads to reduced exposure for firms to systematic risk and increased valuations. In other words, customer resiliency drives firm's stock resiliency. Heinkel, Kraus, and Zechner (2001) develop a model of segmented capital markets where a polluting firm, held by only a subset of investors, carries greater systematic risk. Consequently, green firms, arguably firms with high ES ratings, would have higher valuations. We use advertising expenditures as a proxy for customer loyalty and show that the effect we find is stronger for firms with high ES ratings coupled with high advertising expenditures, consistent with Albuquerque et al. (2019). For the second mechanism, we construct a variable that measures the ES preferences of institutional investors. If firms with high ES ratings have owners with a preference for those stocks, then these firms should perform relatively better during a market sell-off. We do not find evidence for this second mechanism. Further, the point estimates of the coefficients describing the first effect are roughly two times larger than the point estimates of the coefficients for the second effect.

We also document that high ES rated firms display lower volatility of stock returns during the first quarter of 2020. We do this in two ways. First, we compute the standard deviation of daily log returns, raw and CAPM adjusted, for the first quarter of 2020. Second, we use a range-based volatility measure, high minus low daily prices, and estimate difference-in-difference regressions using daily data. We find that volatility is lower for high rated ES firms under both approaches and for the various measures of volatility. Lastly, we document that daily trading volume increases for high ES rated firms relative to low ES firms after the

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February 24 treatment date suggesting that some investors stepped in to stop the downward slide in prices, thus also reducing stock return volatility.

We consider two alternative hypotheses for our findings. One alternative explanation is that the oil price decline in the first quarter of 2020 affected particularly firms in the energy sector, which are known to score low in some dimensions of ES. This alternative explanation would also predict that highly rated ES firms display relatively lower volatility and higher trading volume. We repeat the analysis excluding the firms in the energy sector from our sample. We find very similar results. Another alternative explanation is that some businesses were considered 'essential' and kept on operating in a normal fashion. This may have resulted in some resiliency of cash flows and of stock returns for these businesses. We show that the documented resiliency of high ES rated firms is not a feature of any particular industry. Ten of the Fama-French 12 industries show resiliency of high ES rated firms during the stock market crash, though with significant coefficients for only five of the industries. Further, we account for within industry variation in ES and find the same results. These results suggest that the effect of ES policies on stock returns is not due to some businesses being considered essential in combatting the pandemic.

Similarly to Lins et al. (2017), Cornett, Erhemjamts, and Tehranian (2016) show that U.S. banks' financial performance during the Great Recession is positively related to their ESG score. This evidence is consistent with a flight to quality during the market downturn. The evidence in Ferrell, Liang, and Renneboog (2016) that well-governed firms invest more in ES policies supports this view. In a contemporaneous paper, Shan and Tang (2020) document that Chinese firms with greater employee satisfaction appear to endure the COVID-19 stock market downturn better than other firms, supporting employee satisfaction as one dimension of ES policies creating shareholder value (Edmans, 2011). We show that our results on ES cannot be explained by a good corporate governance effect.

Stocks with high ES ratings were not the only stocks that performed better during the first quarter of 2020. Acharya and Steffen (2020) provide evidence that firms with access to liquidity, either through cash or lines of credit, perform better during the 1st quarter. Ramelli and Wagner (2020) show that non-financial firms with higher cash holdings and lower financial leverage are less affected than other firms. The availability of liquidity is of course valuable in a situation where demand is collapsing and more financially fragile firms may face bankruptcy, but our results are not subsumed by firms' cash or leverage positions. This paper addresses the more complicated question why ES policies provided firms resiliency in the midst of market collapse.

Some recent papers have addressed the relationship between epidemics and stock market developments. Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020) show that no other infectious disease outbreak has had such powerful impact on the U.S. stock market. Alfaro,

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Chari, Greenland, and Schott (2020) link the stock market fall directly to epidemic model revisions of predicted infections. Toda (2020) uses an epidemic model to predict a temporary fall in the stock market of 50%. Schoenfeld (2020) shows that firms systematically underestimated their exposure to the COVID-19 pandemic.

The next section describes the data. Section 3 presents our main results. Section 4 presents robustness results, and Section 4 concludes.

I. Data

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Our main data source on firms' ES performance is Thomson Reuters' Refinitiv ESG database, formerly known as Asset4. Refinitiv collects information from corporate annual reports, sustainability reports, non-governmental organizations, and news sources for publicly traded companies at an annual frequency. Refinitiv ESG evaluates firms' environmental (E) performance in three areas: resource use, emissions, and innovation. Social (S) commitments are measured in four areas: workplace, human rights, community, and product responsibility. Governance (G) is evaluated in three dimensions: management, shareholders, and corporate social responsibility strategy. Refinitiv provides materiality-weighted aggregate scores to investors for each of the three main categories: Environment Pillar Score, Social Pillar Score, and Governance Pillar Score. The scores are based on the relative performance of ESG factors within the firm's sector (for E and S) and country (for G) and range from 0 to 100. They have been used in the prior literature, e.g. by Ferrel, Liang and Renneboog (2016) and Dyck, Lins, Roth, and Wagner (2019). Our main measure, ES, is the average of the environment and social scores in 2018 expressed in percentage terms. We thus omit the Governance Pillar Score.

As an alternative measure, we also obtain firm-level data from MSCI's ESG Research database, previously known as KLD. Firms are rated on a variety of strengths and concerns on seven attributes: community, diversity, employee relations, environment, product, human rights, and governance. We exclude corporate governance attributes from our analysis to focus on non-governance aspects of ESG. We measure ES as the difference between the number of strengths and the number of concerns for each firm in 2016, the last year for which data is available. Given that the number of individual concerns and strengths in each attribute varies over time and across firms, we divide the number of strengths (concerns) for each firm-year across all six ES categories by the maximum possible number of strengths (concerns) in all six categories for each firm. We then subtract the scaled concerns from the scaled strengths to obtain our alternative measure, ES-MSCI, which is bounded between -1 and 1. Our results are very similar using the alternative way of measuring firms' ES performance.

We construct a firm-level investor ES measure based on revealed preference from institutional investors. Investors' ES preference is estimated using institutional investors' equity holdings, following recent studies (Starks, Venkat, and Zhu, 2018, and Gibson, Glossner, Krueger, Matos, and Steffen, 2019). We measure institutional ownership using Thomson Reuters' 13F database, which reports institutional investors' equity holdings collected from regulatory authorities, fund reports, fund associations, and fund management companies at a quarterly frequency. To construct the measure, we first measure an investor's ES preference as the value-weighted average Refinitiv ES score of its portfolio holdings for each quarter in 2018 and then average across the four quarters. Investor-based ES score of a firm is measured as the weighted average of its investors' ES preference based on holdings in the first quarter of 2019.

Table 1: Summary statistics

Variable	Obs.	Mean	Std.Dev.	25%	Median	75%
Abn Return_cum	2,171	-22.875	42.412	-39.780	-17.374	2.753
ES	2,171	0.289	0.212	0.136	0.208	0.384
Investor-based ES	2,123	0.544	0.064	0.514	0.555	0.587
Tobin's Q	1,971	2.268	1.882	1.098	1.545	2.600
Size	2,156	21.555	1.628	20.421	21.438	22.542
Cash	1,972	0.156	0.209	0.023	0.067	0.191
Leverage	1,959	0.321	0.231	0.118	0.307	0.463
ROE	1,971	-0.022	0.691	-0.002	0.092	0.158
Advertising	2,171	0.007	0.020	0.000	0.000	0.002
Volatility	2,171	6.128	2.954	4.446	5.452	7.037
Idio Volatility	2,171	4.768	3.049	2.977	4.010	5.747
Abn Return	134,689	-0.369	5.655	-1.633	-0.140	1.159
Volume	137,493	1.957	5.406	0.197	0.584	1.648
DayPrc_range	137,494	0.060	0.066	0.019	0.038	0.078

This table reports the summary statistics (number of observations, mean, standard deviation, 25th, 50th (median) and 75th percentiles) for all variables. The Appendix provides the definition and data sources for all variables.

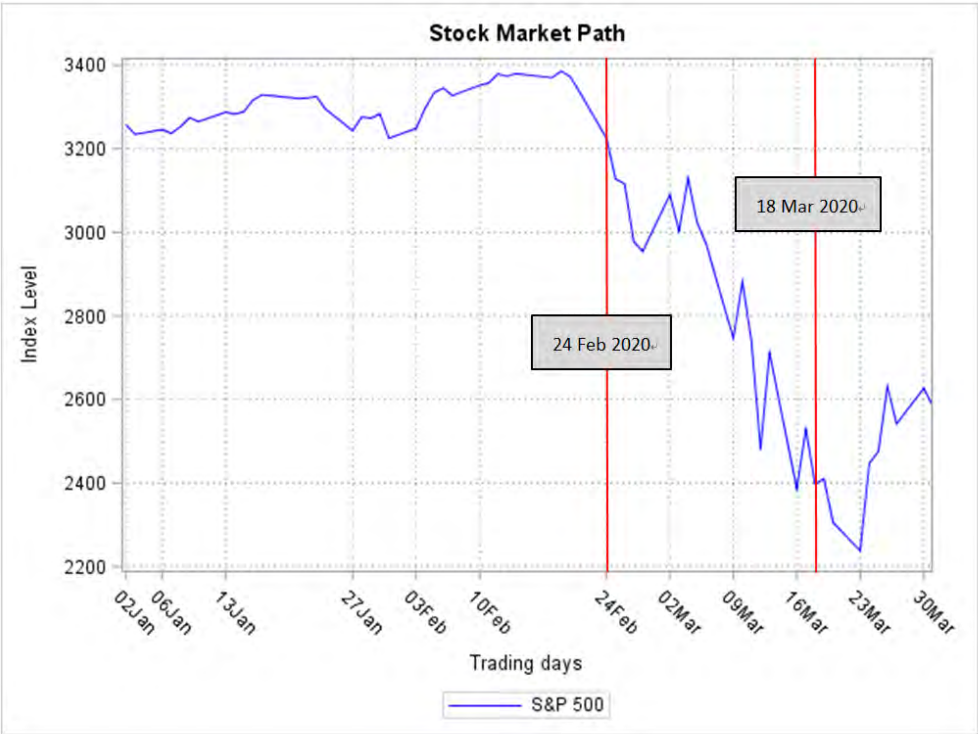
We obtain daily stock returns, daily high and low prices, and trading volumes from Capital IQ North America Daily for the first quarter of 2020 and CRSP from 2017 to 2019. CAPM-adjusted return is estimated as the difference between the daily logarithm return of a stock and the CAPM beta times the daily logarithm market return.[6] The CAPM beta is estimated by using

[6] Our results are similar if instead we use arithmetic returns.

daily returns from 2017 and 2019, where the market index is S&P 500.

Accounting data for 2019 is obtained from Compustat, which are used to construct control variables, i.e. Tobin's Q, Size, Cash, Leverage, Return on Equity, and Advertising. We winsorize all control variables at the 1% level in each tail. All variables are described in the Appendix. After matching all datasets, our sample consists of 134,689 firm-day return observations for 2,171 distinct firms. Summary statistics are presented in **Table 1**. **Figure 1** depicts the stock market performance of the S&P 500 during the first quarter of 2020, with both treatment dates (the 24th February and 18th March 2020) indicated.

Figure 1. S&P 500 during the first quarter of 2020



This figure plots the stock market path of S&P 500 during the first quarter of 2020. The red lines mark our two treatment dates.

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II. Results

Average return effects **Table 2** presents results of regressing quarterly log returns on firms' ES ratings and other firm characteristics. In column (1) we use ES ratings as the only independent variable. In column (2) we add industry fixed effects, and in column (3) we add Tobin's Q, firm size, cash to assets, financial leverage, return on equity, and advertising expenditures as independent variables. The effect of ES ratings on stock returns is significant at 5% level or better, even after controlling for all the variables. The magnitude of the coefficient estimate suggests that one standard deviation increase in ES ratings leads to a higher stock return of 2.1% on average (9.9 times 0.212). Firms with high Tobin's Q, larger firms, firms with high cash, and lower leverage all perform better (see Ramelli and Wagner, 2020, for a discussion of the role of cash and leverage).

Table 2: Cross-sectional regressions of returns

	(1)	(2)	(3)
Dependent variable	Abn Return_cum	Abn Return_cum	Abn Return_cum
ES	15.283***	18.251***	9.913**
	(3.58)	(4.71)	(2.40)
Tobin's Q			3.638***
			(7.11)
Size			3.019***
			(5.13)
Cash			10.559**
			(2.02)
Leverage			-39.450***
			(-11.68)
ROE			1.817
			(1.62)
Advertising			-2.019
			(-0.05)
Constant	-27.289***	-28.147***	-87.750***
	(-17.81)	(-20.46)	(-7.29)
Industry FE	No	Yes	Yes
Number of firms	2,171	2,171	1,945
adj. R^2	0.005	0.229	0.346

*This table reports the results of regressions of first quarter 2020 abnormal returns on firms' ES under several specifications: without firm controls (specification 1), with industry fixed effects (specification 2), and with industry fixed effects and firm controls (specification 3). The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The Appendix contains a detailed description of all the variables*

Next, we conduct a difference-in-difference estimation that attempts to demonstrate a tighter link between the performance of firms with high ES ratings and the COVID-19 pandemic. We construct a COVID-19 treatment dummy. Dummy _COVID equals 1 for each day on or after February 24 until the end of the quarter, and zero otherwise. February 24 is the start of the `fever' period in Ramelli and Wagner (2020). It is also the first trading day after the first lockdown in European soil, in Northern Italy. We construct a second treatment dummy to isolate the effect that the U.S. fiscal policy response to the pandemic had on firms' stock returns. Dummy_Fiscal equals 1 for each day on or after March 18 until the end of the 1st quarter, and zero otherwise. March 18 is the day that President Trump signed the second Coronavirus Emergency Aid Package (the Families First Corona Response Act). The first Coronavirus Emergency Aid Package was a very small package of $8.3 billion targeted specifically to combat the spread of Coronavirus and was signed by President Trump on March 6. The third and largest Coronavirus Emergency Aid Package (the Coronavirus Aid, Relief, and Economic Security Act) was signed by President Trump on March 27.

Table 3: Diff-in-Diff regressions for abnormal returns

	(1)	(2)
Dependent variable	Abn Return	Abn Return
Dummy_ES_High*Dummy_COVID	0.410**	0.410**
	(2.63)	(2.60)
Dummy_ES_High*Dummy_Fiscal	-0.522	-0.522
	(-0.86)	(-0.86)
Dummy_ES_High	0.002	
	(0.06)	
Dummy_COVID	-1.077***	
	(-3.57)	
Dummy_Fiscal	1.261	
	(0.98)	
Constant	-0.128*	-0.393***
	(-1.73)	(-16.00)
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	134,689	134,689
adj. R^2	0.007	0.082

*This table reports the results of Diff-in-Diff estimation of daily abnormal returns during the first quarter of 2020. Dummy_ES_High equals one for high ES firms, and zero otherwise. Dummy_COVID equals one from 24th February to 31st March 2020, and zero before this period. Dummy_Fiscal equals one from 18th March to 31st March 2020, and zero before this period. Firm and day fixed effects are (not) included in Specification 2 (1). Standard errors are clustered by firm and day. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The Appendix contains a detailed description of all the variables.*

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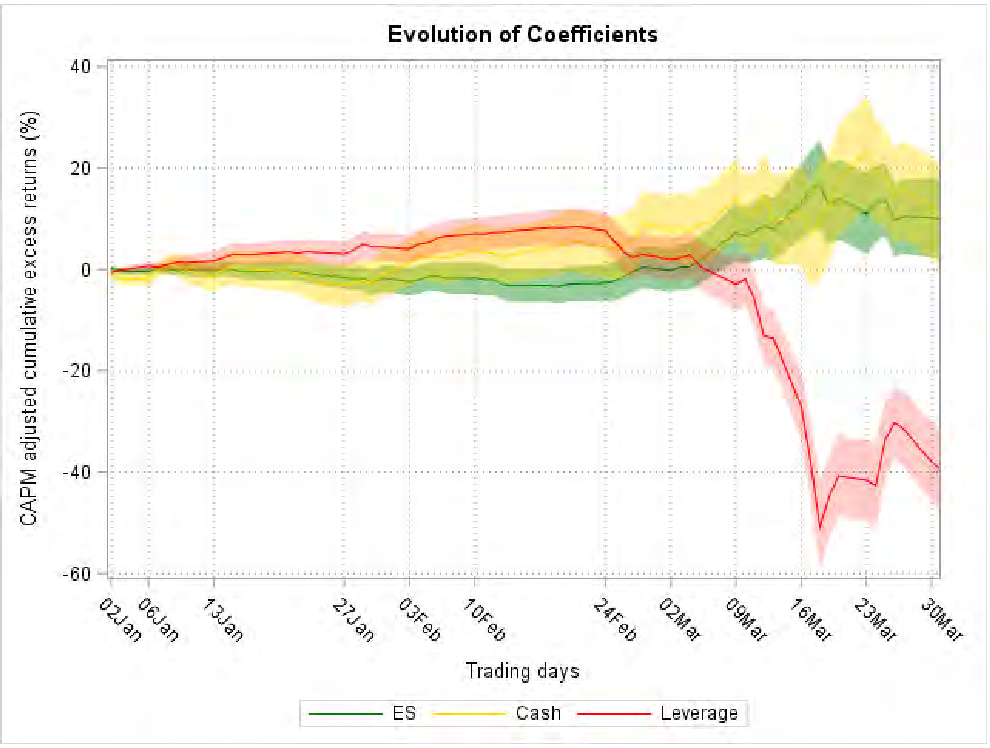
Table 3 contains the results. Column 1 is with no fixed effects and column 2 has both firm and day fixed effects. Standard errors are clustered by firm and day. The results show that the coefficient associated with the interaction between Dummy_COVID and a dummy variable that equals one for the top quartile of ES rated firms (Dummy_ES_High) is positive and significant at the 5% level. High ES rated firms earn an average abnormal daily return of 0.41% relative to other firms from February 24 to March 31 (corresponding to 10% cumulative abnormal return for high ES firms relative to others). The results also show that the fiscal response dummy interacted with the high-ES dummy is insignificant. Overall, investors pay more for firms with higher ES ratings as the market collapses in the first quarter of 2020.

Figure 2. Evolution of coefficients during the first quarter of 2020



This figure plots the evolution of coefficients during the first quarter of 2020 from daily cross-sectional regressions of cumulative stock returns (from the start of the quarter to the day) on ES ratings, Tobin's Q, firm size, cash to assets, financial leverage, return on equity and advertising expenditures (all lagged 2019 values), and industry fixed effects. It plots the daily loading on ES ratings, cash to assets, and leverage with two-standard-error bands.

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To further document the resiliency of stock returns of high ES rated firms, we conduct daily cross-sectional regressions of cumulative stock returns (from start of the quarter to the day) on ES ratings, Tobin's Q, firm size, cash to assets, financial leverage, return on equity and advertising expenditures (all lagged 2019 values), and industry fixed effects (as in Ramelli and Wagner, 2020). **Figure 2** plots the daily loading on ES ratings, cash to assets, and leverage with two standard error bands. The advantage of this analysis relative to the difference-in-difference regressions is that we do not commit to a particular treatment date. The disadvantage is that it does not give an estimate of the average change in stock returns, but rather how the relevance of ES ratings as an explanatory variable changes overtime. The figure shows the loading on ES ratings increasing dramatically sometime at the end of February until it plateaus in mid-March. It describes the building up towards the effect we eventually find in the cross-sectional regressions of quarterly returns (note that the last point estimate in Figure 2 is the point estimate in column 3 of Table 2). The loading on cash to assets also increases reaching similar levels to that of ES. The loading on leverage is negative and falls precipitously with the crisis. This evidence is consistent with Acharya and Steffen (2020) and Ramelli and Wagner (2020). The reasons for the dramatic effect of ES on returns are analysed next.

Two mechanisms of resiliency We study two mechanisms that can potentially explain the resiliency of firms with high ES ratings: customer loyalty and investor segmentation. Both mechanisms predict lower systematic risk of high ES stocks. Luo and Bhattacharya (2009) and Albuquerque, Koskinen, and Zhang (2019) propose that customers are more loyal to firms with a strong reputation and credibility to pursuing ES policies. In Albuquerque et al. (2019) these firms benefit from a lower price elasticity of demand to obtain higher profit margins. These higher profit margins lower operating leverage and reduce firm systematic risk. Intuitively, it is customer resiliency that delivers firm’s stock resiliency. Albuquerque et al. (2019) present some direct evidence of their mechanism by showing that changes in ROA are less positively correlated with the business cycle for high ES firms. We follow Albuquerque et al. (2019) and others in using advertising expenditures as a measure of customer loyalty. We expect that the effect we find is concentrated on those firms with high advertising expenditures.

The second mechanism adapts the segmented capital markets model of Heinkel, Kraus, and Zechner (2001). In that model, polluting firms are only held by a subset of investors since ES investors choose not to hold them. The lack of diversification that polluting firms have then leads to higher systematic risk for these firms. Also, in parallel to customer loyalty, investor loyalty can contribute to the resiliency of ES stocks. The literature on Sustainable and Responsible Investments (SRI) shows that investors are more loyal, and less performance-sensitive to SRI funds than to conventional mutual funds (Bollen, 2007, and Renneboog, Ter Hort, and Zhang, 2011). Our proxy for ES investor preferences is constructed using the idea

of revealed preference.[7] We expect that stocks with investors with a preference for ES have less systematic risk and are more resilient.[8]

Table 4: Triple interactions regressions for abnormal returns

Dependent variable	(1) Abn Return	(2) Abn Return	(3) Abn Return	(4) Abn Return
Dummy_ES_High*Dummy_COVID*Dummy_Advertising_High	0.536**	0.536**		
	(2.37)	(2.35)		
Dummy_ES_High*Dummy_Fiscal*Dummy_Advertising_High	-1.022**	-1.023**		
	(-2.49)	(-2.46)		
Dummy_ES_High*Dummy_COVID*Dummy_InvestorES_High			0.263	0.262
			(1.06)	(1.04)
Dummy_ES_High*Dummy_Fiscal*Dummy_InvestorES_High			0.135	0.137
			(0.31)	(0.30)
All dummies entered separately	Yes	Yes	Yes	Yes
All possible interactions entered	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Day FE	No	Yes	No	Yes
Number of firm-days	134,689	134,689	131,654	131,654
adj. R^2	0.007	0.082	0.007	0.083

*This table reports the results of triple interactions estimation for daily abnormal returns during the first quarter of 2020. Dummy_ES_High equals one for high ES firms, and zero otherwise. Dummy_COVID equals one from 24th February to 31st March 2020, and zero before this period. Dummy_Fiscal equals one from 18th March to 31st March 2020, and zero before this period. Specifications 1 and 2 (3 and 4) are triple interaction regressions for high Advertising (Investor-based ES) firms. Firm and day fixed effects are (not) included in Specifications 2 and 4 (1 and 3). Standard errors are clustered by firm and day. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The Appendix contains a detailed description of all the variables.*

Table 4 displays the results. In our tests, we repeat the difference-in-difference regressions of **Table 4**, expanding the interactions to a triple interaction between Dummy_COVID,

[7] We also use an alternative investor preference measure of ES, which is the institutional ownership of a firm by pension funds and endowments. Starks, Venkat and Zhu (2018) show the long-term investors have a preference for high ES stocks. We do not find that this measure has any effects.

[8] Using data from Morningstar on the sustainability of mutual funds that explores how their investments are made, Hartzmark and Sussman (2019) show evidence that investors value sustainability.

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Dummy_ES_High, and a dummy indicating the firms in the top quartile of advertising expenditures (in columns 1 and 2) and to a triple interaction between Dummy_COVID, Dummy_ES_High, and a dummy indicating the firms in the top quartile of ES investor preference (in columns 3 and 4). In columns 1 and 2, we find positive point estimates on the triple interaction linked to advertising expenditures. Column 2 adds firm and day fixed effects to the regression. In both columns standard errors are clustered by firm and day. Consistent with the predictions from the first mechanism, there is a significant average abnormal return earned by firms with high ES ratings and high advertising expenditures relative to firms with low ES ratings or low advertising expenditures after February 24. The effect is 0.54% in daily returns. Columns 3 to 4 show positive point estimates on the triple interaction of interest linked to ES investor preference. However, the point estimates are not statistically significant. Economically, the point estimate on the ES investor preference triple interaction is half of the effect estimated in the triple interaction with advertising expenditures. Overall, we find strong support for the first resiliency mechanism.

We end this subsection with a note that while these two mechanisms explain why high ES firms may have lower market beta, they do not fully explain the resiliency that we find, because the dependent variable in the tests above is the CAPM-adjusted stock return. It is, however, possible that market beta may have declined during the 1st quarter for high ES firms and that is the reason for the increased loading on ES in the cross sectional regressions that give rise to **Figure 2**. Further analysis on the profitability and productivity of highly rated ES firms during the COVID-19 pandemic will also help shed light on the customer loyalty mechanism. We leave this avenue for future research.

Volatility of stock returns and trading volume Toward the resilience hypothesis of ES firms, we also provide evidence of how volatility of stock returns varies with ES ratings in the cross section. **Table 5** presents the results. In **panel A**, we repeat the regressions in **Table 2** using as the dependent variable the standard deviation of daily raw log returns over the quarter (columns 1,2, and 3) and the idiosyncratic volatility calculated as the standard deviation of CAPM-adjusted daily stock returns over the quarter (columns 4, 5, and 6). In **panel B**, we repeat the regressions in **Table 3** using as dependent variable a range measure of daily volatility, the daily high price minus the daily low price divided by the average price.

In all regression specifications, we find that firms with high ES ratings experience a decrease in stock return volatility as compared to firms with low ES ratings (1% or better of significance). **Panel B**, which uses a daily measure of volatility, suggests that the change in volatility can be traced to the Dummy_COVID treatment variable. There is a drop in range based volatility of stock returns for high rated ES firms relative to low ES rated firms (an amount equal to 10% of the sample average of volatility of the daily price range), even though volatility increases for all firms after the COVID-19 crisis. Overall, the resiliency of high ES stock returns appears to be displayed both in the performance of mean returns as well as in the

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volatility of returns. **Panel B** suggests that the fiscal policy treatment dummy has an added effect contributing to even lower volatility of high ES rated firm returns relative to firms with low ES ratings.

We add one final piece of evidence consistent with our resiliency hypothesis using data on daily trading volume. **Table 6** contains the results. In **Table 6,** we repeat the regression specifications of **Table 3** but with daily stock trading volume as the dependent variable. The results in **Table 6** show a strong increase on daily volume after February 24 for high ES rated firms relative to other firms (an amount equal to 2.05 million shares, which represents a doubling of the trading volume for the average firm), even though trading volume increased for all firms with the COVID-19 crisis. There is a further increase in trading volume with the Dummy_Fiscal for high ES rated firms, but it is of smaller size and only significant in the specification without fixed effects.

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Table 5: Volatility regressions

Panel A: Cross-sectional regressions for volatility

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Volatility	Volatility	Volatility	Idio Volatility	Idio Volatility	Idio Volatility
ES	-2.377***	-2.271***	-0.977***	-2.814***	-2.723***	-0.810***
	(-8.19)	(-8.06)	(-3.52)	(-9.32)	(-9.27)	(-2.90)
Tobin's Q			-0.155***			-0.116***
			(-4.54)			(-3.37)
Size			-0.345***			-0.507***
			(-8.76)			(-12.76)
Cash			0.664*			0.814**
			(1.92)			(2.31)
Leverage			3.189***			3.518***
			(14.08)			(15.42)
ROE			-0.167**			-0.217***
			(-2.23)			(-2.87)
Advertising			0.549			3.599
			(0.22)			(1.44)
Constant	6.806***	6.776***	12.981***	5.582***	5.555***	14.816***
	(65.79)	(68.14)	(16.08)	(51.56)	(53.31)	(18.23)
Industry FE	No	Yes	Yes	No	Yes	Yes
Number of firms	2,171	2,171	1,945	2,171	2,171	1,945
adj. R^2	0.030	0.140	0.282	0.038	0.143	0.328

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Panel B: Diff-in-Diff regressions for the daily price range

	(1)	(2)
Dependent variable	DayPrc_range	DayPrc_range
Dummy_ES_High*Dummy_COVID	-0.006***	-0.006***
	(-3.48)	(-3.33)
Dummy_ES_High*Dummy_Fiscal	-0.006*	-0.006*
	(-1.92)	(-1.84)
Dummy_ES_High	-0.010***	
	(-11.56)	
Dummy_COVID	0.055***	
	(5.86)	
Dummy_Fiscal	0.045***	
	(2.78)	
Constant	0.032***	0.061***
	(42.75)	(335.29)
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	137,494	137,494
adj. R^2	0.323	0.622

This table reports the regression results for the volatility of stock returns during the first quarter of 2020. Panel A reports results for cross-sectional regressions of Volatility and Idio Volatility on firms' ES under several specifications: without firm controls (specifications 1 and 4), with industry fixed effects (specifications 2 and 5), and with industry fixed effects and firm controls (specifications 3 and 6). Panel B reports the results of Diff-in-Diff estimation for the daily price range during the first quarter of 2020. Dummy_ES_High equals one for high ES firms, and zero otherwise. Dummy_COVID equals one from 24th February to 31st March 2020, and zero before this period. Dummy_Fiscal equals one from 18th March to 31st March 2020, and zero before this period. Firm and day fixed effects are (not) included in Specification 2 (1). Standard errors are clustered by firm and day. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The Appendix contains a detailed description of all the variables.

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Table 6: Trading volume regressions

Dependent variable	(1) Volume	(2) Volume
Dummy_ES_High*Dummy_COVID	2.051***	2.051***
	(7.34)	(6.84)
Dummy_ES_High*Dummy_Fiscal	0.418*	0.418
	(1.78)	(1.42)
Dummy_ES_High	1.890***	
	(8.11)	
Dummy_COVID	0.695***	
	(8.38)	
Dummy_Fiscal	0.185	
	(1.55)	
Constant	0.911***	1.716***
	(19.01)	(53.77)
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	137,493	137,493
adj. R^2	0.075	0.727

*This table reports the results of Diff-in-Diff estimation for daily trading volume of stocks during the first quarter of 2020. Dummy_ES_High equals one for high ES firms, and zero otherwise. Dummy_COVID equals one from 24th February to 31st March 2020, and zero before this period. Dummy_Fiscal equals one from 18th March to 31st March 2020, and zero before this period. Firm and day fixed effects are (not) included in Specification 2 (1). Standard errors are clustered by firm and day. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The Appendix contains a detailed description of all the variables.*

III. Robustness

We investigate two competing hypotheses. One such hypothesis is that the oil price decline in the first quarter of 2020 affected particularly firms in the energy sector, which are known to score low in some dimensions of ES. Energy sector firms would then have significantly lower returns, higher volatilities, and possibly also lower trading volumes relative to other firms if liquidity moved out of that sector. We repeat the analysis excluding the firms in the energy sector from our sample and find very similar results.

Another alternative explanation for our results is that some businesses were considered 'essential' and kept on operating in a normal fashion. This may have resulted in some resiliency of cash flows and stock returns for these businesses. We investigate the effect on stock returns by industry. We use the Fama-French classification for 12 industries. We repeat the regression specification in **Table 3** allowing for triple interactions of Dummy_COVID with

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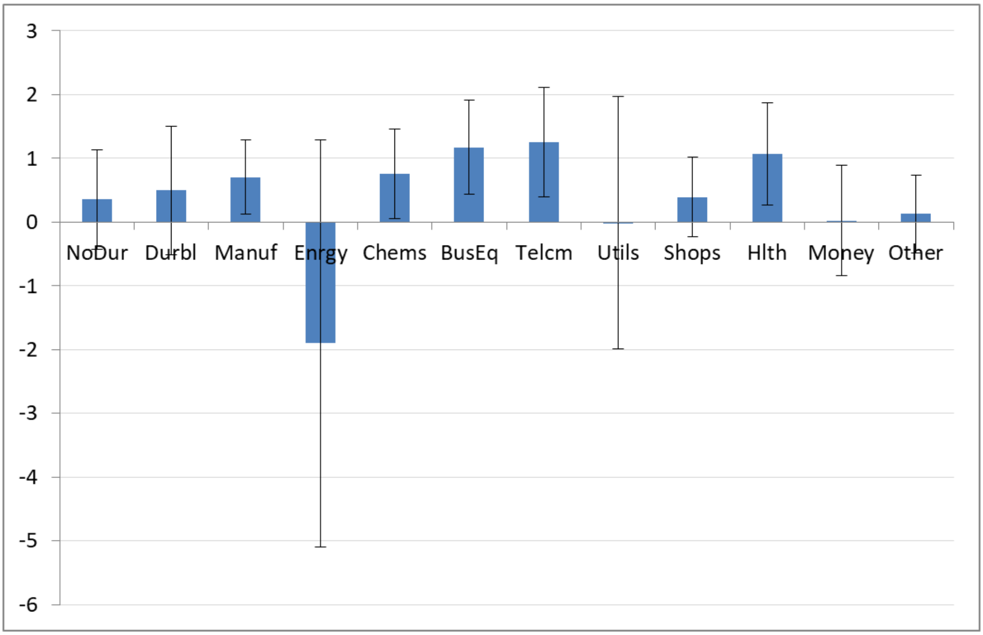
the Dummy_ES_High and a dummy for each of the industries. The results are shown in **Figure 3**. The figure shows that ten out the twelve industries display positive point estimates on the interaction between Dummy_COVID and the Dummy_ES_High. Five of those estimates are statistically significant. The two negative point estimates are both statistically insignificant. Overall, the figure suggests that our findings are not associated with any one industry in particular, but encompass most industries. We go one step further to rule out this hypothesis. It is possible that the Dummy_ES_High is not randomly distributed across industries. We then construct a Dummy_ES_High within each industry. This way we are exploiting cross-sectional variation in ES within each industry. The results of this analysis are very similar to those displayed in **Figure 3**.

We conduct several robustness tests. First, we augment the list of firm level variables in the cross-sectional regressions of quarterly stock returns and quarterly volatility of stock returns with operating leverage and measures of institutional ownership. Operating leverage, calculated as in Albuquerque et al. (2019) and others, leads to a significant drop in observations. Still, our results hold and are quantitatively similar.

Figure 3. Abnormal returns from ES by industry



We extend the regression specification (2) in Table 3 by allowing for triple interactions of Dummy_COVID with Dummy_ES_High and a dummy for each of the Fama and French 12 industries. The figure plots the point estimates of the triple-interaction terms with two-standard-error bands.

Second, we redo the analysis with MSCI ES ratings. The latest ratings available date back to 2016 and also have a slightly smaller sample relative to Refinitiv's ES ratings. We find very similar results with the proxy for ES constructed with MSCI ES data as in Albuquerque et al. (2019). While the MSCI ratings are from 2016, firm ES ratings are fairly sticky, which may explain the results. Another possible explanation for the similarity in results despite the lag in measurement of the ES proxy is that investors care about firm reputation and credibility for ES policies and such reputation depends on a track record of ES performance.

Third, we change the Dummy_COVID to equal 1 from January 30 onwards. January 30 is the day the World Health Organization declares the outbreak a public health emergency. The results corresponding to **Tables 3, 4, Table 5 panel B**, and **Table 6** are somewhat weaker because the coefficients of interest are smaller, but retain significance at 10% level or higher.

Finally, we consider the separate roles of E and S in ES. Using Refinitiv's scores, we show that the results in the paper are very similar if we use only the E score or if we use only the S score. This is perhaps to be expected because the correlation between the two scores is 0.73, and the correlation between the aggregate score ES and either E or S is over 0.91 (untabulated results). Firms appear to do both E and S at the same time and this limits our ability to evaluate their separate contributions.

The last component in ESG, the governance score, has only a correlation of 0.52 with the E score and 0.42 with the S score (untabulated). When we rerun our results with the G score, we find that the G score explains the cross section of stock returns, but only if other firm characteristics are not included in the regression. The G score, however, is also associated with a decline in volatility of returns and with an increase in trading volume. The magnitude of the G score effects, though, is smaller than that of either the E or S score effects. Overall, the results with the G score serve to reassure that our main results are not picking up a good governance effect.

IV. Conclusion

The first quarter of 2020 was an extraordinary time for U.S. stock markets: first calm before the storm, then the fastest collapse ever, and ending with a tremendous rally. This paper examines how firms with highly rated environmental and social policies fare in the tumultuous marketplace. We show that stock prices for those firms perform much better than the prices for other firms. The relative performance boost is comparable to that of firms with large cash balances. The stock market performance is especially strong during the market collapse for high ES stocks that also advertise a lot. In addition, the volatility of stock returns

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is lower for high ES stocks, while the trading volume is higher. The evidence presented in this paper is consistent with the view that consumer behavior is the main driver the resiliency effects of ES policies.

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Appendix: Variables, definitions, and sources.

This table presents the variable definitions and data sources. Compustat and CRSP items are in brackets.

ES	The average between Refinitiv Environment Pillar Score and Social Pillar Score, divided by 100 and measured in 2018. Environment (Social) Pillar Score is the weighted average relative rating of a company based on the reported environmental (social) information and the resulting three (four) environmental (social) category scores. *Dummy_ES_High* is an indicator for firms in the top quartile. *Source: Thomson Reuter's Refinitiv ESG*
Investor-based ES	We first measure an investor's revealed ESG preference as the value-weighted average *ES* score of its portfolio holdings for each quarter in 2018, and then average across the four quarters. *Investor-based ES* of a firm is measured as the weighted average its investors' ES based on holdings at the first quarter of 2019. *Dummy_InvestorES_High* is an indicator for firms in the top quartile. *Source: Own calculation based on Thomson Reuter's 13F and Refinitiv ESG*
ES-MSCI	We divide the number of strengths (concerns) for each firm-year across all six ES categories excluding governance by the maximum possible number of strengths (concerns) in all six categories for each firm-year, to ensure comparability over time and across firms. We then subtract the scaled concerns from the scaled strengths to obtain a net measure. It is measured in 2016. *Source: MSCI's ESG Research*
Dummy_COVID	A dummy variable equals one from 24th February to 31st March 2020, and zero from the 1st January to 23rd February 2020.
Dummy_Fiscal	A dummy variable that equals one from 18th March to 31st March 2020, and zero from the 1st January to 17th March 2020.
Tobin's Q	The book value of assets (item 6) minus book value of equity (item 144) plus the market value of equity (item 25* item 24), all divided by book value of assets (item 6). It is measured in 2019. *Source: Compustat*
Size	The natural log of the market value of equity (PRCCD* CSHOC) as of 31st December 2019. *Source: Capital IQ North America Daily*
Cash	Cash holdings (item 1) over book assets (item 6), measured in 2019. *Source: Compustat*
Leverage	Book value of debt (item 9+ item 34) over book assets (item 6), measured in 2019. *Source: Compustat*
ROE	Ratio of operating income (item 13) to book equity (item 144), measured in 2019. *Source: Compustat*
Advertising	Advertising expenditures [XAD] over total assets [AT]. Missing values are set to zero, following the past literature. *Dummy_Advertising_High* is an indicator for firms in the top quartile. It is measured in 2019. *Source: Compustat*
Abn Return	The difference between the daily logarithm return of a stock and the CAPM beta times the daily logarithm market return during the first quarter of 2020, expressed in percentage. The CAPM beta is estimated by using daily returns from 2017 and 2019, where the market index is S&P 500. *Abn Return_cum* is the sum of *Abn Return* over the first quarter of 2020. *Source: CRSP, Capital IQ North America Daily*
Volatility	The volatility of daily logarithm raw returns of stocks during the first quarter of 2020. *Source: Capital IQ North America Daily*
Idio Volatility	The volatility of daily *Abn Return* of stocks during the first quarter of 2020. *Source: Capital IQ North America Daily*
Volume	Daily trading volume [CSHTRD] of a stock during the first quarter of 2020. Daily trading volume is adjusted for stock splits and dividends. CSHTRD is divided by 1 million to reflect daily trading volumes in unit of millions. *Source: Capital IQ North America Daily*
DayPrc_range	Daily high-low price range of a stock during the first quarter of 2020, scaled by the midpoint of high and low daily prices. The high (low) price [PRCHD] ([PRCLD]) is the highest (lowest) trade price for the date. *Source: Capital IQ North America Daily*

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Saving lives versus saving livelihoods: Can big data technology solve the pandemic dilemma?

Kairong Xiao[1]

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This paper studies the effectiveness of big data technology in mitigating the economic and health impacts of the COVID-19 outbreak. I exploit the staggered implementation of contact-tracing apps called "health code" in 322 Chinese cities during the COVID-19 pandemic. Using high-frequency variations in population movements and greenhouse gas emissions across cities before and after the introduction of health code, I disentangle the effect of big data technology from confounding factors such as public sentiments and government responses. I find that big data technology significantly improves the tradeoff between human toll and economic costs. Cities adopting health code experience a significant increase in economic activities without suffering from higher infection rates. Overall, big data technology creates an economic value of 0.5%-0.75% of GDP during the COVID-19 outbreak in China.

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1 Assistant Professor of Business, Columbia Business School. I have benefitted from valuable comments by Stijn van Nieuwerburgh. I thank Meichen Qian for the excellent research assistance.

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1 Introduction

Pandemics such as COVID-19 present an impossible choice to policymakers between saving lives and saving livelihoods. On the one hand, population movement restrictions such as social distancing and lockdown are deemed necessary to contain the rapid spreads of the disease. On the other hand, such restrictions inflict steep economic costs as normal activities are disrupted. The painful tradeoff between human toll and economic costs has led to heated and sometimes divisive debate in the policy domain.

How can we solve the pandemic dilemma between saving lives and saving the economy? Many believe that the answer lies in big data technology (Ferretti, Wymant, Kendall, Zhao, Nurtay, Abeler-Dörner, Parker, Bonsall, and Fraser, 2020). Using the enormous amount of real-time location data produced by smartphones, we may detect potential carriers of the disease and break the transmission chains. At the same time, big data technology can also identify the group of people who are unlikely to carry the disease so that they can resume normal work and life, which limits the economic damage of the disease. Advocates often cite the successful experiences in China and South Korea where big data technology was aggressively deployed to combat the virus.

However, big data technology is also highly controversial. Critics argue that some countries such as Singapore have seen little success from using contact-tracing apps.[1] Implementing big data technology could also divert critical resources from proven containment methods such as aggressive testing. Big data technology may also disproportionately impact the rights of those under- or misrepresented by the data.[2] Finally, big data technology also raises concerns about privacy infringement and government surveillance. Therefore, using big data to address the public health crisis can potentially do more harm than good.

[1]See WSJ April 22 article, "Singapore Built a Coronavirus App, but It Hasn't Worked So Far".
[2]For instance, the April 12, 2020, AP News article "Europe eyes smartphone location data to stem virus spread" reports that Israeli government's cell phone location-tracking program has caused complaints that the authorities are erroneously confining people to their homes based on inaccurate location data.

This paper sheds light on this debate by studying the effectiveness of big data technology in mitigating the economic and human costs of the COVID-19 outbreak in China. I exploit the staggered implementation of contact-tracing apps called "health code" in 322 Chinese cities amid the COVID-19 pandemic. Using high-frequency variations in population movements and greenhouse emission across cities, I disentangle the effect of big data technology from confounding factors such as public sentiments and government responses. I show that big data technology allows the vast majority of the population to resume economic activities without risking the public health condition. The estimated benefits of this technology seem to dominate the potential costs related to privacy.

I start by describing the institutional background. On February 9, 2020, 17 days after the lockdown of Wuhan, the first "health code" was developed by Ant Financial, a FinTech company afflicted with Alibaba, and adopted by the Hangzhou municipal government, where Ant Financial's headquarter locates. This app uses real-time location data produced by smartphones to predict holders' risks of being infected based on whether the holders are in close contact with confirmed patients. This app assigns a QR code for each holder, which functions as a "traffic permit" within the city. Holders can travel in the city freely if they obtain green codes but face quarantine if their codes are yellow or red. Health code was subsequently expanded to other cities in China. By the end of March 31, 276 cities out of 322 cities in the sample have implemented this system. The adoption of health code represents the largest experiment of big data technology in the public health domain. It offers an invaluable opportunity to examine the effectiveness of big data technology in mitigating economic and human costs inflicted by pandemics.

I collect the adoption dates of health code in each of 322 cities from local government websites and news reports. To measure high-frequency variations in economic activities at the city level, I use within-city population movements constructed from smartphone locations by Baidu and daily emission of greenhouse gases related to industrial activities. I also use

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daily numbers of confirmed COVID-19 cases, cured patients, and death tolls for each city provided by the Chinese Center for Disease Control and Prevention (CCDC). The sample period spans January 1 to March 31, 2020, covering the lockdown of Wuhan on January 23, 2020, and the introduction of the first health code in Hangzhou on February 9, 2020. The staggered implementation of health code across cities allows me to disentangle the causal effects of the big data technology from confounding factors.

The empirical analysis yields three main results. First, I find that the introduction of health code significantly mitigates the negative impact of the COVID-19 outbreak on economic activities by 2-3%. Second, cities that implemented health code attract greater population inflows and experience smaller population outflows. Third, I find that the increase in economic activities does not lead to an increase in infection rates in cities with health code. Overall, the use of big data technology has significantly improved the tradeoff between economic activities and public health, creating an economic value of 0.5%-0.75% GDP during the COVID-19 outbreak in China.

One potential concern on the empirical approach is that cities that adopt health code early could have higher economic importance for the country, thus are forced to reopen before other cities. I address this concern by matching the treated cities to control cities with similar pre-COVID-19 economic activities and find the results are robust. One may also worry that the timing of implementation of health code may be correlated with the successful containment of the outbreak in a city. I address this concern by matching the treated cities to control cities with similar active cases when health code was introduced. The results are also robust to this alternative matching scheme.

Finally, I compare the estimated economic benefits of big data technology with potential costs. I find that the introduction of health code creates an economic value of \$50-75\$ per capita. Comparing this estimate to the value of privacy estimated in the literature (Athey, Catalini, and Tucker, 2017; Tang, 2019), I find that the benefits of big data technology seem

to outweigh the potential costs on privacy.

Why is big data technology an effective tool to mitigate the economic and human costs of pandemics? The answer is that it can address the key amplification mechanism of pandemics: information frictions. Because of the hidden virus, people are afraid of going out, which brings offline consumption to a standstill. Governments have to impose quarantines on the whole population just to stop a few hidden carriers. In such a situation, big data technology can be a powerful tool. By leveraging the enormous amount of data produced in our digital age, big data technology can help to identify the hidden carriers, thus contains the transmission of the virus. Furthermore, it can reduce people's fear of being infected, thus restores economic activities depressed by pandemics.

This paper contributes to the fast-growing literature on the optimal policy response to the pandemic shock (Alvarez, Argente, and Lippi, 2020; Barro, Ursúa, and Weng, 2020; Correia, Luck, and Verner, 1918; Eichenbaum, Rebelo, and Trabandt, 2020; Hall, Jones, and Klenow, 2020; Dewatripont, Goldman, Muraille, and Platteau, 2020; Fang, Wang, and Yang, 2020; Piguillem, Shi, et al., 2020; Jones, Philippon, and Venkateswaran, 2020). This paper is closely related to Alvarez, Argente, and Lippi (2020) and Jones, Philippon, and Venkateswaran (2020) which study the optimal lockdown policy to control the fatalities of a pandemic while minimizing the output costs of the lockdown. Alvarez, Argente, and Lippi (2020) suggest that 60% of the population should be under tight lockdown to contain pandemics like COVID-19. The economic costs of such lockdown are estimated to be at least 8% of the GDP. This paper shows that big data technology can significantly improve the tradeoff between economic and human costs of a pandemic.

This paper also contributes to the literature on the effect of big data on the economy. Farboodi and Veldkamp (2019) and Jones and Tonetti (2019) construct neoclassical growth models in which big data are an important contributor to economic growth. This paper provides micro-level evidence that big data can address frictions that limit economic growth.

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Athey, Catalini, and Tucker (2017) and Tang (2019) use field experiments to estimate the value of privacy. This paper contributes to this literature by showing that personal location data can create substantial economic value in pandemics, which seems to outweigh the value of privacy. Finally, this paper also sheds light on the regulation of big data technology, an issue studied by Acemoglu, Makhdoumi, Malekian, and Ozdaglar (2019), Bergemann, Bonatti, and Gan (2020), and Campbell, Goldfarb, and Tucker (2015).

2 Background and Data

Health code. Health code is a big data technology that uses smartphone location data to predict the risk of an individual to be infected by a disease. It was initially developed by several tech companies in China such as Ant Financial and Tencent in the height of the COVID-19 outbreak. Health code are used as "traffic permits" by numerous local governments. HOlders of green code can freely travel in the city; holders of yellow or red code have to be quarantined for 7 or 14 days, respectively. The codes turn back to green after the the quarantine. Figure 1 shows the three levels of color codes used in China.

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Figure 1: **Hangzhou Health Code**
This figure shows the first health code introduced in China, the Hangzhou health code. Individuals with green code can freely travel in the city. Individuals with yellow code have to be quarantined for 7 days. Individuals with red code have to be quarantined for 14 days. The code turn back to green after the corresponding quarantine periods.

Registering a health code is voluntary and can be easily done in smartphone apps. Because many cities in China have imposed movement restrictions, people have a strong incentive to register the code if they want to enter public space such as supermarkets and subways. Although there is no systematic record on the adoption rates in the population, anecdotal evidence suggests that the adoption rates are quite high. For instance, in Zhejiang province where health code was first introduced, around 90% of the provincial population has obtained health code 15 days after the introduction according to the disclosure of the local government officials.[3] Among all the health codes, 98.2% are green, and 1.8% are yellow or red.

The first health code app was developed by Ant Financial and implemented in its head-

[3]See New York Times article on March 1, 2020: "In Coronavirus Fight, China Gives Citizens a Color Code, With Red Flags", by Paul Mozur, Raymond Zhong and Aaron Krolik.

quarter city, Hangzhou, on February 9, 17 days after the lockdown of Wuhan. 2 days later, a different version of health code app was developed by another tech giant in China, Tencent, and implemented in its headquarter city, Shenzhen. Following Hangzhou and Shenzhen, many provinces and cities adopt their version of health code. It is worth noting that the adoption of health code was not coordinated by the central government. Instead, it is largely initiated by local governments. The decentralized adoption created a patchwork of policies. Cities do not recognize each other's health code. Different versions of health code sometimes show inconsistent results for the same individual. Some people have been required to scan multiple health code from different providers at a single location.

The uncoordinated implementation of health code have created inconvenience and confusion for people who travel across cities to the extent that the central government warned local governments not to go overboard by launching too many versions of health code.[4] However, it is good news for identification purpose. I collect the implementation dates of health code of 322 Chinese cities from the local government websites and local news media. Figure 2 shows the number of cities that adopted health code over time. The adoption process lasts for two months after the initial adoption in Hangzhou.

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[4]See South China Morning Post article on March 9, 2020, "National version of China's controversial health code isn't ready".

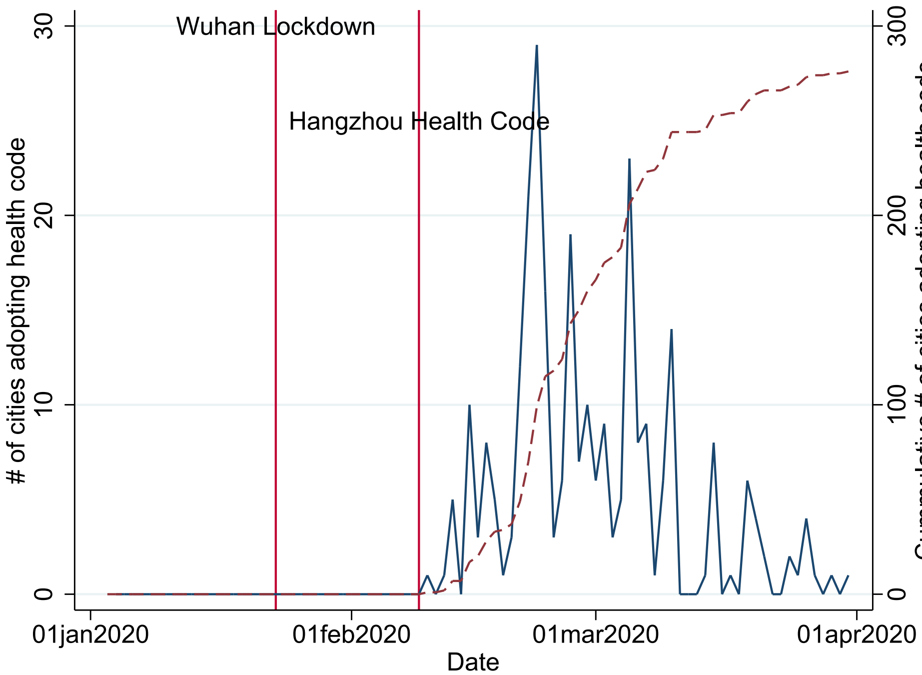

Figure 2: **Implementation of Health Code in Chinese Cities**
This figure plots the number of cities that adopt health code. The first vertical line indicates January 23, 2020, the date of Wuhan lockdown. The second vertical line indicates February 9, 2020, the date when the first health code was introduced in Hangzhou. Data source: government websites, local news report.

Figure 3 shows the fraction of cities that have adopted health code by February 15, February 29, March 15, and March 31, respectively. The adoption appears to be quite idiosyncratic: it is not related to the geographical proximity to the epicenter of the virus outbreak, Hubei. The coastal and inland provinces seem to have a balanced tendency to adopt health code. The staggered introduction of health codes across Chinese cities will provide a great laboratory to identify the causal effect of big data technology on the economy and public health.

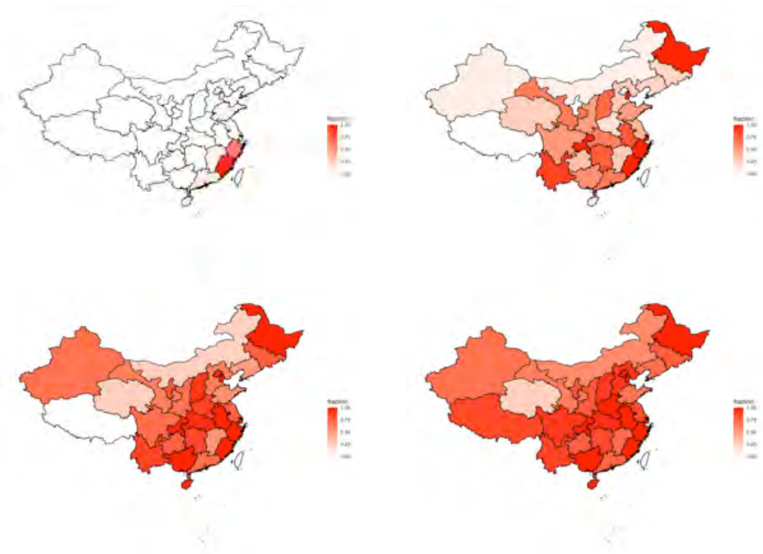

Figure 3: **Implementation of Health Code in Chinese Cities**
This figure shows the fraction of cities that adopted health code in each province. The four snapshots are at February 15t, February 29, March 15, and March 31, 2020. Data source: government websites, local news report.

Economic activities. I use daily within-city population movements as a high-frequency measure of economic activities across cities. The data are created using real-time smartphone phone location data from the largest Chinese search engine in China, Baidu.[5] The population movement data covers 322 Chinese cities between January 1 and April 10 in 2020. The final data is a panel consisting of 28,658 city-day level observations. The high-frequency nature of this data is important for identification because health code was rolled out within 2 months. Therefore, typical macroeconomic data at quarterly or monthly frequency may not capture the effect of the adoption.

Figure 4 plots the national average within-city movement in the sample period. I report the value as a percentage of the average value in the first week of 2020. Note that the

[5]The source of the data can be found on the website of CNEMC: http://https://qianxi.baidu.com/.

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sample period contains the Lunar New Year holiday, during which the economic activities would naturally decrease. To control for the effect of Lunar New Year, I normalize the level of within-city movement using the same day value of the 2019 lunar calendar. Figure 4 shows a steep drop in economic activities after January 23, 2020, the day of Wuhan lockdown. The second vertical red line indicates February 9, 2020, the date when Hangzhou health code was introduced. The within-city movement slowly recovers in mid-February. By the end of the sample period, the within-city movement has rebounded to about 95% of the pre-COVID-19 level.

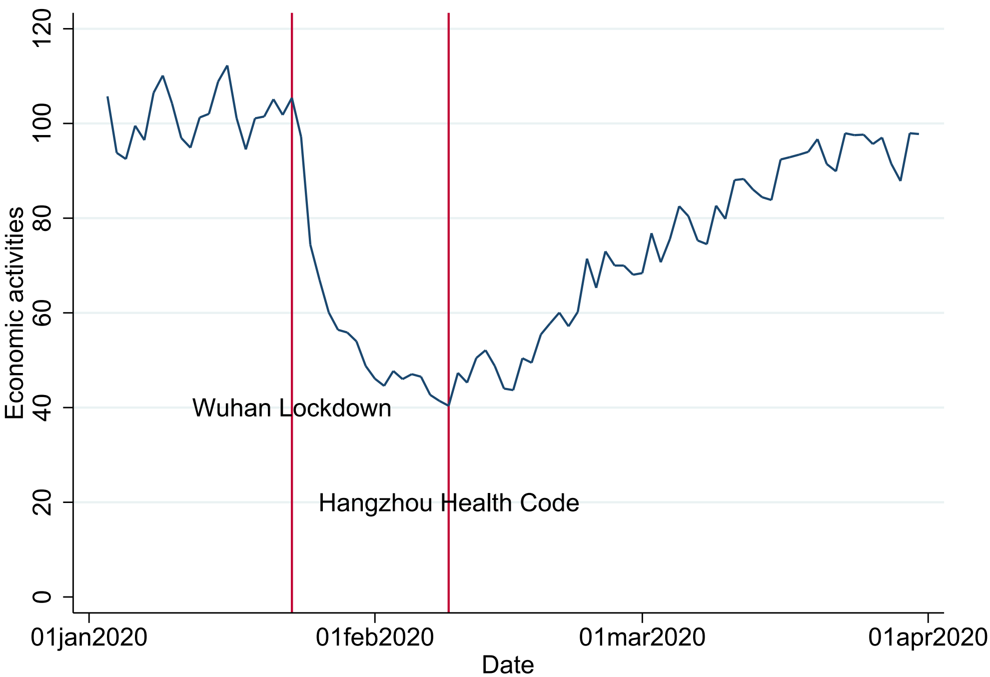

Figure 4: **Economic Activities of Chinese Cities**
This figure plots the average economic activities as measured by within-city population movements. The sample period is from January 1 to March 31, 2020. The first vertical line indicates January 23, 2020, the date of Wuhan lockdown. The second vertical line indicates February 9, 2020, the date when the first health code was introduced in Hangzhou. Data source: Baidu.

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The Baidu data also provides a between-city migration pattern. For each city in the sample, the data shows the top 100 cities of inflows and outflows and the corresponding intensities.

Greenhouse gas emission. One may worry that within-city movements may not capture economic activities that can be conducted without human movements. To address this concern, I use the daily level of Nitrogen Dioxide (NO2) as an alternative high-frequency measure of economic activities. NO2 is a green house gas created by factories and automobiles burning fossil fuels. Because Chinese economy heavily relies on coal as a source of energy, the amount of Nitrogen Dioxide is a good measure of economic activities of China. I collect daily level of NO2 from the China National Environmental Monitoring Center (CNEMC) for each city.[6] Figure 5 plots the average NO2 of the sample cities where the values are normalized by the average of the first two weeks in 2020. A sharp drop occurs after the Wuhan lockdown on January 23, 2020. Economic activities decreased by 40% of the pre-lockdown level at the peak of outbreak. The magnitude of the reduction is similar to the within-city movements. The NO2 level started to slowly recover in March, 2020. The sharp decrease in the NO2 level during the COVID-19 outbreak documented in the data from the China National Environmental Monitoring Center (CNEMC) is consistent with the satellite images produced by the National Aeronautics and Space Administration (NASA) as shown in Figure 6.

[6] The source of the data can be found on the website of CNEMC: http://www.cnemc.cn/.

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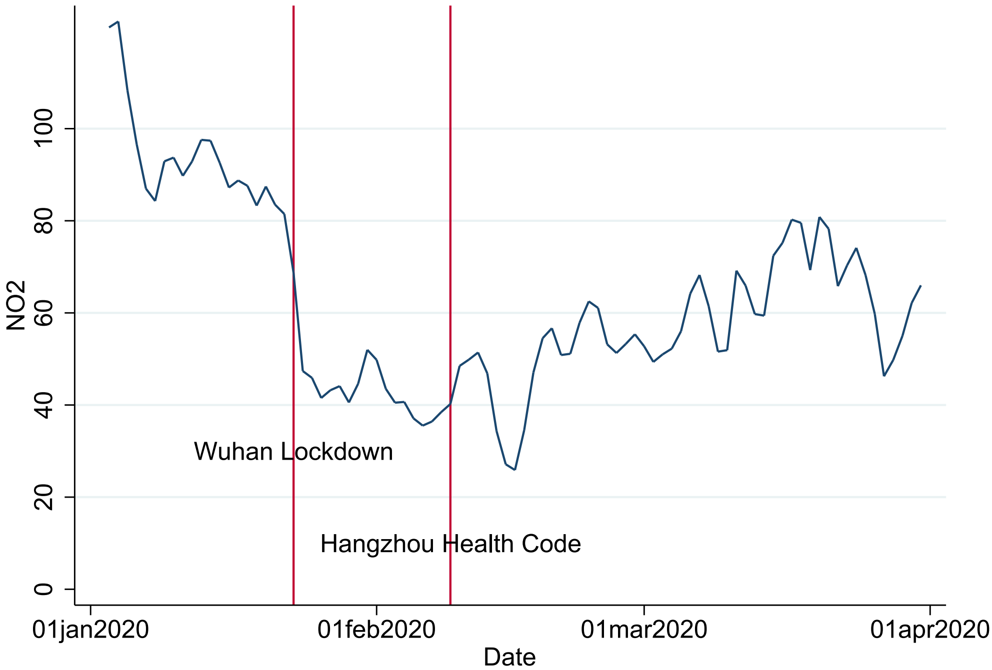

Figure 5: **Average NO2 Level of Chinese Cities**
This figure plots the average NO2 level of Chinese cities. The values are normalized by the average of the first two weeks in 2020. Data source: the China National Environmental Monitoring Center (CNEMC).

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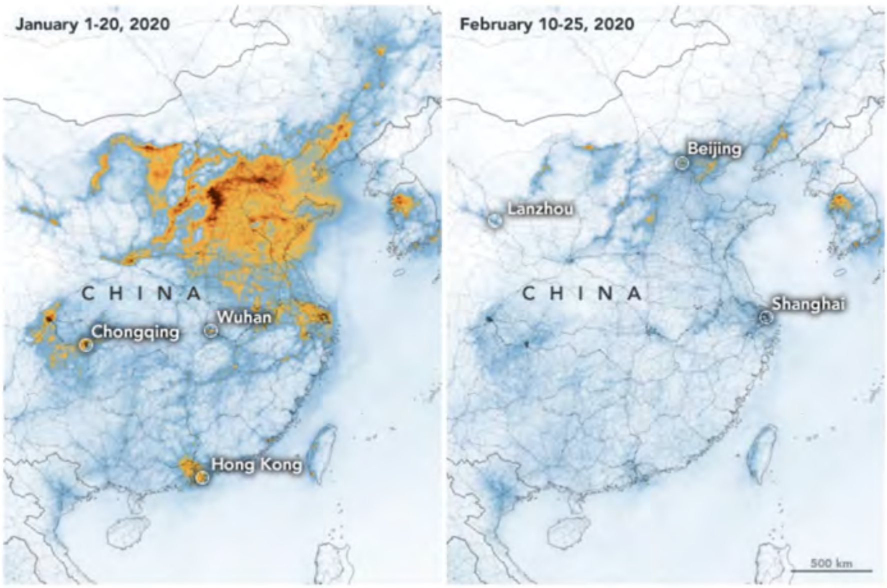

Figure 6: **Nitrogen Dioxide (NO2) Level over China**
This figure shows the heat maps of Nitrogen Dioxide (NO2) level over China. The heat maps are created by the National Aeronautics and Space Administration (NASA).

In addition to NO2, I also use the daily level of fine particulate matter (PM2.5), which is produced by chemical reactions between gases such as Sulfur Dioxide, Nitrogen Oxides, and volatile organic compounds with dust from industrial activities, as a high-frequency measure of economic activities. I also collect daily level of PM2.5 for each city from the China National Environmental Monitoring Center (CNEMC).

Virus outbreak. I collect the daily count of confirmed, dead, and recovered COVID-19 cases of each of 322 cities from the Centers for Disease Control and Prevention of China (CDC).[7] Figure 7 plots the time series of COVID-19 cases in the sample. From January 11 to April 3, 2020, the data cover 81,198 confirmed COVID-19 cases, 3,302 dead cases, and 75,887 recovered cases. The fatality rate amount the confirmed cases is around 4%, which is

[7]The source of the data can be found on the website of CDC: http://2019nCoV.chinacdc.cn/2019-nCoV/.

in line with the fatality rates in other countries. The increase in the confirmed cases levels off in early March. Using this data, I calculate the infection rate, defined as the ratio of newly confirmed cases over the active cases as a measure of the severity of the outbreak.

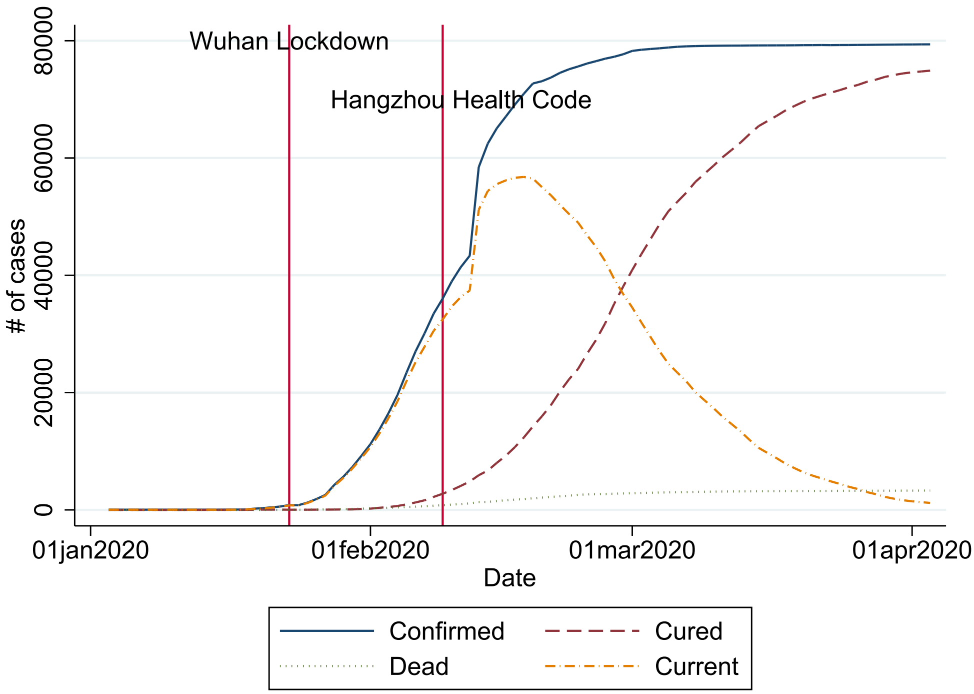

Figure 7: **Confirmed, Cured, Dead, and Current Cases of COVID-19**
This figure plots the cumulative confirmed, cured, dead, and current cases of COVID-19 in the sample. Data source: Chinese Center for Disease Control and Prevention.

One may worry that the numbers of cases in Wuhan and other cities of Hubei can be underestimated because testing capacity was limited at the early stage of the outbreak. Furthermore, government officials in the epicenter cities initially may have also downplayed the severity of the outbreak. Fang, Wang, and Yang (2020) found that there were substantial undocumented infection cases in the early days of the COVID-19 outbreak in cities of Hubei province. Still, they find the gap between the officially reported cases and their estimated

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actual cases narrows significantly as the testing capacity was strengthened in Wuhan. To address this concern, I conduct robustness checks for all the regressions by excluding the observations in Hubei province. It is worth noting that economic activity measures are based on smartphone location or air pollution data, which are unlikely to be subject to the same measurement issue as the confirmed COVID-19 cases.

Summary statistics. Table 1 provides the summary statistics of the final sample. Panel A reports the city-date sample. I use this sample to study the impact of health code on city-level economic activities and the COVID-19 infection rates. The sample period starts from January 1, 2020, and ends on March 31, 2020. All three measures suggest consistent reduction in economic activities: the average within-city movements, NO2, and PM2.5 are around 78%, 63%, and 78% of their normal levels. The average daily infection rate is 2%, which implies that the new confirmed case grows by 2% of the active cases each day.

In addition to the three main data sources, I collect information on the level of the emergency response of each province from the local government websites and news reports. A higher level of emergency gives local governments greater power to impose exceptional measures such as lockdown and social distancing rules. This system classifies the emergency event into four levels. The lowest level is coded as 0 and the highest as 4. The average emergency level in the sample is 2.

Panel B and C report two city pair-day samples on population inflows and outflows, respectively. I use these two samples to study the impact of health code on the between-city migration pattern. The inflows and outflows are expressed as the percentage of the total flows of the corresponding city. The average inflow and outflows are both 1%.

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Table 1: **Summary Statistics**

Panel A: City-level economic activities

	N	mean	sd	p5	p25	p50	p75	p95
Within-city movements	28658	78	26	32	56	84	99	109
NO2	24742	63	30	23	40	58	81	119
PM2.5	24742	78	51	20	43	68	102	171
Infection rate	28658	2	5	0	0	0	0	20
Confirmed cases	28658	144	1986	0	0	8	31	213
Cured cases	28658	83	1252	0	0	3	18	140
Dead cases	28658	5	91	0	0	0	0	3
Emergency level	28658	2	1	0	0	2	3	3

Panel B: City-to-city population inflows

	N	mean	sd	p5	p25	p50	p75	p95
Outflow	1964052	1	4	0	0	0	0	4
Confirmed cases (source)	1964052	143	2020	0	0	8	30	169
Cured cases (source)	1964052	82	1270	0	0	3	18	126
Dead cases (source)	1964052	5	93	0	0	0	0	2
Existing cases (source)	1964052	56	1004	0	0	0	6	54
Emergency level	1964052	2	1	0	0	2	3	3

Panel C: City-to-city population outflows

	N	mean	sd	p5	p25	p50	p75	p95
Outflow	1896486	1	4	0	0	0	0	4
Confirmed cases (source)	1896486	116	1548	0	0	17	49	252
Cured cases (source)	1896486	75	1083	0	0	6	35	173
Dead cases (source)	1896486	3	72	0	0	0	0	3
Existing cases (source)	1896486	37	725	0	0	0	11	76
Emergency level	1896486	2	1	0	0	2	3	3

Note: This table reports summary statistics of the regression sample. The sample is a panel of 322 cities from January 1, 2020 to March 31, 2020. Data sources: Baidu, Chinese Center for Disease Control and Prevention.

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3 Empirical Results

In this section, I exploit the staggered implementation of health code in 322 Chinese cities to identify the causal effects of big data technology on economic activities and public health conditions. Specifically, I use a difference-in-differences (DID) research design to test three main hypotheses: (1) whether the introduction of health code increases local economic activities, (2) whether the introduction of health code affects the migration pattern between cities, and (3) whether the introduction of health code reduces the infection rates of COVID-19.

3.1 Economic activities

I study the effects of big data technology on economic activities measured by within-city population movements:

$$\text{EconomicActivity}_{i,t} = \beta \text{HealthCode}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \quad (1)$$

where $\text{EconomicActivity}_{i,t}$ is measured by within-city population movements of city i on date t, $\text{HealthCode}_{i,t}$ is a dummy variable which equals to 1 if city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,t}$, includes the emergency level of the city and the log number of confirmed, cured, and dead cases. I also include city fixed effects to absorb time-invariant city characteristics, time fixed effects to absorb aggregate shocks. Therefore, the empirical design effectively compares differential changes in economic activities of the treated cities with those of the untreated cities before and after the introduction of health code.

Column 1 of Table 2 presents the baseline results. I find that the introduction of health code significantly increases local economic activities. The regression also shows that the severity of the outbreak also significantly affects local economic activities. In particular, an

increase in confirmed and dead cases significantly reduce local economic activities while an increase in cured cases increases local economic activities.

One may worry whether the above result is purely driven by comparing cities in Hubei province, the epicenter of the virus outbreak, with the rest of the country. Column 2 of Table 2 presents the results, excluding cities in Hubei province. I find the result is largely the same as the baseline.

Another potential concern on the empirical approach is that cities that adopt health code early could have higher economic importance for the country, thus are forced to reopen before other cities. I address this concern by matching treated cities to control cities with similar pre-COVID-19 economic activities. The result is presented in Column 3 of Table 2. The result is robust in the matching sample.

Finally, one may worry that the timing of implementation of health code may be correlated with a differential trajectory of outbreaks in each city. Cities may choose to implement health code because the outbreak is over. I address this concern by matching the treated cities to control cities with a similar number of active cases when health code was introduced. The result is presented in Column 4 of Table 2. The results are also robust to this alternative matching scheme.

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Table 2: **Health Code and Economic Activities**

	(1) Economic activity	(2) Economic activity	(3) Economic activity	(4) Economic activity
Health code	1.038***	0.996***	2.105***	2.106***
	[0.307]	[0.226]	[0.393]	[0.393]
Confirmed cases	-4.569***	-4.519***	-4.450***	-4.436***
	[0.194]	[0.274]	[0.210]	[0.215]
Cured cases	2.204***	2.156***	1.896***	1.878***
	[0.200]	[0.212]	[0.215]	[0.216]
Dead cases	-2.687***	-6.082***	-2.515***	-2.551***
	[0.649]	[0.701]	[0.641]	[0.638]
City F.E.	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
Emergency F.E.	Yes	Yes	Yes	Yes
Sample	Full sample	Excl. Hubei	Match by cases	Match by act.
Observations	28,658	27,145	26,077	27,857
Adj. R-squared	0.851	0.862	0.850	0.850

Note: This table reports the results of the following regression

$$\text{EconomicActivity}_{i,t} = \beta \text{HealthCode}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $\text{EconomicActivity}_{i,t}$ is measured by within-city movement of city i on date t, $\text{HealthCode}_{i,t}$ is a dummy variable which equals to 1 if city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,t}$, includes the emergency level of the city, the log number of confirmed/dead/cured cases, city fixed effects, and time fixed effects. The sample is a panel of 322 cities from January 1, 2020 to March 31, 2020. Standard errors are clustered at date level. Data sources: Baidu, Chinese Center for Disease Control and Prevention.

To investigate the dynamic effects of health code introduction, Figure 8 plots the difference in the economic activities between treated and control cities 20 days before and after the implementation of health code. Before the introduction of health code, there is no pre-trend between the treated and control cities, suggesting that the parallel trend assumption seems to hold in the data. After the introduction of health code, the economic activities of the treatment cities increases by around 2%-3% compared to the controlled cities.

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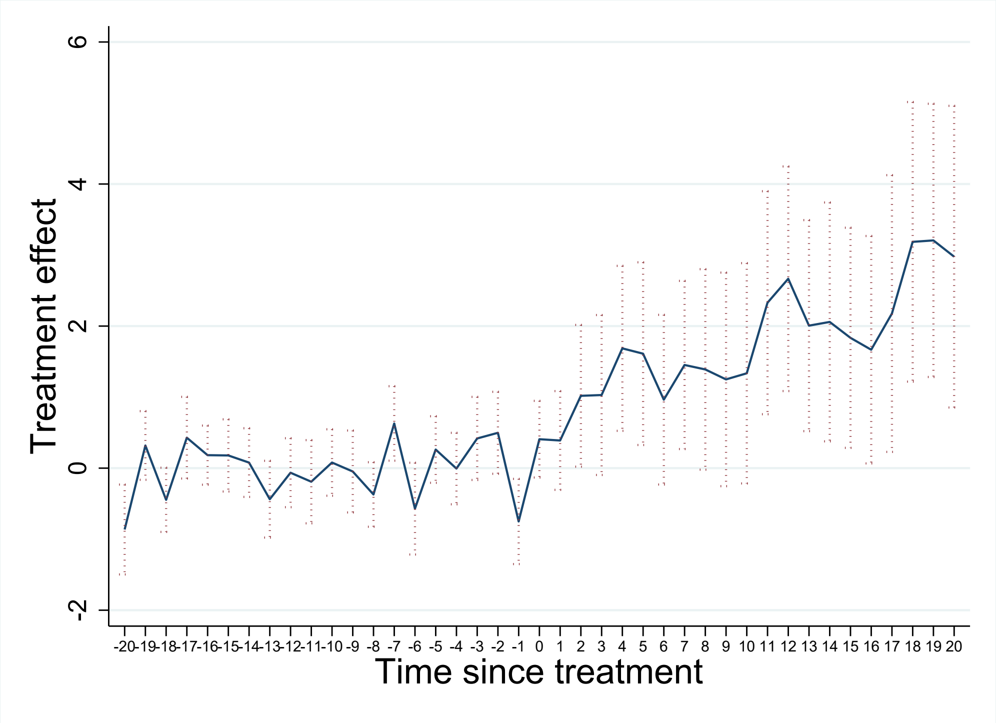

Figure 8: **Difference in Economic Activities in Treated and Control Cities**
This figure plots the difference in economic activities in treated and control cities. The horizontal axis is the date since the adoption of health code. Standard errors are clustered at date level. Data source: Baidu, Chinese Center for Disease Control and Prevention,

Within-city movements may not capture the economic activities can conducted without population movements. To address this concern, I use the concentration level of NO2 and PM2.5 as alternative measures of economic activities. The results are reported in Table 3. Consistent with the baseline measure, I find that the introduction of health code significantly increase economic activities as proxies by the concentration level of NO2 and PM2.5. The economic magnitude is also quite similar: economic activities increase by 2-3% in cities where health code is implemented.

Table 3: **Health Code and Economic Activities (Alternative Measures)**

	(1) NO2	(2) NO2	(3) PM2.5	(4) PM2.5
Health code	2.470***	2.689***	4.636***	4.529***
	[0.838]	[0.875]	[1.503]	[1.586]
Confirmed cases	-1.698**	-2.386***	-0.145	-0.687
	[0.661]	[0.658]	[1.821]	[1.752]
Cured cases	3.872***	4.568***	-0.865	-0.236
	[0.646]	[0.646]	[1.729]	[1.707]
Dead cases	-5.737***	-8.812***	-2.433*	-10.524***
	[0.765]	[1.322]	[1.410]	[3.513]
City F.E.	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
Emergency F.E.	Yes	Yes	Yes	Yes
Sample	Full sample	Excl. Hubei	Full sample	Excl. Hubei
Observations	24,742	23,674	24,742	23,674
Adj. R-squared	0.542	0.534	0.358	0.352

Note: This table reports the results of the following regression

$$\text{EconomicActivity}_{i,t} = \beta \text{HealthCode}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $\text{EconomicActivity}_{i,t}$ is measured by the NO2 or PM2.5 levels of city i on date t, $\text{HealthCode}_{i,t}$ is a dummy variable which equals to 1 if city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,t}$, includes the emergency level of the city, the log number of confirmed/dead/cured cases, city fixed effects, and time fixed effects. The sample is a panel of 322 cities from January 1, 2020 to March 31, 2020. Standard errors are clustered at date level. Data sources: Baidu, Chinese Center for Disease Control and Prevention.

3.2 Between-city migration pattern

Next, I investigate how health code affects the migration pattern between cities. Specifically, I first examine the effect of health code on inflows into cities. The regression model is the following:

$$\text{Inflow}_{i,j,t} = \beta \text{DestinationHealthCode}_{j,t} + \gamma X_{i,j,t} + \epsilon_{i,t},$$

where $\text{Inflow}_{i,j,t}$ is the flow from city i to city j on date t, $\text{DestinationHealthCode}_{j,t}$ is a dummy variable which equals to 1 if destination city j has health code at time t, and 0

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otherwise. The vector of the control variables, $X_{i,j,t}$, includes the emergency level, and the log number of confirmed, cured, and dead cases in the destination city. I also include destination-city fixed effects to absorb time-invariant city characteristics. Finally, I include source city-time fixed effects. The regression compares the flows from the same source city to two similar destination cities, of which one has health code, but the other does not. Table 4 shows the results. I find that the introduction of health code significantly increase the inflows to cities with health code by 11%. This result suggests that cities with health code become more attractive as most residents can move freely and economic activities recover.

Table 4: **Health Code and Population Inflows**

	(1) Inflow	(2) Inflow	(3) Inflow	(4) Inflow
Health Code (destination)	10.276***	10.539***	10.281***	10.267***
	[1.658]	[1.654]	[1.703]	[1.701]
Confirmed cases (destination)	3.486**	3.943**	3.651**	3.643**
	[1.476]	[1.511]	[1.497]	[1.496]
Cured cases (destination)	2.965**	2.929**	2.825**	2.828**
	[1.277]	[1.318]	[1.287]	[1.286]
Dead cases (destination)	-18.916***	-20.169***	-18.899***	-18.890***
	[1.015]	[1.249]	[1.051]	[1.050]
City pair F.E.	Yes	Yes	Yes	Yes
Destination-time F.E.	Yes	Yes	Yes	Yes
Emergency level F.E.	Yes	Yes	Yes	Yes
Sample	Full sample	Excl. Hubei	Match by cases	Match by act.
Observations	1,888,652	1,798,439	1,724,150	1,834,948
Adj. R-squared	0.857	0.859	0.855	0.855

Note: This table reports the results of the following regression

$$\text{Inflow}_{i,j,t} = \beta \text{DestinationHealthCode}_{j,t} + \gamma X_{i,j,t} + \epsilon_{i,j,t},$$

where $\text{Inflow}_{i,j,t}$ is the flow from city i to city j on date t, $\text{DestinationHealthCode}_{j,t}$ is a dummy variable which equals to 1 if destination city j has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,j,t}$, includes the emergency level, and the log number of confirmed/dead/cured cases in the destination city, destination-city fixed effects, and source city-time fixed effects. The sample is a panel of 322 cities from January 1, 2020 to March 31, 2020. Standard errors are clustered at date level. Data sources: Baidu, Chinese Center for Disease Control and Prevention.

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I then examine how health code affects the population outflows from a city. The regression model is the following:

$$\text{Outflow}_{i,j,t} = \beta \text{SourceHealthCode}_{i,t} + \gamma X_{i,j,t} + \epsilon_{i,t}$$

where $\text{Outflow}_{i,j,t}$ is the flow from city i to city j on date t, $\text{SourceHealthCode}_{i,t}$ is a dummy variable which equals to 1 if source city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,j,t}$, includes the emergency level, and the log number of confirmed, cured, and dead cases in the source city. I also include source-city fixed effects to absorb time-invariant city characteristics. Finally, I include source city-time fixed effects. The regression compares the flows from two similar source cities to the same destination city. One of the source cities has health code, but the other does not. Table 5 shows the results. I find that the introduction of health code significantly decrease the outflows from cities with health code by 14%. This result suggests that residents in cities with health code seem to be more willing to stay in the cities, presumably due to the recovery of economic activities.

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Table 5: **Health Code and Population Outflows**

	(1) Outflow	(2) Outflow	(3) Outflow	(4) Outflow
Health Code (source)	-14.120***	-13.200***	-15.080***	-15.233***
	[1.774]	[1.701]	[1.740]	[1.735]
Confirmed cases (source)	-12.913***	-15.333***	-14.245***	-14.626***
	[1.675]	[1.807]	[1.809]	[1.811]
Cured cases (source)	-4.130***	-3.220**	-4.687***	-4.660***
	[1.251]	[1.220]	[1.389]	[1.387]
Dead cases (source)	7.578***	-11.209***	8.867***	8.165***
	[1.657]	[1.866]	[1.772]	[1.807]
City pair F.E.	Yes	Yes	Yes	Yes
Source-time F.E.	Yes	Yes	Yes	Yes
Emergency level F.E.	Yes	Yes	Yes	Yes
Sample	Full sample	Excl. Hubei	Match by cases	Match by act.
Observations	1,887,544	1,834,631	1,784,667	1,846,851
Adj. R-squared	0.860	0.862	0.858	0.858

Note: This table reports the results of the following regression

$$\text{Outflow}_{i,j,t} = \beta \text{SourceHealthCode}_{i,t} + \gamma X_{i,j,t} + \epsilon_{i,j,t},$$

where $\text{Outflow}_{i,j,t}$ is the flow from city i to city j on date t, $\text{SourceHealthCode}_{i,t}$ is a dummy variable which equals to 1 if source city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,j,t}$, includes the emergency level, and the log number of confirmed/dead/cured cases in the source city, source-city fixed effects, and destination city-time fixed effects. The sample is a panel of 322 cities from January 1, 2020 to March 31, 2020. Standard errors are clustered at date level. Data sources: Baidu, Chinese Center for Disease Control and Prevention.

3.3 Infection rate of COVID-19

The previous results offer evidence that the introduction of health code allow the economy to return to normal. However, one important question is whether the reopen of the economy will lead to a resurgence of virus infection in the future. To test this hypothesis, I estimate the following regression model:

$$\text{InfectionRate}_{i,t+7} = \beta \text{HealthCode}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

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where $\text{InfectionRate}_{i,t+7}$ is the infection rate of COVID-19 in city i on date $t+7$; $\text{HealthCode}_{i,t}$ is a dummy variable which equals to 1 if city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,t}$, includes the emergency level of the city and the log number of confirmed, cured, and dead cases. I also include city fixed effects to absorb time-invariant city characteristics, time fixed effects to absorb aggregate shocks. It is worth noting that I use the infection rate in 7 days because 7 days is the median time when symptoms appear after exposure to the virus.

Column 1 of Table 6 presents the baseline results. I find that the introduction of health code does not seem to increase the infection rates of COVID-19 despite that economic activities have significantly increased. Column 2 of Table 6 presents the results excluding cities in Hubei province. I find the result is largely the same as the baseline. This result alleviates the concern that under-reporting in the epicenter of the virus outbreak could drive the result. One may also worry that the timing of implementation of health code may be endogenous to whether the virus outbreak was successfully stopped in a city. I address this concern by matching the existing confirmed cases at the time of the introduction of health code. Column 3 of Table 6 shows that the result in the matched sample is quite similar to the baseline regression as well. Finally, in the sample matched by economic activities, as shown in Column 4, I find the result is virtually the same.

Table 6: **Health Code and Infection Rates**

	(1) Infection rate	(2) Infection rate	(3) Infection rate	(4) Infection rate
Health code	0.079	0.075	0.020	0.026
	[0.076]	[0.076]	[0.086]	[0.085]
Confirmed cases	-0.526*	-0.746**	-0.545*	-0.539*
	[0.314]	[0.317]	[0.322]	[0.316]
Cured cases	-0.889***	-0.759***	-0.862***	-0.861***
	[0.121]	[0.113]	[0.121]	[0.112]
Dead cases	0.411**	1.269**	0.405*	0.415**
	[0.204]	[0.493]	[0.220]	[0.190]
City F.E.	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
Emergency F.E.	Yes	Yes	Yes	Yes
Sample	Full sample	Excl. Hubei	Match by cases	Match by act.
Observations	26,404	25,010	24,026	25,666
Adj. R-squared	0.411	0.388	0.423	0.422

Note: This table reports the results of the following regression

$$\text{InfectionRate}_{i,t+7} = \beta \text{HealthCode}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $\text{InfectionRate}_{i,t+7}$ is infection rate of city i on date $t+7$, $\text{HealthCode}_{i,t}$ is a dummy variable which equals to 1 if city i has health code at time t, and 0 otherwise. The vector of the control variables, $X_{i,t}$, includes the emergency level of the city, the log number of confirmed/dead/cured cases, city fixed effects, and time fixed effects. The sample is a panel of 322 cities from January 1, 2020 to March 31, 2020. Standard errors are clustered at date level. Data sources: Baidu, Chinese Center for Disease Control and Prevention.

Figure 7 reports the dynamic effect of the introduction of health code on infection rates of COVID-19. Again, there is no pre-trend between treated and control cities suggesting the parallel trend assumption is stratified in the data. Furthermore, the introduction of health code do not significantly increase the infection rate.

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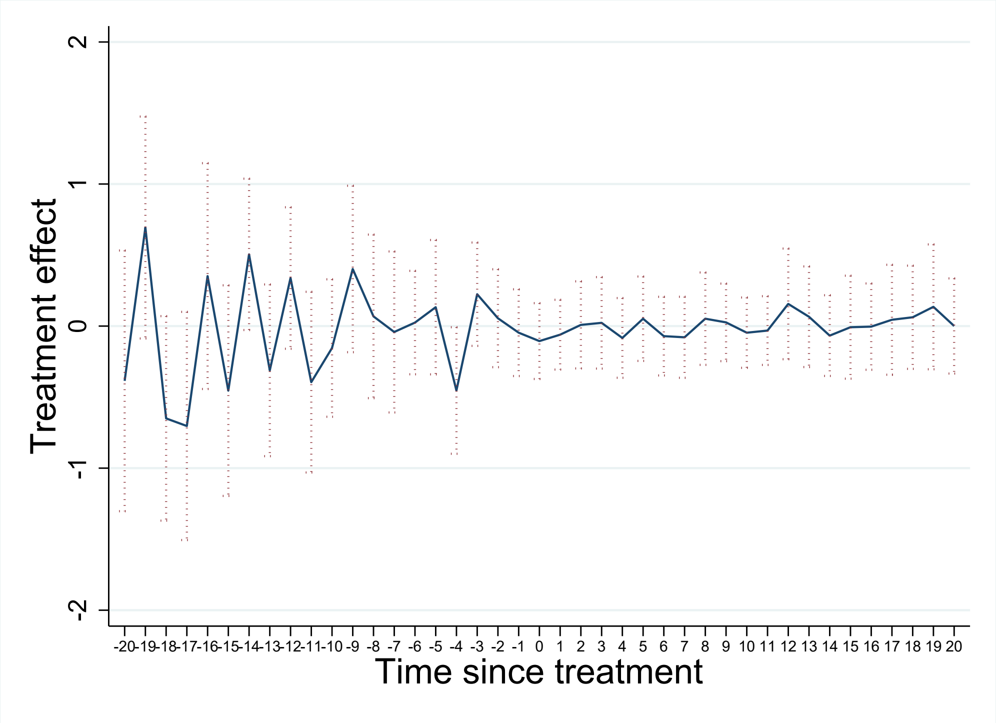

Figure 9: **Difference in Infection Rates in Treated and Control Cities**
This figure plots the difference in infection rates in treated and control cities. The horizontal axis is the date since the adoption of health code. Standard errors are clustered at date level. Data source: Baidu, Chinese Center for Disease Control and Prevention,

3.4 Trade-off between lives and livelihoods?

Finally, I examine whether the big data technology helps to improve the trade-off between lives and livelihoods. Specifically, I estimate the relationship between economic activities and future infection rates with and without health code.

$$\text{InfectionRate}_{i,t+7} = \beta_1 \text{HealthCode}_{i,t} \times \text{EconomicActivity}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

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where $\text{InfectionRate}_{i,t+7}$ is the infection rate of COVID-19 in city i on date t+7; $\text{HealthCode}_{i,t}$ is a dummy variable which equals to 1 if city i has health code at time t, and 0 otherwise; $\text{EconomicActivity}_{i,t}$ is measured by the index of within-city movement of city i on date t. The vector of the control variables, $X_{i,t}$, includes the current infection rate, emergency level fixed effects, city fixed effects, and time fixed effects.

Figure 10 plots the predicted infection rates for each level of economic activities with and without health code, respectively. I find that health code improve the tradeoff between economic activities and virus infection. Specifically, without health code, a 50% increase in economic activities is associated with a 6 bps increase in the daily infection rate. However, with health code, a 50% increase in the economic activities is associated with only 3 bps increase in the daily infection rate.

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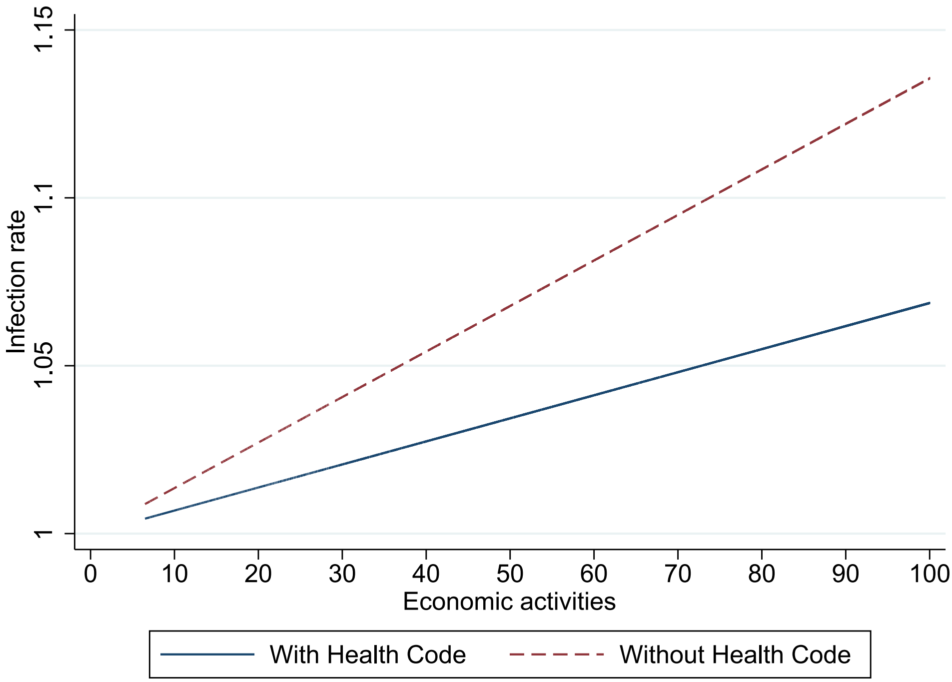

Figure 10: **Trade-off Between Economic Activities and COVID-19 Infection Rate**
This figure plots the trade-off between economic activities and COVID-19 infection rates. Data source: Baidu, Chinese Center for Disease Control and Prevention.

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3.5 Do the benefits of health code justify the costs?

The above results show that health code can significantly improve economic activities without sacrificing the public health. However, using big data technology could lead to other types of costs. The most prominent concern is privacy. Do the benefits created by health code justify its costs on privacy? In this section, I conduct a back-of-the-envelope calculation of the benefits of health code and compare it with the costs of privacy estimated in the literature.

Section 3.1 shows that the introduction of health code increase economic activities by around 2-3%. Assuming that the COVID-19 outbreak lasts for a quarter, then the in-

troduction of health code creates an economic value of 0.5%-0.75% GDP. Given the GDP per capita in China is around $10,000 as of 2018, a 0.5% increase in GDP translates to $0.5\% \times \$10,000 = \$50$ per person.[8] In comparison, Tang (2019) estimate that in a field experiment that Chinese people value their privacy at a value of $33. It seems that the benefits of the health code technology dominate the potential costs of privacy.

A caveat of this cost-benefit analysis is that people in different countries may value privacy differently. However, Athey, Catalini, and Tucker (2017) conduct experiments in the U.S. and find that, even for people who claim to value privacy, they are willing to relinquish their private data to exchange for small benefits. Therefore, big data technology could be welfare improving in many countries where people appear to value privacy a lot. The second caveat is that the above estimate is constructed based on the assumption that the COVID-19 outbreak lasts for a quarter. However, if the COVID-19 outbreak lasts longer, then the benefits should be adjusted accordingly. Third, the value of privacy estimated by Tang (2019) is based on sharing social network ID and employer contact while health code require location data, which may be valued differently by people. Fourth, using big data technology does not necessarily lead to a loss of privacy. If health code is implemented by a trusted entity or is protected by data anonymization technology, then people may be more willing to share their data. Finally, the effectiveness of every big data technology depends on the quality of data input. To make health code effective, it is estimated that three-quarter of the population needs to register. The adoption rate appears to be an issue for Singapore where only 20% of 5.7 million population has registered for their contact tracing app one month after the introduction. The low adoption rate seems to compromise the effectiveness of this technology as the number of cases keeps rising.[9]

[8]See the World Bank data: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=CN
[9]See WSJ April 22 article, "Singapore Built a Coronavirus App, but It Hasn't Worked So Far".

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4 Conclusion

Pandemics such as COVID-19 inflicts enormous costs to the economy. Policymakers are facing the impossible choice between saving human lives and saving the economy. This paper examines the effectiveness of big data technology in addressing the pandemic dilemma using a large experiment of health code in China. Exploiting the staggered implementation of health code in 322 cities in China, I find that the introduction of this technology significantly revives economic activities while keeping the outbreak under control. I find that the benefits of this big data technology seem to outweigh its potential costs on privacy. Given the medical cure of the disease is still elusive, big data technology presents a promising solution to the pandemic dilemma between lives and livelihoods.

This paper argues that big data technology addresses the key amplifier of the economic costs caused pandemics, that is, information friction. This result has many important implications because information friction lies in the hearts of many social and economic problems. By leveraging the enormous amount of data produced in our digital age, big data technology can alleviate this friction and provide better solutions for many existing problems. How to harness the power of big data technology without threatening our privacy will be a big question in the post-COVID-19 world.

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Precaution, social distancing and tests in a model of epidemic disease[1]

Francesc Obiols-Homs[2]

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I develop an extension of a canonical epidemiology model in which the policy in place determines the probability of transmission of an epidemic disease. I use the model to evaluate the effects of isolating symptomatic individuals, of increasing social distancing and of tests of different quality: a poor quality test that can only discriminate between healthy and infected individuals (such as polymerase chain reaction 'PCR' or Rapid Diagnostic Test), and a high quality test that is able to discriminate between immune and vulnerable healthy, and infected individuals (such as a serology test like Neutralization Assay). I find that isolating symptomatic individuals has a large effect at delaying and reducing the pick of infections. The combination of this policy with the poor quality test represents only a negligible improvement, whereas with the high quality test there is an additional delaying and reduction in the pick of infections. Social distancing alone cannot achieve similar effects without incurring in enormous output losses. I explore the combined effect of social distancing at early stages of the epidemic with a following period of tests and find that the best outcome is obtained with a light reduction of human interaction for about three months together with a subsequent test of the population over 40 days.

1 This investigation was conducted under confinement, thus I thank M. Àngels Fernández, and Magalí and Marçal Obiols-Fernández for their interest, patience and excellent company. I also thank Raül Santaeulàlia-Llopis and Charles Wyplosz for helpful comments and suggestions. The usual disclaimer applies.

2 Associate Professor of Economics, Universitat Autònoma de Barcelona, MOVE and Barcelona GSE.

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1 Introduction

As of April 2020 the rapid expansion of Covid-19 is affecting a large fraction of the population all over the world, with thousands of positive tested cases and of deaths in many countries. Precise statistics of the effects of the epidemic are scarce and display substantial variance over time in a given country and also across countries. Perhaps these differences in the available information reflect specific aspects of the local realities and explain the variety of policies undertaken in different countries. The current policies mainly consist of testing the population, of social distancing to reduce human interaction and the possibility of transmission, and in isolating for some time presumably ill individuals and regions with a high density of infected population. The purpose of this paper is to propose a model suitable to study the effects of these policies on the dynamics of the the epidemic and to take into account the impact on output.

The model I propose follows a similar approach to other recent models such as Atkeson (2020), Eichenbaum, Rebelo and Tranbandt (2020), Berger, Herkenhoff and Mongey (2020) and Casares and Khan (2020). These models are based on the relatively simple SIR model of immunology (Kermack and McKendrick, 1927) and consider specific characteristics about the transmission mechanisms of the disease to obtain predictions for the number of deaths, number of infected and recovered individuals and on other economic outcomes. My approach and type of question is closer to Berger, Herkenhoff and Mongey (2020) and to Piguillem and Shi (2020): individuals can be infected, with and without symptoms, and healthy, with immunity or not, and the disease can only be transmitted from an infected individual to a healthy but vulnerable one. The policies in place determine endogenously the probability of transmission of the disease and therefore have an impact on the mass of agents that participate in social and production activities, hence on output.

In the model in this paper I explicitly take into account the severity of social distancing, which takes the form of a reduction in the number of contacts among agents that participate in the market activity.[1] I also take into account the effect of the duration of social distancing. These are important margins because in the model there are "industrial" occupations that observe severe losses with the reduction in the number of contacts among workers, and "services" occupations that can be completed from home with only a small loss of output. As an alternative to the previous policy I study a simple precautionary regime: symptomatic individuals are not tested but kept in isolation for 14 days. Finally I also consider the effects of two different test: test 1 is a poor quality test that is only able to discriminate between healthy and infected agents. This is the outcome of a polymerase chain reaction

[1] Casares and Khan (2020) also take this approach in a related model. Chen and Qius (2020) conduct an empirical evaluation of various non-pharmaceutical interventions for 9 countries using a dynamic-panel SIR model.

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(PCR) or a Rapid Diagnostic Test (RDT) test. With this technology one needs to test repeatedly a large fraction of the population, since healthy agents participate every period in market activities and a fraction of them are likely to become infected. Then I look at test 2, a perfect test which is able to tell the type of healthy individual and the length of the infection in case the individual is infected. This second test is closer to serology testing such as Neutralization Assay that looks for antibodies in the blood of the patient.[2]

I evaluate the effects of the previous policies in a quantitative exercise using a calibration that is similar to the papers in this literature. I find that a simple policy such as precaution is able to delay the pick of infection under *laissez-faire* (or *unawareness*) from day 41 to day 262, and from almost 16% to about 3.6%.[3] Perhaps surprisingly I find that adding the effect of test 1 to precaution is nearly irrelevant, at least at relatively low levels of coverage such as 1% of the population, but also at a level of 3%. Only the combination of precaution with test 2 delays some additional 83 days the pick of infection which then affects 2.2% of the population. Furthermore, with a 3% coverage in this last combination of policies the epidemic does not take place. To obtain an infection rate below 1% using test 1 to control for the disease it would be needed to test 15% of the population over 18 months. These results suggest that there are dramatic differences in the effects of using test type 1 and test type 2. This finding is relevant because in most countries the implementation of tests type 1 is the main strategy (together with confinement) to fight against Covid-19 (as of April 19th Germany is the first European country to start large-scale coronavirus antibody testing). Finally, I find that a social distancing policy consisting in reducing interactions by 10% has positive but very limited effects under *unawareness*, but it is able to also prevent the epidemic from taking place under precaution and its combination with tests. In terms of the effects on output, social distancing is substantially more costly (output falls by more than 50%) than precaution plus test 2 (less than 2% of output with a coverage of 1%, and literally no loss with a coverage of 3%).[4]

Not all is good about the combination of precaution and test 2: the problem is that either the population is constantly tested, or as soon as tests cease the infection is

[2]For a detailed exposition of different types of test see *"Serology-based tests for COVID-19"* from the Center of Health Security, which is updated twice a week and can be found here https://www.centerforhealthsecurity.org/resources/COVID-19/serology/Serology-based-tests-for-COVID-19.html.

[3]A result along this lines is also found in Berger, Herkenhoff and Mongey (2020). In the model it is assumed that the policy has a 100% compliance. The *laissez-faire* can be seen as the lower bound of the effects when compliance decreases.

[4]These results are similar to those in Piguillem and Shi (2020). Their model allows for time varying intensity of quarantine, which takes the form of a reduction in the fraction of the population taking part in the economic activity and they do not consider tests type 1. Here in stead, social distancing does not only affect endogenously the fraction of the population that participates in economic activities but it also limits the extent of the activity, i.e., the number of contacts.

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likely to start again in the near future. The reason is that with test 2 the fraction of healthy and immune individuals is too small to provide "herd immunity" (that is, the mass of immune individuals is too small to prevent the disease from spreading again). Hence, test 2 has benefits in the short run but it may have large costs at a longer run. A severe social distancing policy will produce similar effects, to which in addition one has to add a dramatic output loss. However, a "light" social distancing may have small costs in the sort run but larger benefits in the future. In view of this I conduct a grid search to investigate the effectiveness of the combination of policies. In this final exercise I take into account the cumulative deaths, the infection rate (to control for the possible collapse of the public health network), the level of healthy and immune individuals to meet a herd immunity threshold and the cost of output. My results suggest that it is best to implement a light social distancing to reduce interactions by about 3-7% over 90 days, and then continue with test 2 covering 3% of the population for additional 40 days.

The previous policy recommendation must be taken with caution, as it rests on the fact that preferences are not lexicographic in the number of current deaths and on the fact that an effective cure or vaccine to fight Covid-19 does not seem to be available over the next 12-18 months.[5] My results suggest that without a more effective medical technology the optimal policy reduces the number of deaths by about 20% in the short and in the long run, but unfortunately there is a medium run period in which the cumulative deaths are almost as large as under *laissez-faire*.

The rest of the paper is organized as follows. Section 2 describes the environment, Section 3 explains health distribution dynamics and the various policies, Section 4 introduces output losses, Section 5 conducts the quantitative exploration and Section 6 offers additional discussion and suggestions for further research. There is an Appendix with a few additional results from a sensitivity analysis.

2 Environment

Time is discrete and there is a unit mass of agents. In any given period agents can be in one of the following four states: healthy and immune, healthy but vulnerable, infected with symptoms and infected but asymptomatic, denoted respectively i, v, s and a. The distribution of health status in a period t can be represented by a vector $H_t = (i_t, v_t, s_t, a_t)$ and it satisfies:

$$i_t + v_t + s_t + a_t = 1. \tag{1}$$

For future reference it is convenient to introduce M_t as the mass of agents that participate in market and social activities. ϕ_t denotes the the fraction of healthy

[5] Precisely the lack of a powerful remedy makes this sort of exercise interesting. See however Eichenbaum et al. (2020) and Gonzalez-Eiras and Niepelt (2020) where the possibility of a decisive medical improvement is taken into account.

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agents, thus $\phi_t = i_t + v_t$ and the mass of infected agents is given by $1 - \phi_t$. It is assumed that healthy and infected but asymptomatic agents may die at an exogenous rate $1 - \eta$, and that agents infected with symptoms die at a rate d (that is, d is the *fatality rate*). The population is constant over time because dead agents are replaced with newly born healthy but vulnerable agents.

The nature of the disease is such that the true health state may not be known to the agent. In terms of the transmission of the disease the interaction of two individuals of the same healthy/infected type is inconsequential. Only when an agent type v interacts with an agent type s or type a the disease may be transmitted.

Let $\pi_{n,m}$ denote the probability that after a meeting between an agent type n and one type m (with $n, m = i, v, s, a$) there is a change in the health status of the agent n. For instance, $\pi_{i,m} = \pi_{m,i} = 0$ for all m, and by the same token, $\pi_{s,m} = \pi_{a,m} = 0$ for all m. It is clear however that $\pi_{v,s} = \pi_{v,a} > 0$ (and of course, that $\pi_{s,v} = \pi_{a,v} = 0$). This simply reflects the fact that only the interaction between a healthy but vulnerable agent and an infected agent is able to change the health status of the initially healthy agent. Since only $\pi_{v,s} = \pi_{v,a}$ are strictly positive I simplify notation and denote them by π.

In "normal" times (when economic activity and social interaction takes place under no constraints) each individual maintains N consecutive meetings with other individuals.[6] I denote by p_n the probability of a change in the health status of an agent type $n = i, s, a$ after N random consecutive meetings. Given the previous assumption it follows that $p_i = p_s = p_a = 0$. Given this, let p_t be the probability corresponding to the v type in period t, which satisfies

$$p_t = L(N; H_t). \tag{2}$$

The function $L(\cdot)$ depends on the policy intervention (if any), on the number of meetings and on the distribution of health in the group that meet. The purpose of the paper is to look the effects of several configurations for $L(\cdot)$. Finally, I assume that whether the agent is infected or not is materialized at the end of the period, and in case an agent is infected the symptoms are revealed only with probability ρ.

3 Health distribution dynamics

The time-line of an infection process is as follows. Suppose that a healthy but vulnerable agent gets infected in a period t. I assume that the disease process is deterministic in that conditional on surviving, the infected agent faces an horizon of t_0 periods until recovery. That is, during the t_0 periods of infection the probability

[6] Consecutive meetings simplify a bit the exposition and description but are not fundamental for the results.

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of dying is constant and equal to d. If the agent survives the t_0 periods then it is assumed that she is totally recovered and becomes healthy and immune. In that state the probability of dying is $(1-\eta)$, the same as for the other healthy and for the infected but asymptomatic agents.

The dynamics of health status given an initial H_1 are described below. In particular, it holds that

$$i_{t+1} = i_t\eta + s_t^1(1-d) + a_t^1\eta, \tag{3}$$

where s_t^1 and a_t^1 denote the mass of infected agents that in period t are one period away from recovery. The mass of s agents evolves according to

$$s_{t+1}^j = s_t^{j+1}(1-d), \tag{4}$$

for $j = 1, ..., (t_0 - 1)$, with

$$s_{t+1}^{t_0} = v_t \cdot p_t \cdot \eta \cdot \rho \tag{5}$$

and where $s_t = \sum_{j=1}^{t_0} s_t^j$. The evolution of the a_t is nearly identical, with

$$a_{t+1}^j = a_t^{j+1}\eta, \tag{6}$$

for $j = 1, ..., (t_0 - 1)$, with

$$a_{t+1}^{t_0} = v_t \cdot p_t \cdot \eta \cdot (1-\rho) \tag{7}$$

and with $a_t = \sum_{j=1}^{t_0} a_t^j$ and such that Equation (2) holds. Finally, under the assumption that healthy but vulnerable agents participate it holds that

$$v_{t+1} = 1 - i_{t+1} - s_{t+1} - a_{t+1}. \tag{8}$$

Notice therefore that v_{t+1} includes all v_t agents that survive from t to $t+1$, plus all the agents in every health state that died between t and $t+1$.

I now describe the configuration of $L(\cdot)$ under several canonical policies.

3.1 Unawareness: all agents participate

Even if the symptoms of Covid-19 are revealed, in many cases they consist of a slight increase in temperature and some coughing. I make the assumption that these symptoms are wrongly taken as symptoms of a common cold and thus all agents keep interacting and participating in the N meetings. Under this assumption the mass of agents that participate in the meetings is such that $M_t = 1$ in all periods and thus

$$p_t = \pi(1-\phi_t)\sum_{i=1}^{N}\phi_t^{i-1}. \tag{9}$$

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3.2 Precaution: symptomatic agents do not participate

Assume that once the symptoms are revealed, the agent is confined for t_0 periods. This assumption has dynamic effects for the size of the group that participate and on the probability p_t. In particular, the mass of agents that participate in the meetings satisfies:

$$M_t = \phi_t + a_t, \tag{10}$$

and the probability p_t satisfies

$$p_t = \pi \frac{a_t}{M_t} \sum_{i=1}^{N} \left(\frac{\phi_t}{M_t} \right)^{i-1}. \tag{11}$$

3.3 Testing 1: agents tested to be infected do not participate

A first policy to consider consists of randomly testing individuals among those that do not show symptoms (those with symptoms are not tested but are prevented from participating during t_0 periods, as under *precaution*). This means that all non tested asymptomatic agents, plus all tested to be not infected, will participate. This policy can be implemented in two different ways: by testing a constant fraction of the asymptomatic population, and by making a fixed number of tests. These policies entail repeating the test to a fraction of the population that has been tested before, but they may be appropriate if it is difficult to verify the authenticity of tests realized in the near past. This policy may be the only one available at early stages of the epidemics when the available tests can only discriminate between infected and non infected agents.

3.3.1 Testing a constant fraction of the asymptomatic population

In this case the asymptomatic population in every period is $\phi_t + a_t$, and after the test the population that participates is given by

$$M_t = \phi_t + a_t(1 - \tau). \tag{12}$$

The probability of infection for a healthy but vulnerable agent satisfies

$$p_t = \pi \frac{a_t(1 - \tau)}{M_t} \sum_{i=1}^{N} \left(\frac{\phi_t}{M_t} \right)^{i-1}. \tag{13}$$

3.3.2 Realizing a constant number of tests

Let τ represent the number of tests which are devoted to check the asymptomatic population. If A_t is the asymptomatic population in period t, then the probability

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of being checked is $\tau_t = \tau/A_t$ if $\tau \leq A_t$ (and $\tau_t = 1$ otherwise). The mass of agents participating in the market and the probability of infection for a healthy but vulnerable agent are given respectively by

$$M_t = \phi_t + a_t(1-\tau_t) \tag{14}$$

and

$$p_t = \pi \frac{a_t(1-\tau_t)}{M_t} \sum_{i=1}^{N} \left(\frac{\phi_t}{M_t}\right)^{i-1}. \tag{15}$$

3.4 Testing 2: A perfect test

Suppose now that the available test is able to discriminate among healthy and immune, healthy but vulnerable, and the periods of infection for those that are detected to be infected. In this sense the test is perfect and its results last for as long as the agent is alive. Thus some of the repeated tests that were conducted under the previous testing 1 can be more efficiently used to check the state of not previously checked agents.[7] I will proceed under the assumption that there is a fixed number of tests to be done in every period. I will also assume that infected agents with symptoms are not tested but are not allowed to participate for t_0 periods as soon as the symptoms appear.

As in the case above the mass of asymptomatic agents in any period t is given by $i_t + v_t + a_t$. How many of them would need to be tested in the current period? The answer is of course all those that have not been tested before, thus one needs to keep track of the previously tested agents in each possible group. To facilitate the exposition let $\tilde{n}_t$ be the mass of agents type $n = i, v, a$ that are alive in t and that have been tested before t. Let also $\bar{n}_t$ be the mass of agents type $n = i, v, a$ that are tested for the first time in t. With respect to the i have that:

$$\tilde{i}_t = (\tilde{i}_{t-1} + \bar{i}_{t-1})\eta + s^1_{t-1}(1-d) + (\tilde{a}^1_{t-1} + \bar{a}^1_{t-1})\eta, \tag{16}$$

where it is understood that s^1_t have a medical certificate which acts like the test. Agents that were tested v in the previous period would need to be tested again (since they interacted and it is not know if their type changed). The only ones that will not show up to be tested are the ones that ended the previous period with symptoms. Hence we have that it is as if

$$\tilde{v}_t = v_{t-1} \cdot p_{t-1} \cdot \eta \cdot \rho. \tag{17}$$

[7]The fundamental aspect of the test is that it discriminates the type of healthy individual. The fact that the test also tells the maturity of the infection of infected individuals only simplifies to keep track of them.

With respect to the agents that were detected to be infected but asymptomatic it holds that

$$\tilde{a}_t^j = (\tilde{a}_{t-1}^{j+1} + \bar{a}_{t-1}^{j+1})\eta, \tag{18}$$

for $j = 1, ..., (t_0 - 1)$, with

$$\tilde{a}_t^{t_0} = \tilde{v}_{t-1} \cdot p_{t-1} \cdot \eta \cdot (1 - \rho) \tag{19}$$

and with $\tilde{a}_t = \sum_{j=1}^{t_0} \tilde{a}_t^j$.

Hence the mass of agents that has not been tested is given by

$$\tilde{A}_t = (i_t - \tilde{i}_t) + (v_t - \tilde{v}_t) + (a_t - \tilde{a}_t) \tag{20}$$

and thus the probability of being tested is given by

$$\tau_t = \frac{\tau}{\tilde{A}_t} \tag{21}$$

if $\tau \leq \tilde{A}_t$ and $\tau_t = 1$ otherwise. The mass of newly tested agents in a period t is given by $\bar{i}_t = \tau_t(i_t - \tilde{i}_t), \bar{v}_t = \tau_t(v_t - \tilde{v}_t)$ and $\bar{a}_t = \tau_t(a_t - \tilde{a}_t)$. It follows that the mass of agents that participate in period t is given by

$$M_t = \phi_t + (a_t - \tilde{a}_t - \bar{a}_t), \tag{22}$$

and the corresponding probability satisfies the usual equation:

$$p_t = \pi \frac{a_t - \tilde{a}_t - \bar{a}_t}{M_t} \sum_{i=1}^{N} \left(\frac{\phi_t}{M_t} \right)^{i-1}. \tag{23}$$

3.5 Social distancing

For each of the previous policies the model is able to encompass social distancing by assuming that agents are able to materialize only $n < N$ interactions. Hence the value of n can be seen as the severity of social distancing.

Notice that with the exception of *unawareness* in which $M_t = 1$ in all t, in the other scenarios M_t is the sum of the mass of healthy agents plus different fractions of infected but asymptomatic agents.

4 Output loss in an epidemic episode

A relevant effect of an epidemic episode is observed on the number of workers available to work. In terms of the different scenarios considered above this restriction

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may have no effect, in the unawareness regime, or represent a more severe limitation in the precaution regime and when tested infected agents are prevented from participating.

The model does not distinguish between social meetings, that are valuable in terms of utility but not productive in terms of output, and productive meetings that are mainly valuable because of the output they make possible. To simplify matters it will be assumed that all interaction is related to production, thus the N meetings involve commuting between home and the workplace and interacting with other peers in order to complete a number of tasks.

A policy such as social distancing introduces an additional output effect through the fact that the actual number of meetings, n, will be smaller than the "normal" one, N. That is, for a productive agent I let the value of her output be given by $yf(n)$ where $f(n)$ is non decreasing in n and *i)* $f(0) = 0$, and *ii)* $f(N) = 1$ (this is simply a convenient normalization). With this in mind it is clear that not all occupations suffer the same loss in the face of the same reduction in n. For instance, in the services sector many workers are able to keep working from their homes and their output is very close the "normal" output even if n is severely reduced. However, production in the industrial and in the primary sectors are nearly impossible to be moved at home, so even a small reduction in the number of interactions is able to represent a large reduction in output. I try to take into account this diversity and assume that there are two types of occupations, in the "services" sector and in the "industry" sector, such that $f_j = (n/N)^{\alpha_j}$ for $j = s, i$ and with $\alpha_s \leq 1$ and $\alpha_i \geq 1$. The proportion of workers in each sector is denoted respectively S and $(1 - S)$, and since all workers are alike in terms of their probability of infection, the same proportions prevail among healthy and among ill individuals. With these assumptions output in period t at the aggregate level is given by

$$Y_t = SM_t y_s (n/N)^{\alpha_s} + (1 - S)M_t y_i (n/N)^{\alpha_i}, \tag{24}$$

where M_t is again the mass of agents that participate and where $y_{s,i}$ is the output per worker in sector s, i.

5 A quantitative exploration

5.1 Calibration

In the model a period t is a day. I need values for $N, \pi, \eta, d, t_0, \rho, S, y_s, y_i, \alpha_s$ and α_i. A few of these parameters can be obtained from the literature, but unfortunately there is substantial uncertainty about their true values. The starting distribution is such that there is a fraction 0.001% of infected individuals (the rest are all healthy but vulnerable).

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The value of η is the survival rate in "normal" times on a daily basis. For the US economy life expectancy is about 78,54 years, so $\eta = 0.999965$ is a reasonable approximation. There is a large variation across countries in the case fatality rate of Covid-19 (from above 13% in Algeria and Italy to as low as 0,12% in Qatar). There is evidence that age and pre-clinical condition are relevant. In the US the case fatality rate is reported to be 5.11%.[8] As a starting point I take $d = 3.4\%$ as a reasonable compromise. The recovery period t_0 is taken to be 14 days (but in several countries the recommendation before returning to activity is as large as 30 days). Regarding the fraction of infected individuals that show up the symptoms, Heneghan, Brassey and Jefferson (2020) suggest that based on the available evidence a fraction between 5% and 80% of tested infected individuals are asymptomatic.[9] As a starting point we take $\rho = 0.8$ hence the disease is manifested in 80% of the infected individuals. With respect to the transmission rate of the infection π, Berger, Herkenhoff and Mongey (2020) assume it is 0.0091 in their model with periods of 14 hours. I take this value from that paper and in the current model with periods of 24 hours I fix $\pi = 0,0156$ (this figure is similar to that in Casares and Khan (2020) in their calibration for Spain).

I use data from BLS from 2018 (the last year for which the required information is available) to calibrate S, y_s and y_i.[10] In 2018 there were 161.037,7 jobs in the U.S. (in thousands), and the value of total output was 33.241,9 Billions in chained dollars of 2012. I take employment and output in the "services" sector as including Services-providing excluding special industries minus: wholesale and retail trade, transportation and warehousing, Health care and social assistance and minus leisure and hospitality. The rest of categories are included in the "industry" sector. The fraction of jobs in the "services" sector is approximately 0.442, so I fix $S = 0.442$. The annual value of output per worker in "services" and "industry" is approximately 0.2202 and 0.1954 respectively (in Millions of chained dollars of 2012). On a daily bases this means that $y_s = 603.28$ and $y_i = 536.34$ Dollars. Finally, I fix the "normal" number of interactions to $N = 30$ and in the examples with tests 1.1, 1.2 and 2 I evaluate several options for τ.[11]

We now evaluate several counterfactual situations.

[8]See the evidence in Oke and Henghan (2020) which can be found here https://www.cebm.net/covid-19/global-covid-19-case-fatality-rates/.

[9]This can be found here https://www.cebm.net/covid-19/covid-19-what-proportion-are-asymptomatic/.

[10]The data in these calculations comes from Tables 2.1 and 2.2 from BLS, which can be found in https://www.bls.gov/emp/tables/output-by-major-industry-sector.htm and https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm.

[11]The value for N is similar to 25 used in Casares and Khan (2020).

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5.2 Counterfactual policies

I evaluate the five different scenarios under the baseline calibration discussed in the previous section and over a period of 365 days. To facilitate the exposition I introduce several figures for the fraction of infected and output effects. Figure 1 shows the evolution of the fraction of infected individuals. When the infection evolves under no control it reaches a maximum infection rate of 15.39% in 41 days, and then slowly declines: 200 additional days are needed in order to observe an infection rate below 1%. Compared to this case, the other policies provide: 1) a much slower increase in infections, 2) a much smaller maximum of infections, and 3) a slower recovery. It is interesting to see that even a simple policy such as *precaution* (i.e., stay at home if you do not feel well or if your temperature is higher than normal), represents a substantial improvement with respect to unawareness. Tests 1.1 and 1.2 are nearly identical (hence we wont distinguish between them in the following exercises) and perform slightly better than the *precaution* scenario. Test 2 is clearly better: it delays substantially the pick of infections which in addition is only slightly above 2%. Still, this test must be done every day and yet at a 1% level it seems unable to keep the infection rate below 1%.

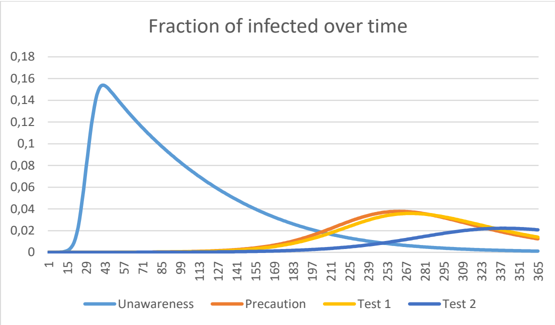

Figure 1: Baseline outcomes.

Figure 2 plots the effects for the infection rate of increasing the number of tests to 3% of the population. This policy has no effect on scenarios 1 and 2 (*unawareness* and *precaution*), but it delays slightly the pick of infections under test 1 (test 1.1 and 1.2 continue to be indistinguishable). Test 1 is now able to lower the infection pick to 3.1% after 297 days (before it reached 3.6% after 270 days). Increasing the number of tests to the 3% of the population has its largest effect with test 2. In this case the fraction of infected is not zero, but it remains always below 0.0021%. Thus a sufficiently large coverage with test 2 in the initial periods has a positive

effect in the periods that follow. How much larger should be the coverage under test 1 to obtain this sort of results? Testing 15% of the population delivers a pick of infection of 0.92% after 551 days. This result suggests that there are dramatic differences between the two types of tests.[12]

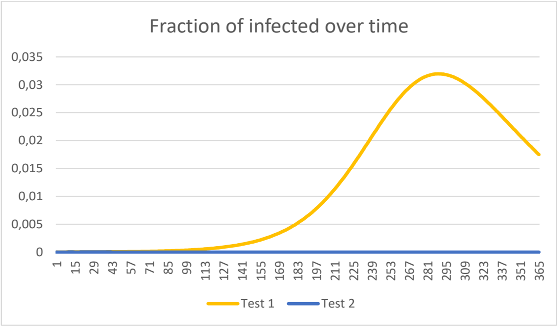

Figure 2: Increasing the fraction of tests, $\tau = 3\%$.

Figure 3 plots the effects of social distancing when all agents participate: it is assumed that the number of contacts is reduced from day 1 to the end of the year to $n = 20$, which represents a reduction of 33.3% of interactions. It is clear that social distancing delays a bit the pick of infections and that it is slightly smaller. This effect comes directly from the smaller p_t. In the other scenarios there is an additional effect, since not only the probability but the mass of participants will change. As an example of these effects Figure 4 shows the probability under *precaution* for various n's, and Figure 5 shows the corresponding ia_t for the first few periods. In the beginning participation declines until the first generation of healthy and immune starts participating. After this point the effect of n on p_t explains the subsequent dynamics: with a "light" social distancing participation continues to decline and the fraction of infected but asymptomatic continues to increase. However, for a sufficiently severe social distancing it happens the opposite, so after a few more periods it is as if only healthy agents participate.

Figure 6 represents the evolution of infections under *precaution* and the two tests (and assuming that the tests cover up to 1% of the population every day). The effect of social distancing appears to be dramatic in all cases, even when only *precaution* is implemented. As before the evolution of infection is better under the implementation of test 2, but the pick of infections is in all cases below 0.0018%.

[12]In the Appendix I report the results of a sensitivity analysis. My results suggest that the differences between test 1 and test2 tend to decrease as t_0 is increased, but test 2 always performs better than test 1 to control the spread of the disease.

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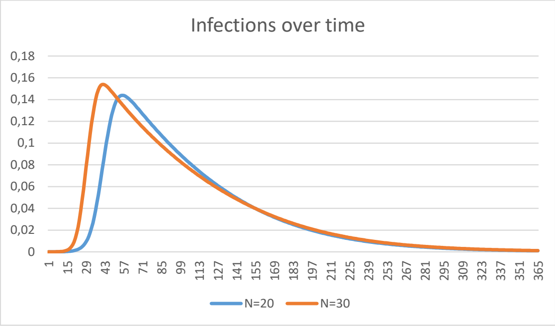

Figure 3: Introducing social distancing under *unawareness*.

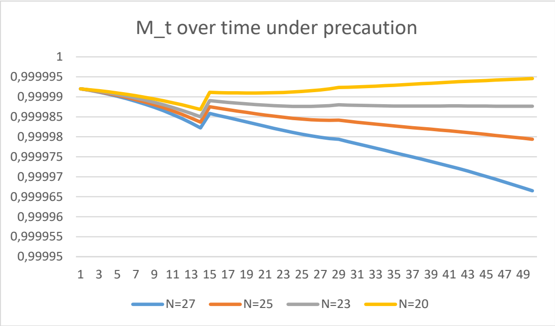

Figure 4: Participation (M_t) with social distancing.

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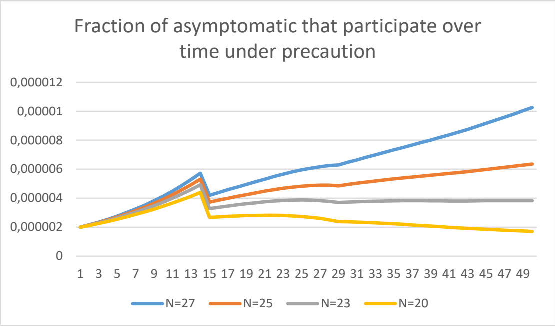

Figure 5: Infected asymptomatic that participate with social distancing.

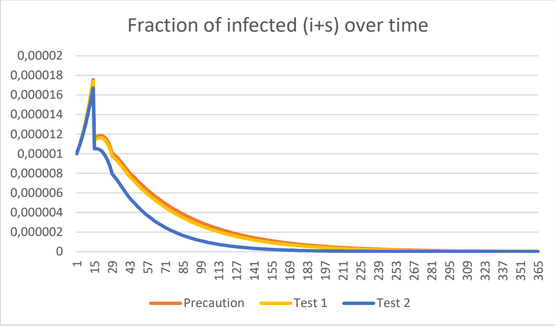

Figure 6: The effect of social distancing with precaution and tests.

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I now look at the output effects in each scenario under the previous policies. Figure 7 represents the level of output relative to the case of no epidemic taking place, so that the output loss in every period is the distance from 1. When all agents participate there is of course no loss, but in the *precaution* and in test 1 the losses can be as large as 3% of daily output. Under test 2 the loss is delayed to the future and it is only about 1.8% (the tests cover again 1% of the population). When the fraction of tests covers 3% of the population then test 1 is able to reduce losses to 2.5%, and not surprisingly, under test 2 there are essentially no losses (see Figure 8). I finally look at the effects of social distancing. It is clear in Figure 9 that reducing n by 1/3 has a dramatic effect on output, which falls below 50% of its "normal" level. In terms of output losses *precaution* is the worst scenario and both tests 1 and 2 show similar effects in the beginning. These results suggest that there is a clear trade-off between the evolution of the infection and the number of deaths, and the evolution of output.

The large negative effects on output are likely to disappear as soon as social distancing ends and n returns to its normal level. If we request the infection rate be declining and no larger than 1% as the threshold level to return to normal levels of activity, then under *precaution* and under all tests the return to normal activity happens after t_0 periods. However, the mass of healthy and immune agents is rather small, so without further actions the outcomes in terms of infection $(s_t + a_t)$ fall pray again of the epidemic disease. This is shown in Figure 10. It is instructive to look at the unawareness case, since in this scenario social distancing has positive but limited effects. Figure 11 shows that at the end of social distancing the fraction of infected grows again, but it rapidly declines. The reason is that in this scenario, the fraction of healthy and immune individuals is large. Figure 12 shows the dynamics of healthy and immune in each scenario. This result suggests that a successful policy to implement a gradual return to normal levels of activity should not only request a low fraction of infected, but also a large fraction of immune.

The results of the previous exercises suggest that relaying on a test like test 2 may be a very effective policy to limit the number of deaths and to preserve the economy in case of an epidemic. This policy requires to test a large fraction the population from the very beginning and over time, which may not be feasible specially at early stages of the episode. Furthermore, under this policy it is likely that a large fraction of the population remains healthy but vulnerable, which means that the population remains exposed to new episodes of the same disease in the near future. This is a dynamic aspect of the whole process that needs to be taken into account. On the other hand with a "light" social distancing strategy the fraction of healthy and immune individuals grows rapidly, but it has an enormous cost in terms of deaths and output losses. Social distancing therefore has costs in the short run but benefits in the long run, exactly the opposite of massive tests. It seems therefore that a successful combination of tests and the severity of social distancing could minimize

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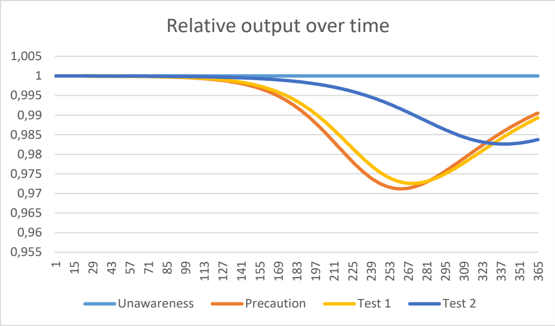

Figure 7: Output relative to no epidemic output, baseline calibration.

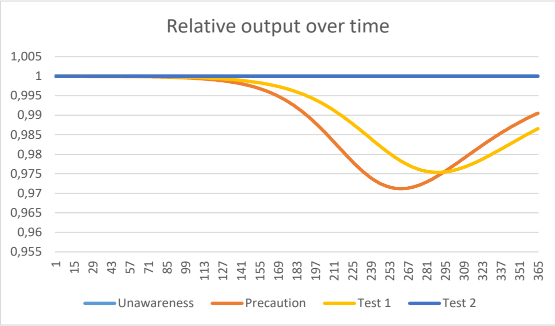

Figure 8: Output relative to no epidemic output with a larger number of tests.

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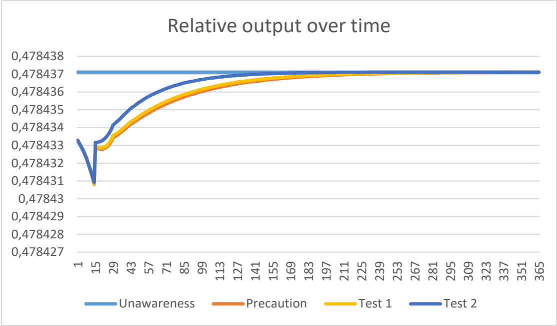

Figure 9: Output relative to no epidemic output under social distancing.

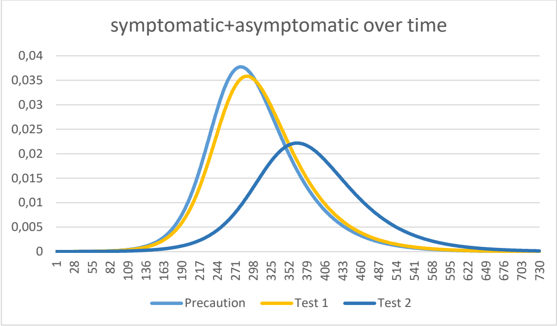

Figure 10: Infection dynamics with an early end of social distancing.

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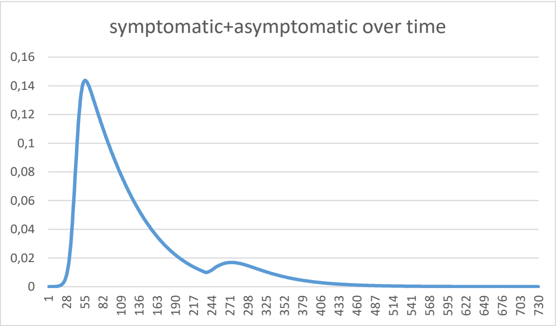

Figure 11: Infection dynamics with an early end of social distancing under *unawareness*.

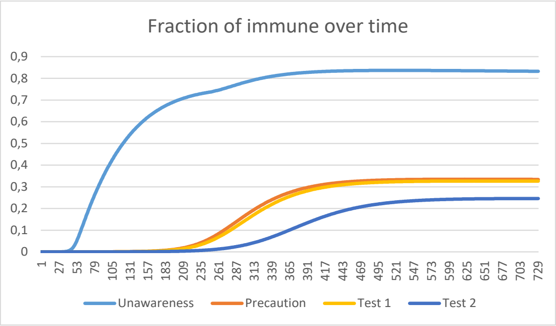

Figure 12: Dynamics of the fraction of immune with an early end of social distancing.

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loses in the short run and maximize benefits in the long run.

I investigate this issue by combining social distancing over the first t_1 periods followed by testing the population for several additional periods. That is, I consider several lengths of social distancing (a larger t_1 period), combined with different levels of its severity (smaller n), and with several values for τ to start being applied from $t_1 + 1$ onwards. It is not obvious how to evaluate the outcomes of the different combinations. I therefore focus the attention on the cumulative deaths due to the infection and the policy in place, the fraction of the population that is healthy and immune at the time of ending social distancing, and on the average output loss per day. I simulate the economy until the mass of agents that participate is close to 1, the no epidemics level. This is organized as a grid search problem, in which the grid is $t_1 = 14, 21, 28, ..., 90, 120$, (weeks, and months at the last two horizons), $n = N - 1, ..., N - 10$ (remember that in the baseline calibration $N = 30$) and $\tau = 0.1, ..., 0, 3$ in increments of 0.05. The fraction of hi at the end of social distancing is a critical variable because it may prevent the disease to spread again. The threshold level of group immunity that prevents the spread of the disease is called the Herd Immunity Threshold (HIT). For instance, the HIT for *influenza* is between 33%-44%, and that of SARS is between 50%-80%.[13] As an approximation, I will request a level of at least 40% for a policy to successfully end the confinement without suffering a new epidemic immediately afterwards.

Rather than reporting a table with all the results it is more interesting to describe three regularities that emerge from this exercise:

R1: The more sever is social distancing (the smaller is n), the larger is the number of weeks that is needed to achieve $hi(t_1) \geq 40\%$. It does not seem possible to achieve the previous threshold level before 70 days, and very often requires 90 or 120 days.

R2: Cumulative deaths decrease with the severity of social distancing (the smaller is n) and given n they increase in the weeks of social distancing, t_1. Furthermore, cumulative deaths decrease the larger is the fraction of the population that is tested. The positive effects of a larger coverage of tests offset the negative effects associated to "light" social distancing.

R3: Output losses are larger the more sever is social distancing (the smaller is n) and the larger is the period of social distancing (the larger is t_1).

These regularities are informative: R1 suggests that it is best to implement a "light" social distancing and R3 reinforces this by suggesting in addition a short period t_1. R2 points to the same direction, provided that there is a sufficiently large coverage of tests. Given the parametrization of the model, $n = 29$, $t_1 = 90$ and $\tau = 0.03$ delivers cumulative deaths of 0.23, a fraction of healthy and immune agents of 41.12% and an average output loss of 10.58% during the 130 days that

[13]See Biggerstaff et al. (2014) and Wallinga and Teunis (2004).

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it takes to return to normality.[14] From this combination of parameters it follows that a smaller t_1 decreases cumulative deaths slightly, but the fraction of health and immune decreases very strongly. If instead t_1 is increased, then $hi(t_1)$ increases above 50%, but cumulative deaths also go above 0.28. Decreasing τ has no effect on $hi(t_1)$, but it has a negative effect on cumulative deaths. If I consider in stead $n = 28$, with the same $t_1 = 90$ and $\tau = 3\%$, there is a small improvement in cumulative deaths (0.228) and a small decrease in $h_i(t_1) = 40.05\%$. However, in this case average output losses increase up to 18,40% (over the same 130 days). These seem to be the best policies, as with a more severe social distancing there is little to gain in terms of cumulative deaths, and a lot to loose in the fraction on healthy and immune and output. For completeness Figure 13 plots the outcome of the best policy (with a reduction of contacts of 0,33%,$n = 29$).

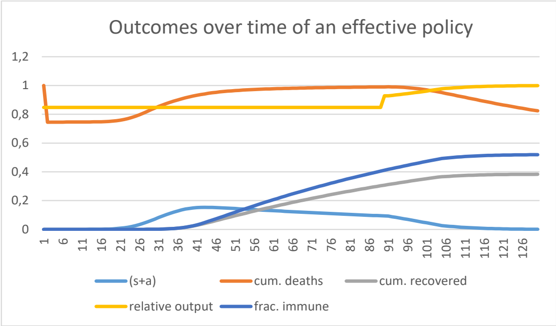

Figure 13: Combining social distancing and tests.

The series of cumulative deaths in Figure 13 measures cumulative deaths relative to the *unawareness* case, thus the avoided deaths with the policy are measured as the distance from 1. Figure 13 reveals that the optimal policy essentially substitutes deaths inter temporally: deaths are smaller in the short and in the long run, but in between they are nearly identical to the *unawareness*/no policy case.

In the calculations above the fraction of infected individuals that may attend a health center has been ignored. This is an important variable from the public health perspective because it may collapse the public health network. I computed the fraction of agents that are infected with symptoms and its maximum level is a bit above 11% in period 45/44. If I assume that only individuals with severe symptoms attend a hospital and that this fraction is equal to the fraction that will die ($d = 0.034$), then I find that the fraction of individuals in the hospital is about

[14]I checked that with $\alpha_s = \alpha_i = 1$ the average output loss per day reduces to 2.6%.

0.39% of the population. This is well below 1% which is some times taken as the rough threshold level at which public health may collapse. If, however, I assume that *all* individuals with symptoms will attend a hospital, then it is needed a reduction of about 73% in the number of contacts for 120 periods to obtain a mass of infected with symptoms of 1.1%. In this case cumulative deaths decrease to 0.034, but the fraction of healthy and infected at t_1 is only slightly above 0.8% and output losses are above 53%.

The previous policy recommendation rests on the fact that preferences are not lexicographic in the number of current deaths and on the fact that an effective cure or vaccine does not seem to be available over the next 6 months. Under these premises any policy exercise conducted in this literature needs to evaluate the trade-off between deaths today versus deaths tomorrow. This trade-off is in the hands of the policy-makers and it can only improve if there are decisive medical advancements.

6 Final remarks

This paper proposes a model to evaluate the effect of policy on health distribution dynamics and on output in an economy that is subject to an epidemic disease. An important conclusion of this research is that a simple precautionary policy may have very positive effects to delay and reduce the pick of infections and that poor quality tests only able to discriminate healthy from infected agents do not represent a significant improvement. The precautionary policy is as easy as to check the temperature of all individuals, keeping a registration of the possibly infected and isolating them for 14 days without further tests.

It is also necessary to emphasize that the use of tests that can only discriminate between infected and non infected individuals, like the widespread PRC, does not represent a noticeable improvement upon the precautionary policy when there are no other significant social distancing measures.

A third important result in this paper is that a high quality test is able to eradicate the disease in the short run provided that there is a large enough coverage of the population. The caveat of this test is that it is likely to leave the population without herd immunity, and thus the possibility of new epidemics in the future remains positive.

I use the model to characterize an effective policy mix. I find that the best combination of policies consists of a "light" social distancing for about three months followed with a large coverage of the population with a high quality test for additional 40 days.

The model in this paper can be improved along several dimensions, including a discrimination of the interactions between social and productive meetings and a

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precise characterization of individuals along the lines in the immunology literature (age, gender, pre-clinical condition). The current representation of output losses is appropriate if the effects of the epidemic extend over a few weeks. Clearly, however, with a longer horizon not only unemployment will rise but also productive capital will be destroyed. It would be very interesting to include the health distribution dynamics of the epidemic in an Aiyagari-Huggett model and evaluate more precisely the effects of taxes and subsidies. This investigation is left for future work.

7 Appendix

I describe here a few additional results of a sensitivity analysis.

1. The power of test 1. The following Table 1 summarizes the effects on the fraction of infected individuals as the coverage of test 1 is increased.

τ (%)	pick day	pick of infections (%)
4	301	3
5	312	2.8
10	394	1.8
15	551	0.91

Table 1: Test 1 with larger coverage.

2. The length of confinement, t_0. I check the effect of t_0 on the differences between test1 and test 2. The baseline value for t_0 is 14 days which is the recommendation of the WHO. I find that increasing t_0 to 18, 20 or 25 days reduces the differences between the tests in the magnitude of the pick of infection and it has small effects on the pick date. Still, the type 2 test performs better than the test type 1. The results are summarized in Table 2.

t_0	TEST 1 pick day	pick of infections (%)	TEST 2 pick day	pick of infections (%)
18	168	9.24	192	7.27
20	160	11.71	181	9.61
25	160	16.83	179	14.59

Table 2: The effect of larger t_0.

3. The effects of N and the power of tests 1 and 2: I described in the text that reducing the number of contacts has a positive effect to delay the pick of infections and to reduce it. With test 2 covering 3% of the population the epidemic does not take place when $N = 30$. When N is increased to 35, 40 and 50 I obtain that the pick of infections is delayed to day 380, day 226 and day 134 respectively, and

the pick of infections increases to 1.33%, 3.6% and 4.5% (also respectively). The epidemic is still far from the *unawareness* outcome, hence test 2 is still effective at a 3% coverage of the population. I repeat the same exercise under test 1. With 35, 40 and 50 contacts the pick occurs on days 189, 146 and 105, and reaches 6%, 8.15% and 10.9%. The results when only *precaution* is in place are pick occurring at days 177, 136 and 101 and reaching 6.54%, 8.6% and 11.24%. The conclusion is that the effect of a larger N goes in the expected direction, but it does not change the conclusion that test 2 is substantially more effective than test 1 to fight the epidemic. Since there are no differences in the probability of transmission of the infection across occupations changes in N do not change the shape of the optimal policy.

4. The curvature in the production function. In the calibration exercise I found that the value of a job in the "services" sector is only slightly larger than that in the "industry" sector. The effect of a reduction in n is different in the two sectors because of the curvature in $f(n)$. When I take the two functions simultaneously closer to the linear case output losses under the optimal policy decrease at an almost constant rate from 10.58% to 2.6%, when $\alpha_s = \alpha_i = 1$ and thus the loss in output is proportional to n/N. Changes in the curvature do not change the optimal combination of policies.

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Time for bed(s): Hospital capacity and mortality from COVID-19

Nathan Sussman[1]

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Public response to rising deaths from COVID-19 was immediate and, in many cases, drastic, leading to substantial economic and institutional costs. In this paper, I focus on mortality from COVID-19. Using cross-country evidence and controlling for a variety of contributing factors, I find that increasing the number of hospital beds has a significant and quite substantial impact on mortality rates. Hospital beds likely capture the capacity of ICU, laboratories, and other hospital-related equipment. Facing a potential second or third wave of infection following an exit from lockdown policies, countries short on medical infrastructures should increase them immediately.

1 Professor of economics, Director of the Centre for Finance and Development, Graduate Institute Geneva and CEPR Research Fellow.

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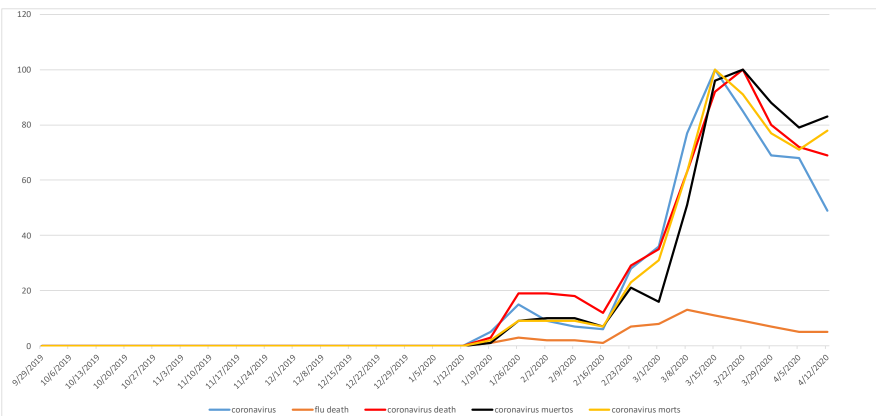
Introduction

As the COVID-19 was striking China in January 2020, most advanced Western economies exhibited complacency if not denial. By February 23rd, when Italy recorded its first deaths amid a rapid increase in cases, the government closed schools.[2] A week later, on February 28th, as deaths climbed to 20, Italy was the first European country to close workplaces. Media accounts suggest that policymakers reacted very strongly to fatality counts. In the U.K, with the Italian data available to policymakers, it wasn't until the first deaths on English soil that policy abruptly reversed course.[3] It seems that in weighing the economic cost of lockdowns, fatalities, rather than infections, played first fiddle. Case-fatality ratios became household expressions.

Figure 1

Public Interest in COVID-19 Deaths

(Google Trends: October 2019-April 2020)



Data from GoogleTrends on searches on the words: *coronavirus, coronavirus deaths*, in 3 major Western languages (**Figure 1**), exemplifies the rapidly rising public interest in coronavirus ***deaths***. It accelerated and peaked only when deaths hit close to home. Interestingly, the interest in deaths from COVID-19 is now relatively higher than the interest in the disease. As the economic toll of lockouts rises, the debate between those

[2] Data on policy response to COVID-19 us taken from Oxford University's policy response tracker. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

[3] For eample, see the denial by deputy chief medical officer on March 8th and the following day discussion in the media that already hints at reversal.

arguing for a faster resumption of economic activity and those in favor of continued lockdown centers on death rates. Some of the debate is focused on comparisons with mortality from seasonal flu and other respiratory illnesses.[4] However, ultimately, the fatality count is a significant factor in determining policy choices.

While epidemiologists and medical researchers are studying the factors that account for the death toll from the virus, the economists can test for contributing factors that can affect the policy discussion regarding the containment of the virus and its impact on the economy. In this paper, I focus on mortality from COVID-19. Using cross-country evidence and controlling for a variety of contributing factors, I find that increasing the number of hospital beds has a significant and quite substantial impact on mortality rates. Absent more detailed hospital infrastructure data, the number of beds likely captures also the availability of ICU units, testing facilities, laboratories, etc. This result substantiates a recent paper by Favero (2020) and the focus on hospital capacity constraints. Our analysis offers an interesting twist on the famous 'Reversal of Fortune' hypothesis (Acemoglu et al. 2002). In that paper, countries with higher mortality ended with inferior institutions. My findings suggest that countries that rank higher on the rule of law indices suffered more mortality, and countries with more effective governments had lower mortality.

The policy implications of this paper are that increasing hospital capacity reduces mortality in cases of highly contagious diseases. The indirect economic benefit of hospital beds' capacity in these situations is to attenuate a costly policy response that could also affect future institutional quality.

Methodology

Deaths versus Cases

In this paper, I study deaths from COVID-19. There is an ongoing debate on whether we should look at cases or deaths from COVID-19. Most websites record both and provide case-fatality ratios and case-per-capita ratios but not per capita death ratios. Since testing rates differ from country to country, the use of case-fatality ratios could

[4]Financial times March 30 https://www.ft.com/content/f3796baf-e4f0-4862-8887-d09c7f706553. Washingtom Post, April 10, https://www.washingtonpost.com/politics/2020/04/10/not-that-bad-or-not-that-high-how-advocates-return-normal-misrepresent-coronavirus-deaths/.

be misleading.[5] Arguably, the death count is more accurate. Moreover, for comparisons with past virus outbreaks, we can only use death rates as we do not have historical case data.

Mortality *rates* in country *i* (*Mi*) are a function of the incidence *rate* (*Ci*) times the case-fatality ratio:

$$(1) M_i = C_i * \left({}^{M_i}/_{C_i}\right)$$

The incidence of the disease is a function of variables that affect contagion. The case-fatality ratio is a function of variables that determine how deadly the disease is. Following the standard discussion in the medical research literature, two groups of factors affect contagion and mortality: natural and intervention. We can further classify natural causes as those affected by individual characteristics (age, general health condition, etc.) and environmental variables. Environmental variables include both the geographical environment (temperature, humidity, etc.') and the human environment (pollution, population density, norms of hygiene, etc.').

Research hypothesis:

The main hypothesis tested in this paper is whether *better* medical infrastructure, as captured by the number of hospital beds per capita (b_i), *reduces* the case-fatality ratio in country *i*.

Empirical strategy

Unlike the medical-research literature, I am not interested in determinants of *individual* mortality but rather in the macro case-fatality rate. I defend this approach on two grounds: a) given my research hypothesis, capacity constraints in hospitals create an *externality* to the individual probability of survival. b) in the absence of widespread daily testing, the policies applied were at the macro level as well. I, therefore, used cross country data for the latest mortality ratios (April 14, 2020).

At the macro level, it is difficult to distinguish between control variables that affect contagion and those that cause death. As we see in equation (1), the case fatality ratio

[5] See for example World Economic Forum, April 4, 2020
https://www.weforum.org/agenda/2020/04/we-could-be-vastly-overestimating-the-death-rate-for-covid-19-heres-why/

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is *endogenous*. Nevertheless, in what follows, I use a set of variables that are *exogenous* to both contagion and deaths. The model in its generalized form is:

$$(2) M_i = \boldsymbol{\beta X_i} + \boldsymbol{\gamma E_i} + \boldsymbol{\delta I_i} + \mu \boldsymbol{H_i} + \theta b_i + \tau \boldsymbol{T}_i$$

Where:

$\boldsymbol{X}$ is a vector of country-specific general controls.

$\boldsymbol{E}$ is a vector of country-specific economic controls.

$\boldsymbol{I}$ is a vector of country-specific institutional controls.

$\boldsymbol{H}$ is a vector of country-specific health system controls, excluding, $\boldsymbol{b}$**,** the number of beds per capita.

$\boldsymbol{T}$ is a vector of country-specific time controls.

The hypothesis to be tested is whether $\theta \neq 0$?

Data

While data on the COVID-19 cases and deaths is available for almost all countries, the controls used below limit the set of countries used to 66 in the smallest sample. The small sample is biased towards more advanced economies, for which more data is available. However, the more advanced economies, for now, have more significant exposure to COVID-19.[6]

Country specific control variables: Since the spread of a COVID-19 is believed to be dependent on weather conditions, I control for countries' geographical location by including their latitude and longitude position. Mortality from COVID-19 is concentrated among the elderly, I, therefore, use as controls the share of the population above the age of 80. Another factor that could affect contagion is urbanization. Therefore, I also control for the percent of the population living in urban areas. Since there could be other country-specific variables that affect mortality from flu viruses, such as pollution, hygiene norms, etc., I use as controls, the death rate from influenza from 2018. As argued above, I cannot distinguish between the effect of these variables on contagion and their effect on deaths. For example, weather can affect the spread of the virus, but also the vulnerability of those who catch it. The variation in countries'

[6] A short appendix details the data sources used.

historical death rates from the flu reflects both the rates of contagion and case-fatality rates, etc. Nevertheless, all these are *exogenous* to COVID-19 death rates.

Economic Controls: I used GDP per capita as a proxy for the population's well being, education, etc. that could contribute to either contagion and/or death rates. I used the degree of country openness to trade as a proxy for exposure to imported COVID-19.

Institutional controls: The media has argued that institutional variables can account for the spread of COVID 19 – for example, the reluctance of Western democracies to close borders between them, the success of authoritarian regimes in enforcing lockdowns, etc. I, therefore, control for several commonly used institutional indices, such as the rule of law, protection of private property rights, effectiveness of the government, etc. I also control for 'neo-liberal' inclined governments by using government spending to GDP ratio. Again, media accounts suggest that more market-oriented economies tended to postpone the imposition of restrictions.

Health system controls: I used the health expenditure to GDP ratio and the number of physicians per capita and, more important as we shall see, the number of beds per capita. Ideally, given that acute COVID-19 treatment requires ICU units and ventilators, I would have liked to have more detailed cross-country data on additional medical infrastructure variables. I assume that there is a positive correlation between these additional variables and hospital beds. In the estimation, I also used the number of beds squared to reflect possible nonlinearities in hospital size.

Time controls: since COVID-19 did not hit all countries at once and since death rates are rising over time, I included a time control – counting the number of days since the first recorded death. Since some countries instituted measures to contain the spread of COVID-19 – to 'flatten the curve,' I also included a control variable that measures the time elapsed since the introduction of these measures.

Estimation and results

Basic specifications

We begin with a simple specification that allows us to use data from 94 countries. The specification includes the geographical setting – latitude, longitude, the 2018 death rate from influenza, the percent of the urban population, and the percent of the population

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above 80.[7] I also control, as in all regressions, for the time elapsed since the first death from COVID-19 was recorded in a country. All regressions were estimated as a cross-country regression using least squares with errors clustered by World Bank country groupings.

We can see (**Table 1**, column 1), that this simple specification can account for almost 60 percent of the variation in death rates in our broad sample. Analytical plots (**Figures 3a-3b**) show that the equation is well behaved and that given the higher share of elderly in the economy, Italy and Spain and Belgium that recorded high mortality rates, have higher mortality then their demographics imply. Japan, on the other hand, stands as an outlier with low death rates given its demographics. The coefficient of the percent of urbanization is positive but not significant. As we shall soon see, controlling for additional variables, the positive effect of urbanization on mortality is reversed. We can also see, (**Table 1**, column 2), that when we decrease the sample to 66 countries for which we have all data, the results remain unchanged.

The effect of economic activity

I next introduce economic controls: GDP per capita and the degree of openness of the economy. The results (**Table 1** column 3) show that countries with higher GDP per capita and a higher degree of openness to trade are subject to higher death rates. It is likely that higher death rates in advanced economies are caused by greater contagion rather than by higher case-fatality ratios. Note that when including economic activity controls the sign of the coefficient of the degree of urbanization is now negative. We interpret this result as suggesting that for a given (a higher) rate of contagion in advanced economies, case-fatality ratios are lower in more urbanized economies due to better medical infrastructure. Our findings below on health infrastructure confirm this hypothesis.

Effect of quality of institutions

The long term effect of institutions is captured by GDP per Capita, Urbanization, and longevity (Aecmoglu et al. 2002). Media accounts alluded to the weakness of Western democracies, open societies, in dealing with COVID-19 because of reluctance to restrict

[7] Controlling for the normal death rate from influenza reduces significantly the sample size. However, omitting it would bias our results as it

movement and monitor citizens. The inclusion of institutional quality variables confirms (**Table 1** col. 4.) some of the assertions in the media. Institutional variables that are related to upholding the rule of law, allowing for voice and accountability, are associated with higher rates of mortality from COVID. In contrast, institutions that capture political stability, quality of regulation, and government effectiveness are associated with lower mortality rates. However, given that the coefficients are measured at the mean of the institutional variables, there is no real constraint to increase government effectiveness without having to lower civil liberties.

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Health infrastructure

Geographic, economic, and institutional factors account for a substantial proportion of the variation in death rates in our sample. I end the analysis with the introduction of health infrastructure as captured by the number of beds per 1000 residents and the number of physicians per 1000. **Table1**, column 5, reports the preferred specification that uses the number of beds squared (accounting for non-linearities in hospital infrastructure). We can readily see that a more abundant supply of hospital beds reduces mortality significantly (Fisher et al. 2000).

Figure 3c shows that the results are not driven by outliers. **Figure 3d** shows the added value plot of the number of beds. The effect of the number of physicians per capita was insignificant (Appendix table col 5). Hospital bed capacity is also related to the supply of other components of medical infrastructures, such as ICU units, testing, and laboratory facilities.

Controlling for other covariates, the number of available beds can account for most of the differences in death rates between Italy or Spain and Japan (**Figure 3d**). One source of concern is the statistic influence of Japan on the coefficient on the number of beds. Dropping Japan from the regression reduces the coefficient, but it remains highly significant and substantial (see **Appendix Figure**). Note that the coefficient on urbanization declines and becomes insignificant. This result suggests that before introducing the supply of hospital beds, the urbanization variable captured the higher and often better quality supply of medical care in large cities.

The introduction of the number of beds variables affects the coefficient on the percent of people above 80 significantly. This is because there is a high correlation (0.56) between the number of beds and the share of the elderly population. In a regression of the number of beds on the percentage of the population above 80 (available from the author upon request), we find that Japan is an outlier with a very high ratio of beds to the elderly, whereas, ***tragically***, Italy and Spain are opposite outliers with a low number of beds. As it happens, COVID-19, which affects mainly the elderly, hit the Achilles heel of those countries' medical systems.

How substantial is the impact of the supply of hospital beds on the death rate from COVID-19? A useful example is to take the death rate in Italy, one of the countries with the highest number of deaths and the lowest supply of beds (**Figure** 2b). Using the

coefficient estimate on the number of beds squared shows us that, other things equal, if Italy had the same number of beds per capita as Japan, the number of deaths would have been reduced to Japanese levels – a few hundred. If we exclude Japan, an outlier in the number of beds per capita (**Appendix** table col 4), we get a reduction of deaths to about 3,600 people (given death rates at the time of writing this paper).

Table 1

Dependent variable: Log COVID-19 deaths per capita

	(1)	(2)	(3)	(4)	(5)	(6)
Log flu deaths per capita	0.316*	0.381*	0.371**	0.246*	0.282*	0.260*
	(0.137)	(0.171)	(0.098)	(0.104)	(0.124)	(0.122)
Perecent above 80	21.365**	15.935**	10.477*	12.326**	32.295***	27.007**
	(5.951)	(5.843)	(4.813)	(4.155)	(4.142)	(8.549)
Percent urban	0.469	1.335	-0.816**	-0.416*	-0.186	-0.022
	(0.953)	(1.011)	(0.275)	(0.201)	(0.500)	(0.628)
Log GDP per capita			0.897***	1.171***	1.060***	0.904**
			(0.216)	(0.141)	(0.178)	(0.302)
Imports to GDP			0.769***	1.935**	1.413*	1.521*
			(0.119)	(0.557)	(0.662)	(0.735)
Voice and Accountability				0.638**	0.449**	0.374*
				(0.161)	(0.127)	(0.177)
Government Effectiveness				-0.534	-0.787	-0.822
				(0.548)	(0.585)	(0.494)
Rule of Law				1.248***	0.766*	0.711**
				(0.209)	(0.316)	(0.223)
Regulatory Quality				-1.275***	-0.755***	-0.700***
				(0.240)	(0.085)	(0.161)
Political Stability				-0.738	-0.335	-0.282
				(0.388)	(0.286)	(0.229)
Control of Corruption				0.255	0.255	0.501
				(0.293)	(0.388)	(0.386)
Beds per 1000 squared					-0.024***	-0.022***
					(0.004)	(0.004)
Obs.	94	66	66	66	66	66
R-squared	0.596	0.615	0.673	0.729	0.790	0.809
Time Effects	yes	yes	yes	Yes	yes	yes
Geo position	yes	yes	yes	Yes	yes	yes
COVID-19 Mitigation						yes

Notes: Data sources see data appendix. All regressions were estimated with errors clustered by the World Bank region classification.
Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Mitigation efforts.

Many countries launched a variety of COVID mitigation policies. These are tracked by Oxford University's policy response tracker. Albeit the short time that elapsed since their introduction, I controlled for the time elapsed, the squared time, and the index of the stringency of the measures. The results (**Table1** col 6) did not change significantly. Moreover, these controls are determined simultaneously with mortality rates (Jones et

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al., 2020). Owing to their small marginal contribution to the explanatory power and the simultaneity issues, I leave them for Appendix regressions.

Figure 3

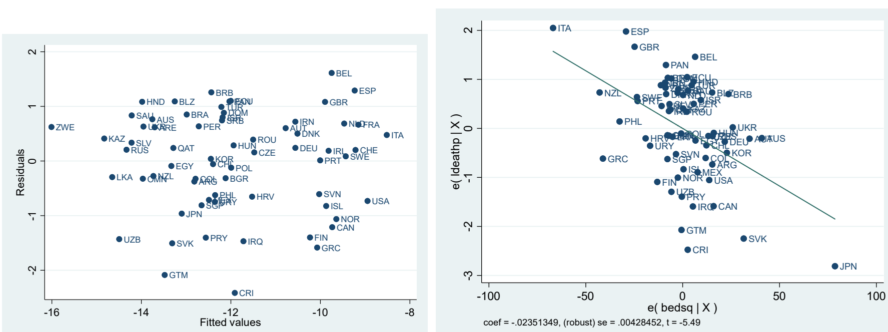
Fitted versus residual plot **Added value plot**

Percent above 80 on COVID-19 mortality rates

a **b**

c **d**

Beds squared per capita on COVID-19 mortality rates



Notes: panels **a** and **b** based on column 2 in Table 1. Panels **c** and **d** based on column 5 in Table 1.

Discussion and policy implications

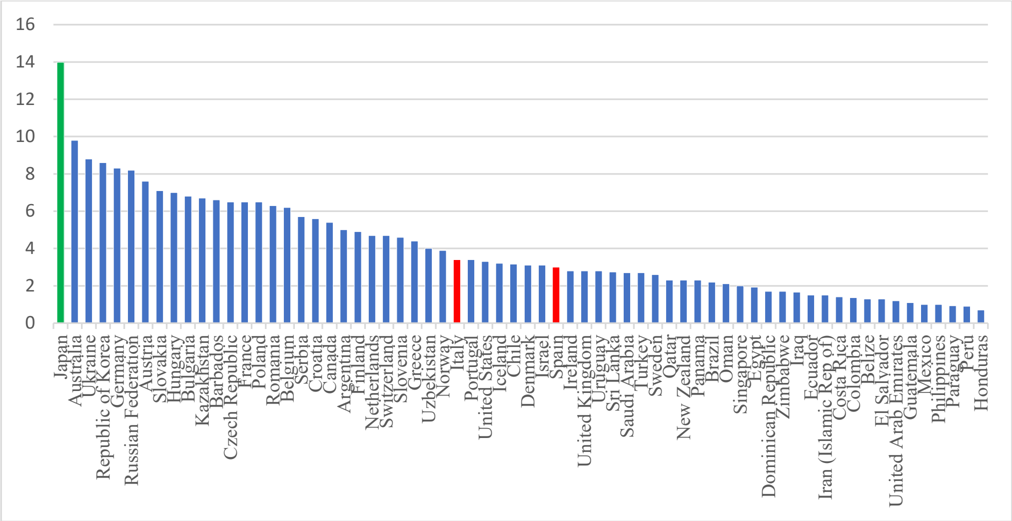
Since the pandemic is recent and its global spread is still in process, the conclusions from data available at the time of writing this note should be taken with more than the usual caveats. Nevertheless, our regressions confirm that death rates from COVID-19 are higher in advanced and open economies suggesting higher degrees of contagion due to more contact and travel. The results also suggest that controlling for income per

capita, countries that rank higher in indices of the rule of law and property rights protection exhibit higher death rates, and countries with more efficient and stable governments exhibit lower death rates. The degree of government spending in the economy, as a proxy of a greater or smaller degree of redistribution policies, does not seem to have an impact on death rates (**Appendix Table**). On a more positive note, our findings suggest that other things equal, living in an urban environment, saves lives – mainly by providing access to medical facilities.

Mitigation policies seem to have been, to a large extent, endogenous to rising deaths than preventive, and their impact on death rates is yet insignificant. However, due to the substantial lags between the imposition of restrictions, their effect on contagion, and ultimately deaths, these results should be taken with a grain of salt.

Figure 3

Hospital beds per 1000 people



Note: For countries used in the regression analysis.
Source: World bank Hospital beds per 1000 people

The most important empirical finding is the large and significant role played by hospital beds capacity on death rates. Our findings echo horror accounts from the heavily affected regions in Italy and Spain. Our results show that hospital capacity is crucial in reducing the deaths of infected people. It can also indirectly reduce contagion by

removing infected people from their home surroundings to hospitals. A smaller supply of hospital beds leads to higher mortality rates that induce governments to take more stringent closure measures that have greater economic costs. Higher mortality could also affect consumer confidence, bring about panic-driven decisions that also affect the economy adversely.

Our analysis has a clear policy implication – to increase hospital capacity. Given our findings that the disease affects more wealthy economies, it seems that these economies can afford the cost of increasing the supply. Of course, the economic costs of hospital beds' shortages are more significant for wealthier economies.

An interesting parallel between COVID-19 and "reversal of fortune" (Acemoglu et al. (2002)) can be drawn. In that seminal paper, more advanced and urbanized economies in 1500 were more prone to deaths from Malaria and Yellow Fever. It seems that COVID-19 similarily affects the more advanced economies. In the historical setting, settler mortality led to the adoption of inferior institutions that did not uphold the rule of law and offered weaker protection of property rights. Inferior institutions led to slower rates of economic growth that persist to this day in many of the affected areas. Some policy reactions to COVID-19, such as sending the military to enforce lockdown in Italy and more tracking and monitoring in more authoritarian regimes, may have similar consequences as in the historical 'settler mortality' environment– to weaken the institutions that contributed to economic growth.

While the pandemic could be short-lived, institutional responses to it could be long-lived. Investment in medical capacity becomes, therefore, even more crucial. Increasing hospital capacity, availability of testing, and protective equipment does not only save lives but may also save us from long-term consequences of taking measures that affect institutional quality. In the likely event of a second or even third wave of the pandemic, countries in need of medical capacity should start doing so with no delay.

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Appendix

Data:

Countries (*countries* dropped from the final sample because of missing data in *italics*):

Albania, Argentina, *Armenia*, Australia, Austria, *Azerbaijan*, Barbados, *Belarus*, Belgium, Belize, *Bosnia and Herzegovina*, Brazil, Bulgaria, Canada, Chile, Colombia, Costa Rica, Croatia, *Cuba*, *Cyprus*, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, *Estonia*, Finland, France, *Georgia*, Germany, Greece, Guatemala, *Guyana*, *Haiti*, Honduras, *Hong Kong SAR*, Hungary, Iceland, Iran (Islamic Rep of), Iraq, Ireland, Israel, Italy, *Jamaica*, Japan, Kazakhstan, *Kuwait*, *Kyrgyzstan*, *Latvia*, *Lithuania*, *Luxembourg*, Mexico, *Montenegro*, *Morocco*, Netherlands, New Zealand, Norway, Oman, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Republic of Korea, *Republic of Moldova*, Romania, Russian Federation, Saudi Arabia, Serbia, Singapore, Slovakia, Slovenia, *South Africa*, Spain, Sri Lanka, Sweden, Switzerland, *Syrian Arab Republic*, *TFYR Macedonia*, *Thailand*, *Tunisia*, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, *Venezuela (Bolivarian Republic of)*, *West Bank and Gaza*, Zimbabwe.

Sources:

COVID-19 mortality data: COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) (April 14th, 2020)

GDP per capita at PPP, Imports as a percent of GDP, Urbanization rate, Percent of government expenditures of GDP, Hospital beds per 1000 people, Physicians per 1000 people: World Bank database

Population and population 80 years and above: United Nations, Department of Economic and Social Affairs, Population Division (2019). World Population Prospects, 2019, Online Edition. Rev. 1.

Mortality from Influenza: WHO Causes of death database.

Institutional quality indices: World Bank Governance Indicators.

Mitigation policies, timing, and stringency: Oxford University's policy response tracker.

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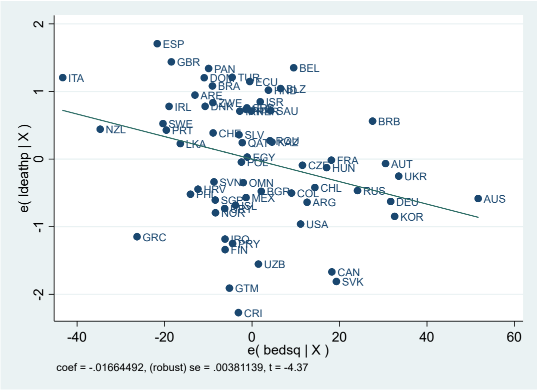
Table Appendix
Dependent variable: Log COVID-19 deaths per capita

	(1)	(2)	(3)	(4)	(5)
Log flu deaths per capita	0.285***	0.107	0.248*	0.297*	0.260
	(0.048)	(0.092)	(0.101)	(0.136)	(0.177)
Perecent above 80	14.541**	8.303	10.579**	34.584***	21.193**
	(5.277)	(6.174)	(3.155)	(5.649)	(6.662)
Percent urban	-1.409*	-1.092	-0.676	0.097	-0.417
	(0.682)	(0.823)	(0.420)	(0.329)	(0.731)
Log GDP per capita	0.754***	0.700*	1.184***	0.968***	0.912
	(0.128)	(0.337)	(0.119)	(0.154)	(0.480)
Imports to GDP	-0.080	0.365	1.922**	1.373*	1.580
		(0.365)	(0.582)	(0.580)	(0.797)
Voice and Accountability		0.694*	0.601***	0.273*	0.311
		(0.337)	(0.127)	(0.133)	(0.280)
Government Effectiveness		-0.117	-0.477	-0.818	-0.882
		(0.623)	(0.558)	(0.607)	(0.682)
Rule of Law		0.593**	1.198***	0.848*	0.707*
		(0.192)	(0.225)	(0.370)	(0.297)
Regulatory Quality		-0.885**	-1.208***	-0.720***	-0.525**
		(0.326)	(0.227)	(0.104)	(0.184)
Political Stability		-0.512	-0.699	-0.331	-0.240
		(0.321)	(0.387)	(0.257)	(0.281)
Control of Corruption		0.354	0.193	0.299	0.379
		(0.377)	(0.236)	(0.290)	(0.304)
G to GDP		1.071	2.308		2.955
		(3.268)	(3.175)		(4.288)
Beds per 1000 squared				-0.017***	-0.022***
				(0.004)	(0.003)
Doctors per 1000					0.073
					(0.092)
Health expen. to GDP					0.037
					(0.136)
Obs.	91	90	66	65	66
R-squared	0.635	0.682	0.730	0.796	0.813
Time Effects	yes	yes	yes	yes	yes
Geo position	yes	yes	yes	yes	yes
COVID-19 Mitigation					yes

Figure Appendix
Added value plot of beds squared per capita on COVID-19 mortality rates
Table Appendix, column (4), excluding Japan



COVID-19, fiscal stimulus, and credit ratings[1]

Anuragh Balajee,[2] Shekhar Tomar,[3] and Gautham Udupa[4]

Date submitted: 19 April 2020; **Date accepted:** 23 April 2020

The COVID-19 pandemic has rattled the global economy and has required governments to undertake massive fiscal stimulus to prevent the economic fallout of social distancing policies. In this paper, we compare the fiscal response of governments from around the world and its main determinants. We find sovereign credit ratings as one of the most critical factors determining their choice. First, the countries with one level worse rating announced 0.3 percentage points lower fiscal stimulus (as a percentage of their GDP). Second, these countries also delayed their fiscal stimulus by an average of 1.7 days. We identify 22 most vulnerable countries, based on their rating and stringency, and find that a stimulus equal to 1 percent of their GDP adds up to USD 87 billion. In order to fight the pandemic, long term loans from multilateral institutions can help these stimulus starved economies.

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1 We thank the editor Charles Wyplosz, one anonymous referee, and Viral Acharya for their valuable comments and feedback on the paper. This paper is preliminary. We have used the most updated data on fiscal stimulus, which might get updated over time, and some results can change. The views and opinions expressed in this paper are those of the authors and do not necessarily represent the views of CAFRAL or other affiliated institutions.

2 Research Associate, CAFRAL, Mumbai.
3 Assistant Professor, Indian School of Business, Hyderabad.
4 Research Director, CAFRAL, Mumbai.

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1 Introduction

The new decade has started with weak economic growth due to the COVID-19 pandemic. The virus has hit advanced and emerging countries alike, and governments around the world are scrambling for funds to prevent a breakdown of their health infrastructure and economy. The enforced shutdown around the world is helping to contain the spread, but at substantial economic costs.[1]

In this paper, we evaluate the fiscal response of governments[2] around the world to COVID-19. Our exercise is motivated by the different constraints faced by rich and poor countries. These constraints determine their behavior. For instance, we find countries that are constrained by credit ratings are unable to spend. In contrast, others such as Saudi Arabia have already spent significant amounts, but may also face debt overhang problems in the future. To allay these concerns, the International Monetary Fund (IMF) has recently announced debt-relief to twenty-five member countries, most of them from the African continent, totaling about USD 500 billion (IMF [2020]).[3] We provide our analysis around this issue and identify countries that are under-spending due to macroeconomic concerns.[4]

We argue that credit rating downgrade is a critical macroeconomic concern faced by countries at the border of the investment-grade rating category. The risk of credit rating downgrade can have a significant negative impact on the capability of a country to raise resources to fight COVID-19. For instance, Moody's recently downgraded the sovereign credit rating of South Africa on March 27, 2020.[5] It was then followed by a similar downgrade for four of its banks four days later. In its analysis, Moody's cited high fiscal deficit in

[1] Health crises of the scale of epidemics and pandemics can have substantial costs. Noy et al. [2019] study a pre-COVID-19 period and establish that the economic costs are particularly high in most of Africa, the Indian Subcontinent, China, and Southeast Asia.

[2] Fornaro and Wolf [2020] evaluates the optimal fiscal policy response for the US to fight COVID-19.

[3] According to IMF, investors have already pulled out USD 83 billion from emerging markets since the start of the crisis. The problem can be further exacerbated by rating downgrades or countries not spending enough to protect their ratings. Nearly 80 countries have already requested help from the IMF.

[4] Elgin et al. [April 2020] construct a COVID-19 Economic Stimulus Index (CESI) index to summarize the overall economic responses by governments around the world.

[5] Moody's downgrade South Africa.

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the current financial year, possibly reaching 8.5 percent of GDP, as well as debt overhang problems as a reason behind the downgrade. Such events of rating downgrade are associated not only with an increase in credit spread (Cantor and Packer [1996]), but also a flight of capital as many institutional investors are not allowed to invest in non-investment grade securities (Becker and Milbourn [2011]). We explore if downgrade concerns are, therefore, affecting countries' responses to the current pandemic.[6]

To undertake this exercise, we prepare cross-sectional country-level data on credit ratings and other COVID-19 related variables from OxCGRT (Oxford COVID-19 Government Response Tracker). In our sample of 116 countries, only 67 have declared a stimulus till April 9, 2020. Even out of these 67, many countries have pledged minimal amounts. The average stimulus stands at 2.9 percent of GDP, with a standard deviation of 4.2 percent.

So what determines the level of fiscal stimulus? To evaluate these factors, we regress total fiscal stimulus against country-level exogenous variables, including a measure of economic stringency[7] during the pandemic, the sovereign bond rating, confirmed cases count, and country-level controls. We find that both economic stringency and rating determine fiscal spending, but not the number of confirmed COVID-19 cases. More stringent measures constrain economic activity and cause severe disruptions. We find that one percent higher stringency results in 0.11 percentage points higher fiscal spending. On the rating side, our estimates suggest that a one-level upgrade in credit rating increases fiscal stimulus by 0.3 percentage points of GDP. This suggests that countries around the world are concerned about the effect of fiscal stimulus on their credit ratings, which inhibits them from reacting to the stringent measures they have imposed on the economy. Since the pandemic is an exogenous event and countries have to allocate unanticipated funds to fight the economic stringency, our results capture the risk associated with rating downgrade.

We also find that countries with credit-rating risk imposed harsher lockdowns much

[6]Economic stimulus required to fight COVID-19 can lead to a large fiscal deficit in the current year. Balajee et al. [2020] estimate that it can go up to 8.8 percent of GDP for India.

[7]We compute the average level of stringency index from the index defined in OxCGRT.

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earlier and provided fiscal stimulus only much later. In other words, they delayed fiscal stimulus in an environment where strict lockdown measures had made such stimulus all the more necessary. Figure 4 shows these patterns graphically. Each sub-figure plots economic stringency (blue) and fiscal stimulus (red) over time for a given country. Starting from January 1, 2020, we see that the blue lines rise much earlier than the red ones. The gap between the two is our measure of the delay in fiscal stimulus. An overview of the figures shows that there is substantial heterogeneity in stimulus delay. This is confirmed by Figure 5, which plots the density of our primary delay variable. Most countries announced fiscal stimulus only a few days after imposing a 50% level of stringency. Some countries at the extreme waited more than 25 days after imposing a 50% stringency (like the Philippines), while some announced fiscal stimulus even before imposing harsh containment (like the United Kingdom). We formally test this proposition in a regression framework and find that countries with a low credit-rating waited longer to announce their fiscal stimulus package.

Our results thus suggest that the vulnerable population in countries with low credit ratings may face considerable economic hardship due to a lack of support from their government. The fiscal response of governments in such countries is both small as well as delayed. Based on our indicators (mean credit rating and mean stringency), we identify twenty-two countries that are extremely vulnerable and might need external support to fight the crisis. In terms of the policy, long-term loans from multilateral institutions such as the World Bank and the International Monetary Fund (IMF) at low-interest rates will ensure that fiscal stimulus will have minimum impact on government budget in the current fiscal year. If each of these countries receives 1 percent of their GDP as loans, it will amount to a total of 87 billion USD. Thus, an international emergency finance package can help bridge the funding gap for these countries.

Our paper contributes to the broad literature on the importance of credit ratings. Sovereign credit ratings contain information beyond observable macroeconomic indicators (Dell'Ariccia et al. [2006] and Eichengreen and Mody [1998]). Sovereign credit rating downgrades result

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in a rise in sovereign risk premium, which spills over to private sector credit markets (Uribe and Yue [2006], Almeida et al. [2017]). Credit rating downgrades thus have real economic implications. In contrast, our study documents reduced spending by governments *to prevent potential* rating downgrades. It has important policy implications as countries need large funds to support the economy during COVID-19, but they are probably unable to do so for fear of inviting a rating downgrade. More generally, our work also highlights the role of global economic cooperation perspective during the pandemic. For instance, Bahaj and Reis [2020] study the role of swap lines extended by the US Fed to other central banks.

In the next section, we describe our data. In section 3, we provide the impact of credit ratings on fiscal stimulus and delay in stimulus announcement. In section 4, we provide the list of most vulnerable countries and the quantum of support required to fight COVID-19. Finally, section 5 concludes.

2 Data

We have used three primary sources of data for our analysis. First, we use crisis-related data from the Oxford COVID-19 Government Response Tracker(OxCGRT) as of April 9, 2020 (Hale and Webster [2020]). It gives us country-wise statistics on COVID-19 related variables, both health and economy. We use the information on the stringency index (normalized between 0-100), which captures the level of containment of economic activities by a country. An index of 0 corresponds to a business-as-usual scenario, while 100 corresponds to maximum disruption. For instance, the United States has an index of 66 on April 9, 2020, while Italy has 95, pointing to a higher disruption in Italy. We also use the information on fiscal stimulus collected by OxCGRT, both on the level and timing of stimulus (as on April 9, 2020). Second, we hand collect fiscal stimulus numbers from the IMF policy response tracker (as on April 16, 2020).[8] To calculate the fiscal stimulus, we aggregate all the payments which increase government expenditures in the current financial year. We exclude loan guarantees and tax

[8]IMF policy response tracker

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deferrals. Our methodology is similar to the one used by OECD Country Policy Tracker.[9] The fiscal stimulus numbers in the IMF and OxCGRT datasets broadly match each other (Figure 7).

The third set of data consists of most recent economic variables, like GDP and GDP per capita, from the IMF. Most importantly, we collect data on the most recent sovereign bond ratings from S&P, Moody's, and Fitch rating agencies as on April 9, 2020. The sovereign ratings capture the general macroeconomic health of a country.

3 Rating affects the fiscal response of countries

In this section, we study how credit ratings influence the level and timing of fiscal stimulus announced by countries. We first describe our methodology and then present the results.

3.1 Size of a fiscal stimulus depends on credit ratings

To test whether the level of a fiscal stimulus depends on sovereign ratings, we regress the government response - measured as government spending as a share of GDP - against a slew of measures on a cross-section of countries. First is the severity of the crisis. We average daily stringency index for each country between January 1 - April 9, 2020. The average measure, therefore, takes into account the loss in economic output since January 1. It is a better measure than using the daily index measure because it takes into account the aggregate economic loss since the beginning of the year. We substitute for fiscal health by the distance of sovereign bond ratings from the junk category. For instance, India has a Baa2 rating from Fitch, which is two categories above junk (non-investment grade), so India receives a distance score of two. The minimum distance from the junk rating is 0, and the maximum is 10. We use the average distance from non-investment grade for the three rating agencies

[9] OECD Country Policy Tracker. OECD also uses the data from IMF Policy Response Tracker for fiscal stimulus calculation.

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in our primary analysis.[10] We finally estimate the following equation:

$$\text{Stimulus}_i = \beta_0 + \beta_1 * \overline{\text{Stringency}}_i + \beta_2 * \log(\text{COVID cases})_i + \beta_3 * \overline{\text{Rating}}_i + \text{Controls}_i + \epsilon_i \quad (1)$$

where Stimulus_i is the ratio of fiscal spending to GDP ratio for country i. The variable Stimulus_i is the sum of all stimulus packages announced by the country i till April 9, 2020. The independent variables include $\overline{\text{Stringency}}_i$, the mean stringency, and $\log(\text{COVID cases})_i$, the log of the number of confirmed cases in country i till April 9, 2020. The variables, $\log(\text{COVID cases})_i$ and $\overline{\text{Stringency}}_i$, can be correlated because the severity of COVID-19 spread influenced the level of economic shutdown measures announced by the government. A country more impact by COVID-19 should spend more, and thus the expected sign on the two coefficients, β_1 and β_2, should be positive. Finally, our primary variable of interest, $\overline{\text{Rating}}_i$, should have a positive coefficient. A country with a better credit rating is better placed to undertake high government spending, as it can issue higher debt with less risk.

Before we discuss the results, it is essential to mention that the variable $\overline{\text{Stringency}}_i$ is better defined compared to the total number of confirmed COVID cases. The total number of COVID cases has been influenced by country-specific health policies and the availability of testing kits. Hence, it is not uniformly measured across countries and suffers from measurement error issues. In comparison, once announced, the economic stringency index is more uniformly measured across countries.

Results: We present the raw correlation between $\overline{\text{Stringency}}_i$ and Stimulus_i in Figure 1 through a binscatter. It shows that for every 10 percent increase in stringency, the stimulus goes up by 2 percent of GDP. Similarly, we find that stimulus has a positive correlation with mean ratings and log(COVID-19 cases), as shown in Figure 2 and 3 respectively.

We report the results from estimating the equation 3 in Table 2. In column (1), when we

[10] For some countries, rating information is only available from one or two agencies, in which case we take the average over the available ratings.

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regress stimulus only on mean stringency, we find that the coefficient $\beta_1 = 0.19$. It shows that the correlation between stimulus and repression is positive and significant. A 10 percent increase in mean stringency (roughly equal to one standard deviation) increases the fiscal stimulus by 1.9 percent of GDP. Our results differ from Elgin et al. [April 2020] in that they do not find stringency to be a statistically significant factor driving overall economic response by a country. This is because they consider the correlation of stringency with an index constructed from an array of economic measures and not just fiscal stimulus. Also, they use the recently reported stringency index instead of a mean stringency index like us. In column (2), we report the results when the stimulus is regressed only on $\overline{\text{Rating}}_i$. Here again, we find that countries with higher rating have a higher stimulus. We find that a one-level decrease in a credit rating is also associated with a 0.47 percentage point decrease in the stimulus. Similarly, in column (3), we find that stimulus is also higher in countries with a high number of COVID-19 cases.

In columns (4), (5), and (6), we report results based on using two of the independent variables together. When we include mean stringency and mean ratings as in column (4), we find both have a positive and significant correlation with stimulus. Similarly, both mean stringency and log of COVID-19 cases are positive and significant in column (5). In column (7), when we include all three of these variables, only the coefficients on mean stringency and mean ratings stay positive and significant. Finally, in column (8), we also include other country-specific controls like GDP in our regression. Even in this case, we find that the coefficient on mean stringency and mean credit rating stays positive and significant. In this case, a one-level fall in mean ratings decreases the fiscal stimulus by 0.32 percentage points of GDP. In column (9) we also include log(GDP per capita) in the regression. In this case the coefficient on the mean ratings variable through positive is not significant. This could be because log(GDP per capita) and mean ratings are highly correlated (correlation coefficient = 0.8), which makes collinearity a possible concern.[11] However, the two variables are jointly

[11]GDP per capita is an important fundamental variable determining sovereign credit rating. Hence, it is not surprising that the two are highly correlated.

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significant. The hypothesis that both log(GDP per capita) and mean ratings are zero is rejected with an F-statistic of 4.21 and has an associated p-value of 0.018. In general, our results show that the mean ratings is one of the most significant factors that determine the fiscal stimulus of a country. The stimulus also seems to be correlated with the mean stringency of the country in most cases.

Robustness: We also test the robustness of the above results based on fiscal stimulus data from the IMF. These results are reported in Table 3. The results on mean ratings are robust to using alternate fiscal stimulus measures. We find sovereign credit rating is the most important determinant of stimulus package (column (9)), even after the inclusion of log(GDP per capita). In this case, the results are different from column (9) in Table 2 because the IMF numbers are less dispersed for countries with low credit ratings. This change can be noticed by comparing the binscatter in Figure 9 with Figure 2. The binscatter in Figure 9 has a better fit for the mean ratings closer to zero. Overall, the coefficient on $\overline{\text{Rating}}$ is positive and significant in all the specifications in Table 3.

3.2 Credit ratings correlated with the delay between containment and stimulus announcement

The fight against COVID-19 has involved both health and economic response at the same time. However, countries have differed in their reaction horizon when it comes to these two responses. As mentioned in the introduction, we plot the time series of raw daily stringency measures and normalized fiscal stimulus package announced until given date t in Figure 4. For most of the countries, the health response becomes more stringent before the stimulus package is declared. For instance, India declared a 100 percent lockdown on March 24, 2020, but the main stimulus package was announced on March 26, 2020. On the other hand, there are some outlier countries like the UK whose economic response preceded the containment announcement by 12 days.

Another way to look at it is to compute the difference in the number of days between

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the first day of threshold stringency and stimulus package. We compute this difference for threshold stringency of 50, 60, and 70 percent and the day of the first stimulus package. The density function for stimulus delay is shown in Figure 5. We find that the three distributions overlap with each other as countries quickly increased the intensity of stringency measures once the number of cases started rising quickly. The median delay between the date of 50 percent stringency and the date of the fiscal announcement is three days. However, there is a large heterogeneity in the response of countries. It is also important to highlight that many countries did not announce any fiscal measures and are thus not captured in this figure. Out of 95 countries in our final sample, 29 did not declare any stimulus package. We report the average rating and whether a country declared stimulus in Table 1. We find that out of 29 countries that did not declare any fiscal stimulus, 22 have a non-investment grade or junk rating.

We now formally test whether the time gap between imposing containment measures and the stimulus package is correlated with any country-specific parameters. We use the following estimation equation based on the cross-section of countries that have announced a non-zero stimulus:

$$\text{Stimulus Delay}_i = \beta_0 + \beta_1 * \overline{\text{Stringency}}_i^{T_i} + \beta_2 * \log(\text{COVID cases})_i^{T_i} + \beta_3 * \overline{\text{Rating}}_i + \text{Controls}_i + \epsilon_i \tag{2}$$

where, Stimulus Delay_i is the number of days between the two announcements, threshold containment, and first fiscal package by country i. The variable $\overline{\text{Stringency}}_i^{T_S}$ corresponds to the mean stringency level in country i on the day, T_i, first stimulus package was announced. Each country has a different date T_i corresponding to the day of the first stimulus for country i. We also control for the log number of cases on date T_i. Once again, our main variable of interest is $\overline{\text{Rating}}_i$, which captures whether countries with lower ratings delay their fiscal response.

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A priory, we expect that countries should have a reason to delay their economic response to the crisis. An early fiscal stimulus, relative to stringency, is a measure of an economy with strong fundamentals that can support fiscal expenditure and vice-versa for a country with weak fundamentals. It should be reflected through a negative coefficient on the mean credit ratings in equation 3, i.e., β_3 should be negative. We present the binscatter for these two variables in Figure 6 and find a negative correlation. The coefficient on mean stringency, $\overline{\text{Stringency}}_i^{T_i}$, is more difficult to predict. The countries can announce mild stringency measures very early to contain the spread of the virus. This can reduce the expected number of days of total containment and, thus, total economic cost. In this case, the mean stringency on T_i can allow for a delay in the fiscal stimulus. Conversely, a high level of $\overline{\text{Stringency}}_i^{T_i}$ can also push governments to announce fiscal stimulus sooner rather than later. Finally, we also include the log(COVID Cases) on the day of the stimulus announcement. If more days have passed between the threshold stringency and fiscal stimulus, it means more days for the COVID-19 to spread. So, these two can be positively correlated, without signifying any direction of causation.

We present the OLS estimates for this regression in Table 4. In column (1), we report the results by regressing the delay in stimulus on mean stringency on the day of the fiscal announcement. We find that there is a positive correlation between the two. A 10 percent higher mean stringency leads to a delay of 7.9 days in the stimulus. We also find that a higher sovereign rating reduces the delay in the fiscal stimulus (column (2)). A country with five steps away from junk bond status announces stimulus 6.5 days in advance, relative to a country with a rating of 0. We also find that coefficient on $\log(\text{COVID cases})_i^{T_i}$ is also positive and significant in column (3). In the rest of the columns (4)-(7), we use different combinations of these variables, and we find that the coefficient on the mean rating is always negative and significant. In column (7), which includes all the independent variables, we find every single step of rating is associated with 1.7 days of delay. The coefficient on the mean rating in column (7) is also more negative than the one reported in column (1). The

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results are similar when we include log(GDP) in the regression, as reported in column (8).[12]

We also find that these results are robust for other threshold levels of stringency, 60 or 70 percent. It is not surprising since the densities in Figure 5 overlap with each other as most countries went from an almost negligible level to a very high level of stringency in one step. The results for mean rating hold for a battery of other definitions for mean stringency and number of COVID-19 cases. Overall, these results suggest that sovereign ratings are an important ingredient in determining the timing of fiscal stimulus. Furthermore, these results do not even account for countries, which did not declare any stimulus until now despite imposing strong stringency measures. The results will look starker once these countries announce some level of stimulus in the future. In the next section, we discuss the countries that are most vulnerable to COVID-19 due to their inability to respond to the crisis using fiscal measures.

4 Vulnerable countries

Our arguments have shown so far that countries with low credit ratings are stuck in a ratings-COVID-19 crisis trap. Based on the results from the previous section, we now identify countries that are vulnerable based on two characteristics - mean stringency and mean credit rating. The countries with above-median stringency and below-median credit rating are those that need immediate assistance. There are twenty-two such countries, ranging from South Africa with a mean stringency of 20 to Burkina Faso, which has a mean stringency of 49 as of April 9, 2020. The fiscal stimulus in these countries has been low, ranging from zero (Burkina Faso, Russia, Costa Rica, Iraq, Lebanon, Venezuela, Vietnam, and Ecuador) to the highest among these countries at 4.7 percent of GDP (Peru). Portugal is also included in the list, although its ability to access Euro bonds makes it less susceptible. Indeed, Portugal has spent 4.4 percent of GDP by the end of our sample period and does not need immediate

[12] We cannot use the IMF policy response tracker to construct a measure of stimulus delay because the IMF does not report fiscal stimulus announcement dates for all countries.

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assistance.

The full list of countries and their characteristics is provided in Table 5. We calculate the financial support needed by these countries under three different scenarios. The columns (9), (10) and (11) give the difference (USD billion) between threshold stimulus package (1, 2, and 5 percent of GDP) and the announced fiscal stimulus (percent of GDP) by a country until April 9, 2020. The numbers are zero if a country has already announced its stimulus above the threshold level. Based on our calculations, these countries need USD 36 billion support in the 1 percent stimulus scenario, while the number jumps to USD 98 and 342 billion for 2 and 5 percent stimulus scenario. If one excludes India and Russia, the loans needed for a 5 percent stimulus support drop from USD 342 billion to 138 billion. These numbers are well below the USD 1 trillion lending capacity that the IMF is willing to deploy if needed (IMF [2020]).

As a note of caution, our sample only includes those countries that have imposed higher stringency and provided low fiscal stimulus. So it excludes those vulnerable countries that might not have imposed any stringency measures fearing economic slowdown. Thus, a broader international support policy will also need to cover the countries that are not present in Table 5.

5 Conclusions

The COVID-19 pandemic continues to impact the global economy. In this backdrop, fiscal stimulus is seen as one of the few ways to support the economies during a period of forced containment. Fiscal spending at this juncture can support households that have lost their jobs and firms that are in dire need of liquidity. However, as documented above, not all countries have been able to raise the necessary funding required for support. Using a cross-section of countries, we find that fear of rating downgrades is an important driver that is preventing countries from providing stimulus. Furthermore, countries that face tighter

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funding conditions due to fear of credit downgrades also delay the fiscal stimulus. This delay can happen despite the stringent containment measures imposed by them to contain the virus, thereby exposing their most vulnerable population to economic hardships in addition to the health risks. Finally, we provide the list of most vulnerable countries based on our measures and the funding support needed to help them provide a threshold level stimulus.

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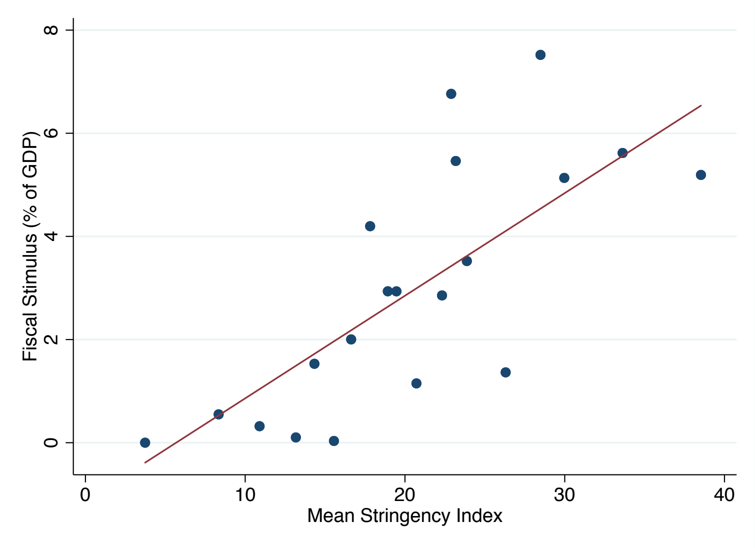
Figures

Figure 1: Fiscal Stimulus vs. Mean Stringency Index



Notes: The figure shows the cross-country binscatter between fiscal stimulus and mean stringency index. It corresponds to the regression specification (1) in Table 2. Fiscal stimulus is the sum of stimulus announced (as a percentage of 2019 GDP), while mean stringency index is the simple average of the daily stringency index until April 9, 2020. (Data Source: OxCGRT)

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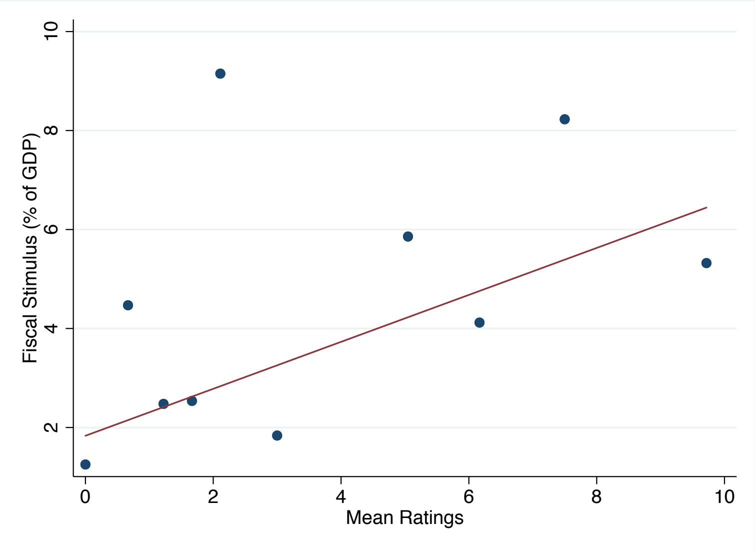
Figure 2: Fiscal Stimulus (OxCGRT) vs. Mean Rating



Notes: The figure shows the cross-country binscatter between fiscal stimulus and mean rating. It corresponds to the regression specification (2) in Table 2. Fiscal stimulus is the sum of stimulus announced (as a percentage of 2019 GDP) until April 9, 2020. The mean rating is the simple average of the sovereign credit ratings from Moody's, Fitch and S&P as on April 9, 2020. (Data Source: OxCGRT and countryeconomy.com)

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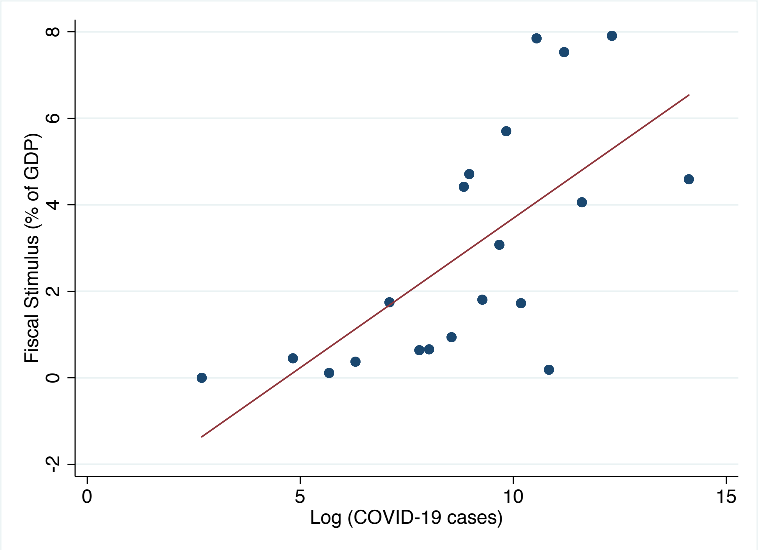
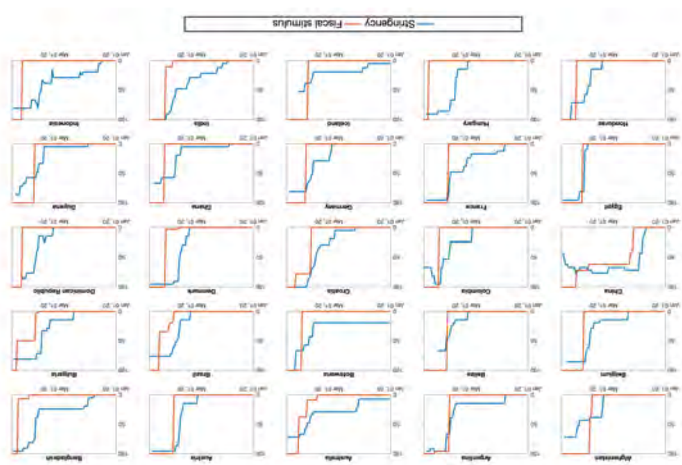
Figure 3: Fiscal Stimulus vs. Log(COVID-19 cases)



Notes: The figure shows the cross-country binscatter between fiscal stimulus and Log(COVID-19 cases). It corresponds to the regression specification (3) in Table 2. Fiscal stimulus is the sum of stimulus announced (as a percentage of 2019 GDP) until April 9, 2020. The Log(COVID-19 cases) is based on the reported COVID-19 cases as on April 9, 2020. (Data Source: OxCGRT)

Figure 4: Time Series of Fiscal Stimulus vs. Stringency Measures



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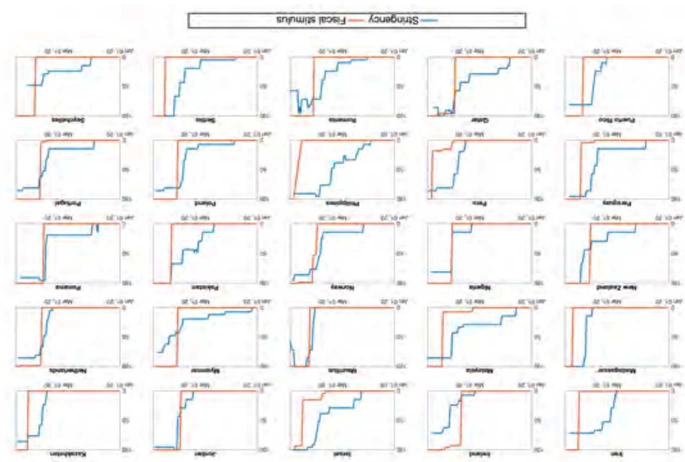

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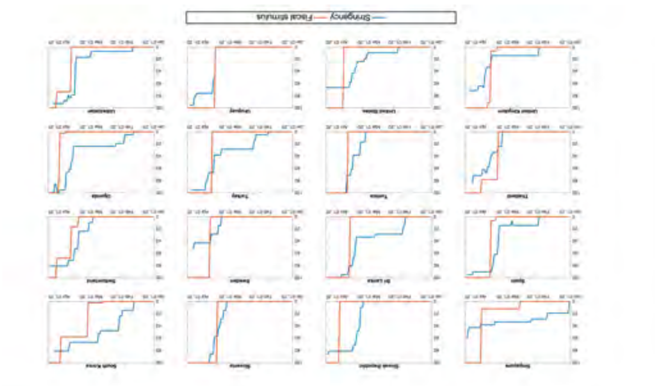

Notes: Each panel in the figure shows the time series evolution of stringency (blue) and fiscal stimulus (red) for countries that have declared fiscal stimulus between January 1-April 9, 2020. The stringency measure is the raw index, while the fiscal stimulus is the percentage of stimulus declared by the country until date t. For most countries, fiscal measures only follow after the announcement of strong stringency measures. (Data Source: OxCGRT)

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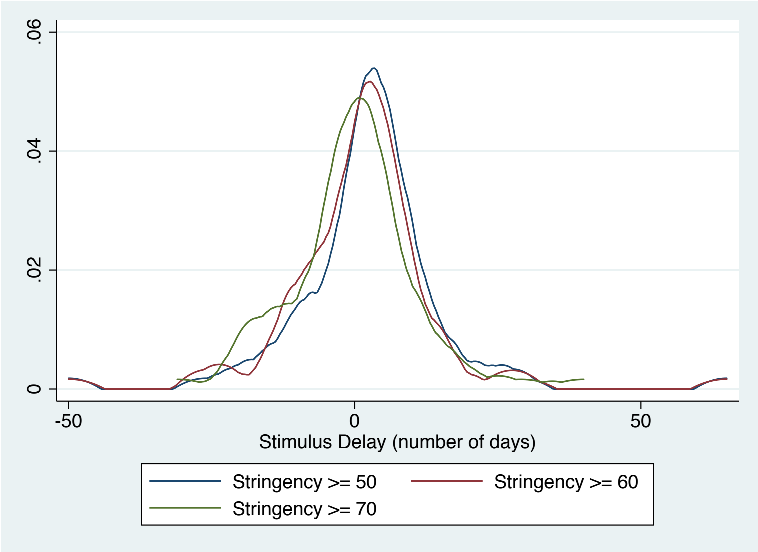
Figure 5: Number of Days Between Stimulus Declaration and Threshold Stringency Level



Notes: The figure shows the kernel density plot of delay (number of days) in the announcement of the first fiscal stimulus after the imposition of a threshold stringency level. Each line corresponds to a different threshold stringency level, 50, 60, and 70 percent. (Data Source: OxCGRT)

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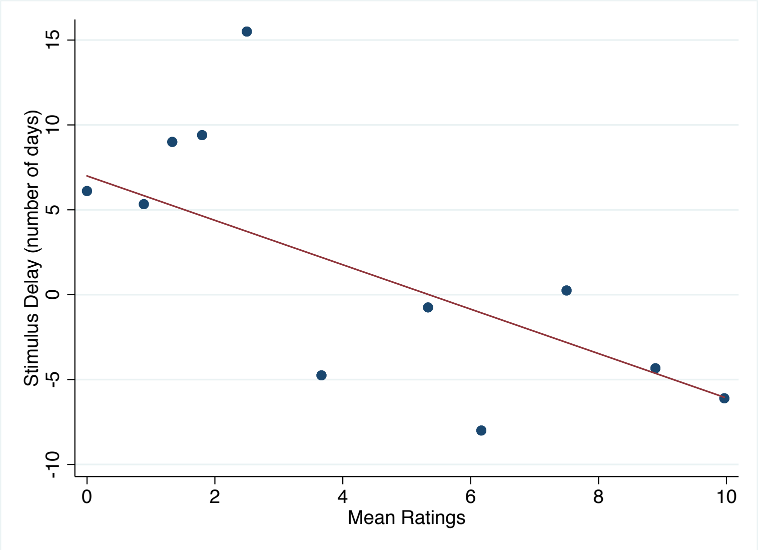
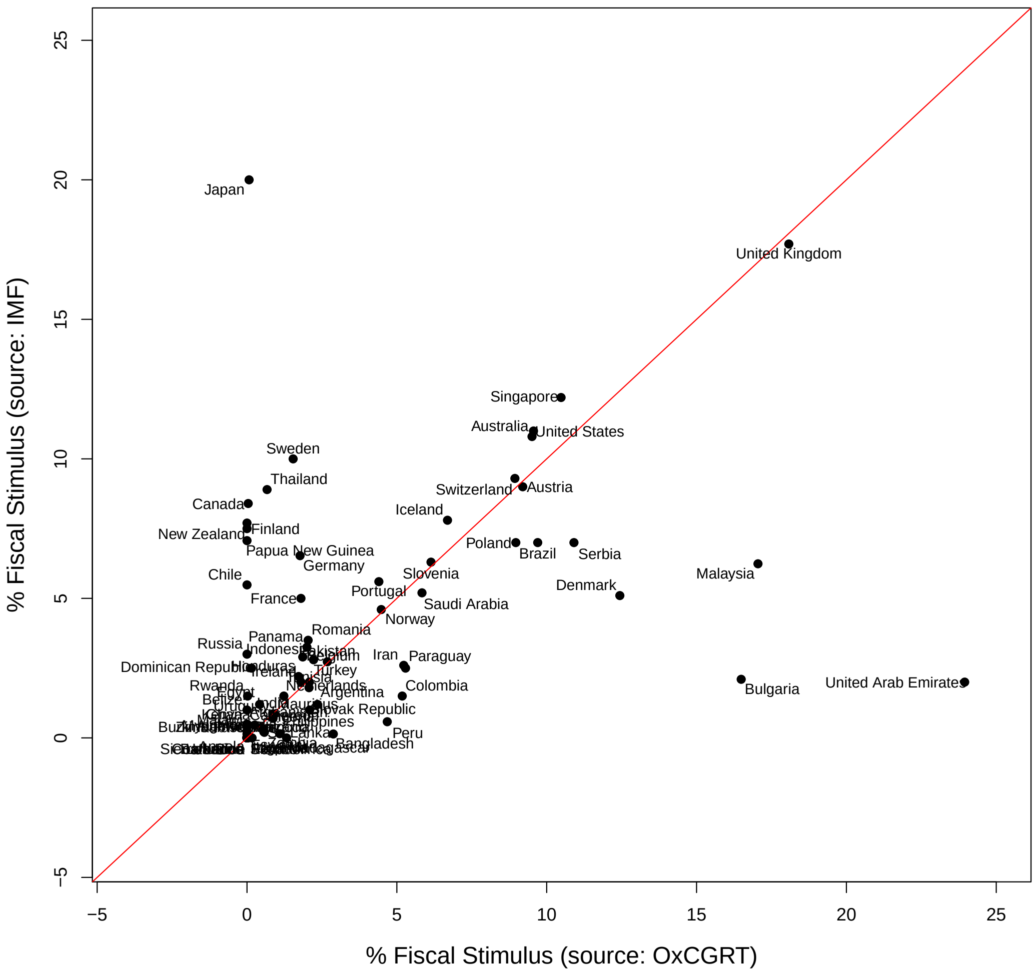
Figure 6: Delay in Stimulus Declaration vs. Mean Ratings



Notes: The figure shows the cross-country binscatter between stimulus delay (number of days) and mean ratings. It corresponds to the regression specification (2) in Table 4. Stimulus delay is calculated w.r.t. to a threshold stringency level of 50. The mean ratings is the simple average of the sovereign credit ratings from Moody's, Fitch and S&P as on April 9, 2020. (Data Source: OxCGRT and countryeconomy.com)

Figure 7: Comparison of OxCGRT and IMF Stimulus Data - Full Sample



Notes: This figure compares the fiscal stimulus (%) from the IMF and OxCGRT for all countries in our sample. We could not calculate the fiscal stimulus for some countries using the IMF policy response tracker data. There was no data available for Venezuela. The information was unclear to calculate a precise number for fiscal stimulus in the case of the following countries: Guatemala, Croatia, Uzbekistan, El Salvador, Qatar, Kazakhstan, Spain, Hungary, Jordan, Greece, and Seychelles. (Source: IMF policy response tracker as on April 16, 2020 and OxCGRT as on April 9, 2020)

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Tables

Table 1: Average Rating and Fiscal Stimulus Status (By country)

Mean	Fiscal Stimulus		
Rating	Yes	No	NA
< 1	26	22	3
1-2	9	2	0
2-3	4	1	0
3-4	2	1	1
4-5	3	0	0
5-6	5	1	1
6-7	3	0	0
7-8	4	0	0
8-9	2	1	1
9-10	11	1	0
Total	69	29	6

Notes: The mean rating is the simple average of the sovereign credit ratings from Moody's, Fitch and S&P as on April 9, 2020. The mean rating is the distance from non-investment grade rating and varies from 0-10, where 0 is equal to junk and 10 is equal to prime status. (Data Source: OxCGRT and countryeconomy.com)

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Table 2: Fiscal Stimulus (OxCGRT) vs. Mean Ratings

	Stimulus (percent of GDP)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{\text{Stringency}}$	0.199***			0.138**	0.099		0.109	0.110	0.116
	(0.050)			(0.054)	(0.074)		(0.074)	(0.074)	(0.074)
$\overline{\text{Rating}}$		0.474***		0.379***		0.286*	0.307**	0.326**	0.213
		(0.132)		(0.139)		(0.153)	(0.147)	(0.148)	(0.188)
log(COVID-19 Cases)			0.691***		0.494**	0.436***	0.214	0.451*	0.343
			(0.129)		(0.215)	(0.149)	(0.235)	(0.247)	(0.262)
log(GDP)								-0.463	-0.374
								(0.369)	(0.378)
log(GDP per capita)									0.456
									(0.351)
Constant	-1.130	1.833***	-3.223***	-0.825	-3.476***	-1.641	-1.963*	1.366	-2.702
	(0.847)	(0.416)	(0.924)	(0.916)	(0.948)	(1.040)	(1.077)	(3.199)	(4.516)
Observations	94	87	94	87	94	87	87	87	87
R-squared	0.153	0.159	0.187	0.218	0.210	0.198	0.225	0.236	0.242

Notes: The table is based on regression equation 2. All variables are based on the information released until April 9, 2020. The stimulus (percent of GDP) is the percentage of aggregate fiscal stimulus to GDP declared by country i to fight COVID-19. The $\overline{\text{Stringency}}$ is the cumulative level of economic repression in country i as measured until April 9, while log(COVID-19 Cases) is based on the number of reported cases until April 9. The $\overline{\text{Rating}}$ is the average distance from junk rating. We report robust standard errors. ***- $p < 0.01$, **- $p < 0.05$ and * - $p < 0.1$

Estimation equation:

$$\text{Stimulus}_i = \beta_0 + \beta_1 * \overline{\text{Stringency}}_i + \beta_2 * \log(\text{COVID cases})_i + \beta_3 * \overline{\text{Rating}}_i + \text{Controls}_i + \epsilon_i$$

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Table 3: Fiscal Stimulus (IMF) vs. Mean Ratings

	Stimulus (percent of GDP)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{\text{Stringency}}$	0.156**			0.034	-0.052		-0.012	-0.015	-0.015
	(0.062)			(0.053)	(0.078)		(0.071)	(0.070)	(0.069)
$\overline{\text{Rating}}$		0.726***		0.710***		0.621***	0.618***	0.588***	0.375**
		(0.104)		(0.105)		(0.117)	(0.122)	(0.114)	(0.163)
log(COVID-19 Cases)			0.842***		0.932***	0.273	0.296	-0.006	-0.177
			(0.184)		(0.240)	(0.211)	(0.270)	(0.427)	(0.462)
log(GDP)								0.564	0.675
								(0.534)	(0.547)
log(GDP per capita)									0.826*
									(0.489)
Constant	-0.477	1.348***	-4.934***	0.567	-4.554***	-1.067	-0.986	-4.655	-11.171*
	(1.391)	(0.317)	(1.712)	(1.206)	(1.713)	(1.922)	(1.890)	(3.840)	(6.469)
Observations	83	76	83	76	83	76	76	76	76
R-squared	0.071	0.426	0.270	0.429	0.274	0.442	0.442	0.460	0.479

Notes: The table is based on regression equation below. All variables are based on the information released until April 19, 2020. The stimulus (percent of GDP) is the percentage of aggregate fiscal stimulus to GDP declared by country i to fight COVID-19. The $\overline{\text{Stringency}}$ is the cumulative level of economic repression in country i as measured until April 19, while log(COVID-19 Cases) is based on the number of reported cases until April 19. The $\overline{\text{Rating}}$ is the average distance from junk rating. We report robust standard errors. ***- $p < 0.01$, **- $p < 0.05$ and * - $p < 0.1$

Estimation equation:

$$\text{Stimulus}_i = \beta_0 + \beta_1 * \overline{\text{Stringency}}_i + \beta_2 * \log(\text{COVID cases})_i + \beta_3 * \overline{\text{Rating}}_i + \text{Controls}_i + \epsilon_i$$

Table 4: Delay in Stimulus vs. Mean Rating

	Stimulus delay (number of days)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{\text{Stringency}}^T$	0.79***			0.74***		0.76***	0.62**	0.57*
	(0.25)			(0.25)		(0.28)	(0.31)	(0.29)
$\overline{\text{Rating}}$		-1.30***		-1.09**	-2.07***		-1.68***	-1.32**
		(0.44)		(0.47)	(0.45)		(0.56)	(0.60)
log(COVID-19 Cases)^T			1.10**		2.49***	0.55	1.79**	2.45***
			(0.44)		(0.55)	(0.43)	(0.70)	(0.72)
log(GDP)								-2.34***
								(0.76)
Observations	78	72	78	72	72	78	72	72
R-squared	0.282	0.132	0.046	0.382	0.304	0.293	0.465	0.516

Notes: The table is based on regression equation 3. All variables are based on the information released until April 9, 2020 by OxCGRT. Stimulus delay (number of days) is calculated w.r.t. to a threshold stringency level of 50 and first announcement of fiscal stimulus on date T. The $\overline{\text{Stringency}}^T$ is the average of economic stringency and Log(COVID-19 Cases)^T are the number of reported cases in country i on date T. The $\overline{\text{Rating}}$ is the average distance from junk rating. We report robust standard errors. ***- $p < 0.01$, **- $p < 0.05$ and * - $p < 0.1$

Estimation Equation:

$$\text{Stimulus Delay}_i = \beta_0 + \beta_1 * \overline{\text{Stringency}}_i^{T_i} + \beta_2 * \log(\text{COVID cases})_i^{T_i} + \beta_3 * \overline{\text{Rating}}_i + \text{Controls}_i + \epsilon_i \tag{3}$$

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Table 5: List of Vulnerable Countries

Country	Confirmed Cases	Stringency	Nominal GDP (USD bn) (2019)	GDP per Capita (USD) (2019)	Fiscal Stimulus (% of GDP)	Moody's Ratings	S&P Ratings	Fitch Ratings	Stimulus (USD bn) (1%)	(2%)	(5%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
BURKINA FASO	2824	49	15	718	0.0	NA	B	NA	0	0	1
COSTA RICA	6114	23	61	12015	0.0	B2	B+	B+	1	1	3
ECUADOR	45054	23	108	6249	0.0	Caa3	CCC-	CC	1	2	5
EGYPT	14909	20	302	3047	0.4	B2	B	B+	2	5	14
HUNGARY	9089	25	170	17463	2.3	Baa3	BBB	BBB	0	0	5
INDIA	54155	37	2936	2172	0.9	Baa2	BBB-	BBB-	4	33	122
INDONESIA	29704	33	1112	4164	2.2	Baa2	BBB	BBB	0	0	31
IRAQ	10267	31	224	5738	0.0	NA	NA	B-	2	4	11
JORDAN	4841	23	44	4387	1.6	B1	B+	BB-	0	0	2
LEBANON	7610	28	59	9655	0.0	Ca	SD	RD	1	1	3
PAKISTAN	31650	29	284	1388	2.7	B3	B-	B-	0	0	7
PANAMA	16566	23	69	16245	2.0	Baa1	BBB+	BBB	0	0	2
PERU	26083	23	229	7047	4.7	A3	BBB+	BBB+	0	0	1
PORTUGAL	133431	23	236	23031	4.4	Baa3	BBB	BBB	0	0	1
ROMANIA	17028	22	244	12483	2.0	Baa3	BBB-	BBB-	0	0	7
RUSSIA	55405	25	1638	11163	0.0	Baa3	BBB-	BBB	16	33	82
SOUTH AFRICA	17772	20	359	6100	0.0	Ba1	BB	BB	3	7	18
SRI LANKA	2593	35	87	3947	0.6	B2	B	B	0	1	4
TUNISIA	4686	22	39	3287	2.1	B2	NR	B+	0	0	1
UKRAINE	16063	24	150	3592	0.0	Caa1	B	B	1	3	8
VENEZUELA	2495	21	70	2548	0.0	C	B-	WD	1	1	4
VIETNAM	4739	42	262	2740	0.0	NA	NA	BB	3	5	13
Total									36	98	342

Notes: The vulnerable country list is based on mean stringency index ≥ 20.1 (cross-country median), and mean credit rating ≤ 5. We drop all countries whose stimulus already exceed 5 percent of GDP as on April 9, 2020. The columns (9), (10) and (11) give the difference (USD bn value) between threshold stimulus package (1, 2, and 5 percent of GDP) and the announced fiscal stimulus (percent of GDP) by a country until April 9, 2020 according to OxCGRT. If this difference is negative, we report it as zero.

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Table 6: Data Sources

Variable	Source
Daily Stringency Index	Oxford COVID-19 Government Response Tracker (OxCGRT)
Daily confirmed cases	Oxford COVID-19 Government Response Tracker (OxCGRT)
Daily fiscal measures	Oxford COVID-19 Government Response Tracker (OxCGRT)
Fiscal Measures	IMF Policy Response Tracker
Sovereign credit rating	countryeconomy.com & tradingeconomics.com
Nominal GDP (2019)	IMF
GDP per capita (2019)	IMF

Notes: This table lists the sources of data used in this paper.

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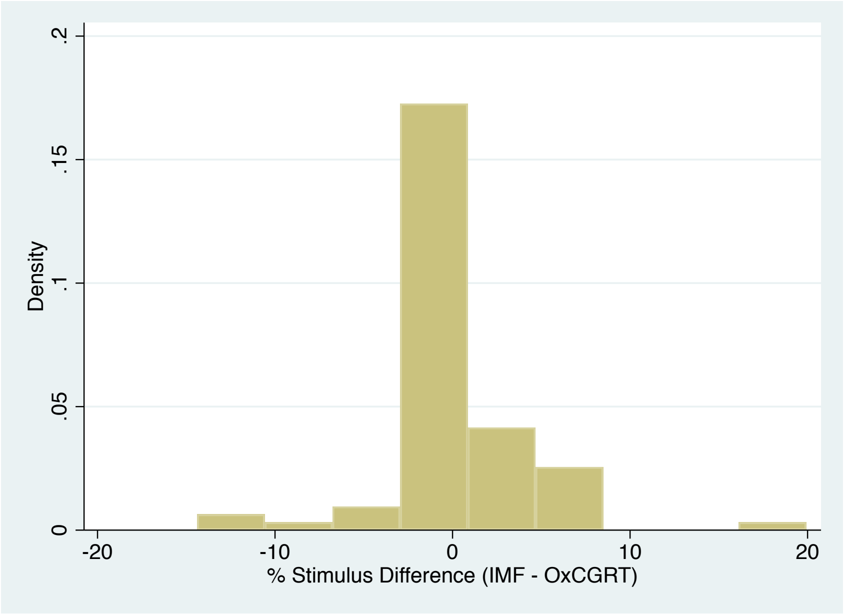
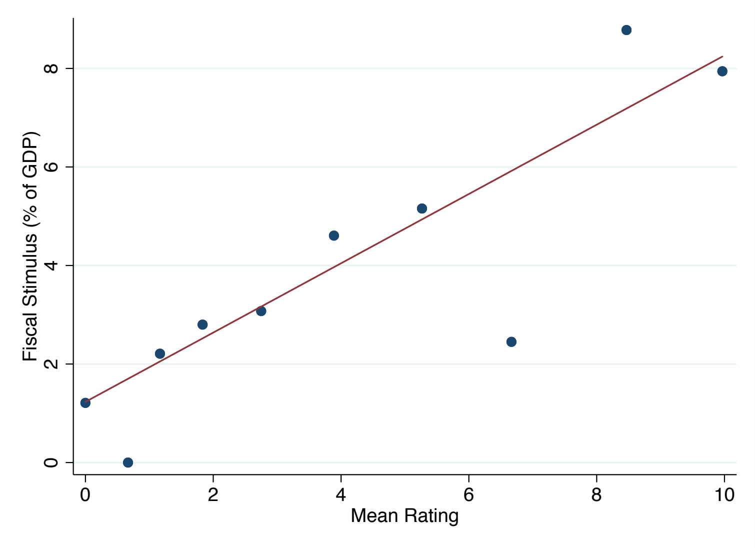
Appendix

Figure 8: Difference between IMF and OxCGRT Fiscal Stimulus - Full Sample



Notes: This figure reports the histogram of the difference between % Fiscal stimulus (IMF) and % Fiscal Stimulus (OxCGRT). Many of the countries with positive value of the difference corresponds to those which have declared additional stimulus after April 9, 2020 (our original sample end period). There are a few countries with significant discrepancies, which arises for two reasons. First, in OxCGRT, some of the loan guarantees were counted as stimulus (for instance, Bulgaria and China), which we exclude while aggregating the numbers from the IMF. Second, some countries have announced additional fiscal stimulus since our calculations based on OxCGRT data on April 9, 2020. (Source: IMF policy response tracker as on April 16, 2020 and OxCGRT as on April 9, 2020)

Figure 9: Fiscal Stimulus (IMF) vs. Mean Rating



Notes: The figure shows the cross-country binscatter between fiscal stimulus and mean rating. It corresponds to the regression specification (2) in Table 3. Fiscal stimulus is the sum of stimulus announced (as a percentage of 2019 GDP) until April 16, 2020 (IMF data). The mean rating is the simple average of the sovereign credit ratings from Moody's, Fitch and S&P as on April 16, 2020. (Data Source: IMF and countryeconomy.com)

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