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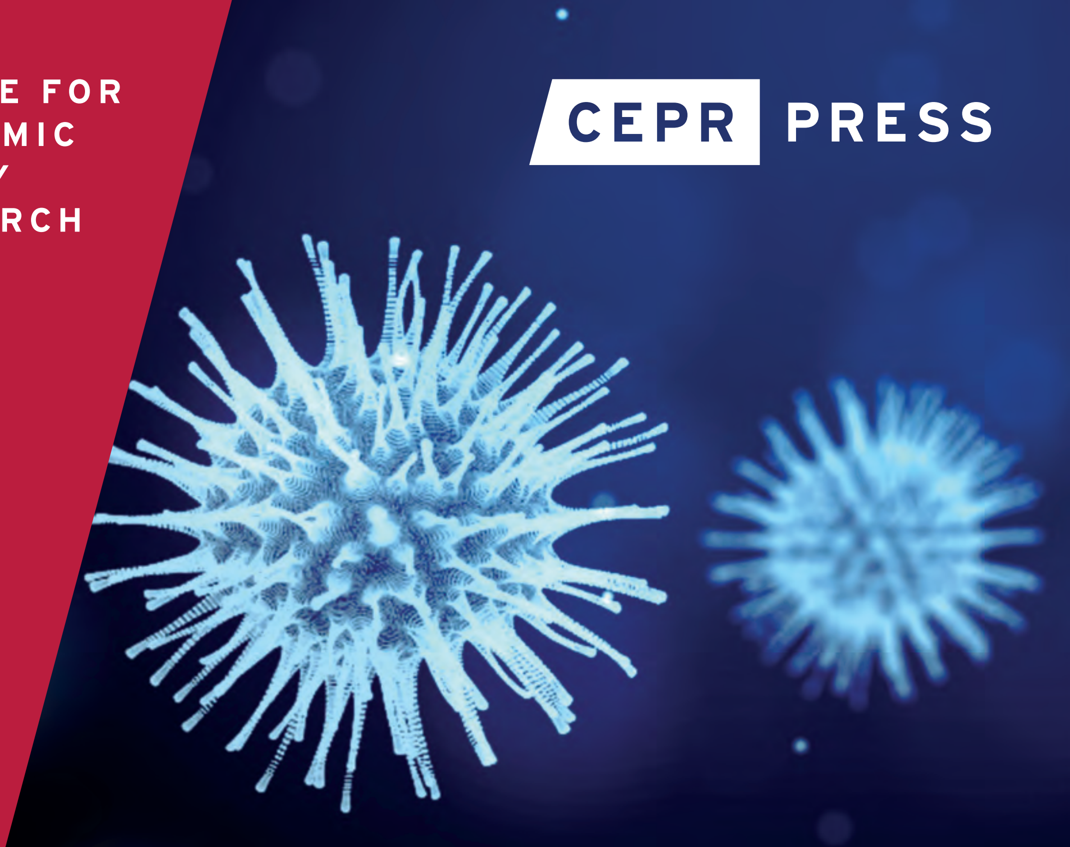

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

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13 MAY 2020

Covid Economics
Vetted and Real-Time Papers

Covid Economics, Vetted and Real-Time Papers, from CEPR, brings together formal investigations on the economic issues emanating from the Covid outbreak, based on explicit theory and/or empirical evidence, to improve the knowledge base.

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Covid Economics will feature high quality analyses of economic aspects of the health crisis. However, the pandemic also raises a number of complex ethical issues. Economists tend to think about trade-offs, in this case lives vs. costs, patient selection at a time of scarcity, and more. In the spirit of academic freedom, neither the Editors of *Covid Economics* nor CEPR take a stand on these issues and therefore do not bear any responsibility for views expressed in the articles.

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The following journals have indicated that they will accept submissions of papers featured in *Covid Economics* because they are working papers. Most expect revised versions. This list will be updated regularly.

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American Economic Review, Applied Economics

American Economic Review, Insights

American Economic Review, Economic Policy

American Economic Review, Macroeconomics

American Economic Review, Microeconomics

Economic Journal

Journal of Development Economics

*Journal of Econometrics**

Journal of Economic Growth

Journal of Economic Theory

*Journal of the European Economic Association**

Journal of Finance

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*Journal of Labor Economics**

Journal of Monetary Economics

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*Quarterly Journal of Economics**

Review of Economics and Statistics

*Review of Economic Studies**

Review of Financial Studies

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

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Vetted and Real-Time Papers

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Covid Economics **Issue 17, 13 May 2020**

Pandemic lockdown: The role of government commitment[1]

Christian Moser[2] and Pierre Yared[3]

Date submitted: 6 May 2020; **Date accepted:** 8 May 2020

This note studies optimal lockdown policy in a model in which the government can limit a pandemic's impact via a lockdown at the cost of lower economic output. A government would like to commit to limit the extent of future lockdown in order to support more optimistic investor expectations in the present. However, such a commitment is not credible since investment decisions are sunk when the government makes the lockdown decision in the future. The commitment problem is more severe if lockdown is sufficiently effective at limiting disease spread or if the size of the susceptible population is sufficiently large. Credible rules that limit a government's ability to lock down the economy in the future can improve the efficiency of lockdown policy.

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1 We thank Andy Atkeson, Andrés Drenik, Émilien Gouin-Bonenfant, Rick Mishkin, Ben Moll, Trish Mosser, Tommaso Porzio, Jesse Schreger, Steve Zeldes, and seminar participants at Columbia University for helpful comments. Rachel Williams provided excellent research assistance. Any errors are our own.

2 Assistant Professor of Business, Columbia University.
3 MUTB Professor of International Business, Columbia University.

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1 Introduction

In response to the COVID-19 pandemic, governments across the world implemented lockdown policies to limit the spread of infections. In numerous cases, these policies were eventually extended. For example, on March 22, 2020, New York Governor Andrew Cuomo extended the statewide lockdown from April 19 to April 29. Then on April 16, the lockdown was further extended from April 29 to May 15. By the end of the following day, a total of 23 state governors had extended lockdown policies beyond their initial plans, some by over one month.[1] Notably, the first wave of lockdowns were imposed using executive orders without specifying conditions under which they would be extended or lifted. More recently, in his daily briefing on May 4, 2020, New York Governor Andrew Cuomo committed to a list of four quantifiable conditions or "core factors" that would need to be met in order for regional economies to reopen for business.

In this note, we study the value of government commitment in choosing a lockdown policy. We consider a simple economy that captures policy tradeoffs based on commonly used SIR models of pandemics (Kermack and McKendrick, 1927; Ferguson et al., 2020; Wang et al., 2020). Investors provide capital, the government chooses a lockdown policy, and workers supply labor. A lockdown imposes an upper bound on labor supply while also limiting disease spread and health costs. Our framework is general and subsumes key mechanics of many other macroeconomic SIR models with lockdown or mitigation elements in the literature.[2] An important feature of our model is that investment is made before future lockdown policy is chosen. We think of this feature as capturing the long-term investments in inventory, employee training, and marketing that businesses make while anticipating the future trajectory of a lockdown policy.

The optimal policy under government commitment trades off the aggregate output cost with the health benefit associated with lockdown. Aggregate output decreases with the intensity of the lockdown through two channels. First, it decreases directly through lower labor supply, which is curbed by the lockdown. Second, it decreases indirectly through lower investment, which results from investors' expectation of a lower marginal product of capital due to the lockdown. The health benefit of a lockdown is higher if the lockdown technology is more effective at limiting infections

[1]These states include Colorado, Connecticut, Georgia, Idaho, Illinois, Indiana, Kansas, Louisiana, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, New Mexico, New York, Ohio, Rhode Island, South Carolina, Tennessee, Vermont, Washington, and Wisconsin.

[2]See for example Acemoglu et al. (2020), Alvarez et al. (2020), Atkeson (2020a,b), Baqaee and Farhi (2020a,b), Berger et al. (2020), Eichenbaum et al. (2020a,b), Farboodi et al. (n.d.), Glover et al. (2020), Jones et al. (2020), Kaplan et al. (2020), and Piguillem and Shi (2020).

or if the share of the initial susceptible population is larger.

Our main result focuses on how the extent of a lockdown is impacted by the government's lack of commitment. A government would like to commit to limit the extent of future lockdown in order to support more optimistic investor expectations in the present. However, such a commitment may be not credible since investment decisions are sunk when the government makes the lockdown decision in the future. In this situation, a government without commitment imposes a more stringent lockdown relative to the optimal policy under commitment. Investors rationally anticipate the government's lack of commitment, causing them to invest less than they would in anticipation of the policy under commitment. Through this mechanism, lack of commitment results in a larger reduction in investment and output during a lockdown than is socially optimal.

We establish conditions under which lack of commitment by the government reduces social welfare. If the lockdown is sufficiently effective at limiting disease spread or if the number of susceptible individuals is sufficiently high, then the optimal policy is time-inconsistent, leading to social welfare losses. Investors provide less capital and the government chooses a more stringent lockdown relative to what would happen under commitment. In contrast, if a lockdown is not very effective or if the size of the susceptible population is low, then the optimal policy under commitment involves no lockdown and is time-consistent.

These results suggest that commitment problems leading to welfare losses during a lockdown are more likely to arise in environments with greater capacity to limit disease spread through lockdown, such as urban areas in advanced economies. A similar commitment problem arises when considering lockdowns early in a pandemic, when the size of the susceptible population is high and herd immunity has not yet developed.

Our results imply that a credible government lockdown policy plan can improve the efficiency of lockdown policy. In principle, such a plan can depend on new information that arrives during a lockdown, such as estimates of disease mortality, the state of the economy, the likelihood of vaccine discovery, or the medical system's capacity. Some of this information may not be contractible, in which case a rigid plan can be too constraining, and policy flexibility is desirable. To capture this value of flexibility, we extend our model to allow the government to learn new noncontractible information before choosing a lockdown policy. In this extended model, we show that rules that impose limits on future lockdown policy can increase social welfare, even though policy flexibility is valuable. The reason is that a government lacking commitment chooses more lockdown in the

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future than is socially desirable. As such, a marginally binding rule increases social welfare by raising investment and output at no cost of reduced policy flexibility.

Importantly, our analysis does not imply that lockdowns are socially harmful. In fact, reducing or lifting the lockdown in our model is detrimental if the resulting health costs exceed the immediate economic gains. Our model abstracts from policy mistakes involving insufficient degrees of lockdown by assuming that policy is chosen by a benevolent government that maximizes long-run social welfare.[3] Our analysis points to the value of a government plan that defines limits on the extent of *future* lockdown. Such a plan is beneficial if the expected *future* economic gains of those limits—from stimulating investment toward its efficient level—exceed the health costs.

Our work relates to the nascent literature on optimal policy in a pandemic, with some recent contributions listed in footnote 2. This literature focuses on various aspects of government policy, including the optimal intensity and timing of lockdowns. We depart from this literature by focusing on the value of government commitment in the context of lockdown policy.

The mechanism underlying the time inconsistency of optimal policy in our setting is in line with the broader insights in the seminal work of Kydland and Prescott (1980), and in particular the literature that studies government commitment in the context of capital taxation (Chari and Kehoe, 1990; Klein et al., 2008; Aguiar et al., 2009). While lack of commitment in our model distorts capital investment as in these frameworks, there are two important differences. First, a lockdown distorts capital investment not directly via taxation, but indirectly by suppressing labor. Second, in our setting, these distortions from lockdown do not increase the government budget, but reduce the long-term health costs of disease spread. Since health costs derive from an underlying SIR model, the value of reducing these costs cannot be represented by a simple concave function, as in a typical model of public goods. This means that the usual methods for comparative statics cannot be applied here.

Our analysis of rules in the presence of noncontractible information relates to the literature on commitment versus flexibility in policymaking (Amador et al., 2006; Athey et al., 2005; Halac and Yared, 2014, 2018). The result that rules can strictly increase social welfare even if flexibility is valuable is consistent with that work. However, in contrast to that work, we obtain this result under milder restrictions on the utility function and the distribution of noncontractible information.

[3]This assumption may be violated in an extension of our model in which political economy considerations lead the government to overweigh immediate economic gains relative to future health costs of relaxing a lockdown.

2 Model

We consider a simple three-period economy. In the first period, investors provide capital. In the second period, the government chooses a lockdown policy and workers supply labor. In the third period, disease spread follows an SIR model of disease spread and is affected by the lockdown policies of the second period. Lockdown imposes an upper bound on labor supply in the second period while also limiting disease spread and health costs from the third period onward. Importantly, the government chooses an optimal lockdown policy after capital investment is sunk.

2.1 Economic Environment

There are three periods $t = 0, 1, 2$. At $t = 0$, competitive external investors provide capital k. At $t = 1$, a continuum of mass 1 of workers supply up to one unit of labor inelastically subject to a binding upper bound $\ell \in [0, 1]$ representing the degree of lockdown. If $\ell = 1$, there is no lockdown and the maximum amount of labor is supplied. If $\ell = 0$ there is maximal lockdown. A worker's budget constraint is

$$c = w\ell, \tag{1}$$

where c is consumption and w is the market wage. Workers have linear utility over consumption c and receive continuation value V as a function of the future state of the economy.

Capital k combined with labor input ℓ generates output y according to the following production function:

$$y = k^{\alpha}\ell^{1-\alpha}, \tag{2}$$

where $\alpha \in (0, 1)$. We assume for simplicity that capital depreciates fully. Investors can invest domestically or abroad at a rate of return r^*.[4] As such, in a competitive equilibrium, the marginal product of capital obeys the following no-arbitrage condition:

$$r^* = \alpha k^{\alpha-1}\ell^{1-\alpha} \tag{3}$$

[4]We consider an open economy for simplicity. The analysis can be easily extended to a closed economy with workers and capitalists.

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Labor is competitively supplied so wages equal their marginal product given by

$$w = (1-\alpha)\, k^{\alpha} \ell^{-\alpha}. \tag{4}$$

Combining (3) and (4), it follows that in a competitive equilibrium—where capital adjusts to the anticipated level labor supply—consumption given by equation (1) satisfies

$$c = A\ell, \tag{5}$$

where $A = (1-\alpha)(\alpha/r^*)^{\alpha/(1-\alpha)}$. Note that equation (5) features consumption that is linear in labor input ℓ because capital optimally adjusts to the given level of labor input.

2.2 Disease Spread and Lockdown Policy

We model disease spread as following an SIR model (Kermack and McKendrick, 1927; Ferguson et al., 2020; Wang et al., 2020), which we allow to depend on a lockdown policy, as in Atkeson (2020a), Eichenbaum et al. (2020a), and Alvarez et al. (2020). Specifically, we define the state of the economy at time $t = 1, 2$ as $\Omega_t = \{S_t, I_t, R_t, D_t\}$, where $S_t \geq 0$ is the mass of susceptible individuals, $I_t \geq 0$ is the mass of infected and contagious individuals, $R_t \geq 0$ is the mass of recovered individuals, and $D_t \geq 0$ is the mass of deceased individuals. Since the population at date $t = 1$ of worker is normalized to 1 and $D_1 = 0$ without loss of generality, it follows that

$$S_1 + I_1 + R_1 = 1 \quad \text{and} \tag{6}$$

$$S_2 + I_2 + R_2 + D_2 = 1. \tag{7}$$

An SIR model defines a mapping $\Gamma(\cdot)$ that implies a law of motion

$$\Omega_2 = \Gamma(\Omega_1, \ell, \kappa), \tag{8}$$

where the state at date $t = 2$ is a function of the state at date $t = 1$, the degree of lockdown at date $t = 1$, and a parameter $\kappa \in [0, 1]$ capturing the effectiveness of the lockdown technology. Note that implicit in our formulation is the existence of a state Ω_0 and initial lockdown policy at date $t = 0$ that determine Ω_1. Because these are exogenous, we take the state Ω_1 as given without loss

of generality.

Social welfare equals

$$c + V\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right), \tag{9}$$

where $V(\cdot)$ is a continuation value to society that is a function of the future state. The continuation value $V(\cdot)$ captures the long-term costs of bad health and mortality associated with disease spread, as guided by the future law of motion of the state Ω_t. Note that through the law of motion for Ω_2 given by equation (8), the continuation value will be impacted by the degree of lockdown, which determines ℓ, and its effectiveness κ.

We make the following intuitive assumption.

Assumption 1. *The value of $V\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right)$ is independent of ℓ if either (i) $\kappa = 0$ or (ii) $S_1 = 0$.*

The first part of Assumption 1 states that the continuation value to society is independent of the degree of lockdown if the lockdown technology is maximally ineffective at limiting disease spread (i.e., if $\kappa = 0$). Since disease spread is independent of the degree of lockdown in this case, future payoffs will not depend on lockdown decisions.

The second part of Assumption 1 states that lockdown also becomes irrelevant if the size of the initial susceptible population is zero (i.e., if $S_1 = 0$). That there are no susceptible individuals means that the entire population is either infected, recovered, or dead, meaning that the disease cannot spread. As such, we assume that disease dynamics are determined only by epidemiological parameters guiding recovery and death rates, which we assume are independent of lockdown.

In addition to this intuitive assumption, we make the following technical assumption. In the statement of this assumption and for the remainder of our paper, we consider comparative statics with respect to variations in the susceptible population S_1 that are accommodated by variations in the recovered population R_1.

Assumption 2. *The function $V\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right)$ is differentiable in ℓ and the derivative of $V\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right)$ with respect to ℓ, conditional on any $\ell \in (0,1)$, is (i) continuous in κ and (ii) continuous in S_1.*

Assumption 2 is a technical assumption that guarantees that the continuation value is well-behaved. This assumption allows us to prove our results, which rely on the marginal payoffs from lockdown changing gradually with respect to parameters κ and S_1.

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Assumptions 1 and 2 together are sufficient to support our theoretical conclusions. Note that these assumptions are satisfied in many recent macroeconomic models with SIR modules in which disease dynamics respond smoothly to lockdown policies. In these frameworks, the probability of a person's transition from the susceptible state to the infected state is continuously decreasing in the effectiveness of the lockdown technology κ and continuously increasing in the size of the susceptible population S_1. See Eichenbaum et al. (2020a) and Alvarez et al. (2020) for examples of models consistent with these assumptions.

2.3 Timeline

The order of events is as follows:

1. At $t = 0$, investors choose investment k;
2. At $t = 1$, the government chooses lockdown policy ℓ, workers supply labor subject to the lockdown policy, output y is produced, and workers and investors consume their respective shares of income; and
3. At $t = 2$, the disease spread progresses according to the transition function Γ.

A key feature of our model is that investment is made before the lockdown policy is chosen. We think of this feature as capturing the long-term investments that businesses make while anticipating the future trajectory of a lockdown policy. In support of this idea, recent survey evidence shows that businesses that expect a more prolonged crisis are more likely to expect to shut down (Bartik et al., 2020). We will explore in detail the implications of this sequencing of investment and lockdown decision for the optimal policy under commitment compared to that under lack of commitment.

3 Optimal Policy under Commitment

Suppose that the government can commit to a lockdown policy ℓ prior to investment decisions. This means that capital optimally adjusts to anticipated labor supply, which, in turn, is determined by the lockdown policy. Substituting consumption under the capital no-arbitrage condition from

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equation (5) into (9), the government under commitment solves the following problem:

$$\max_{\ell\in[0,1]} \{A\ell + V(\Gamma(\Omega_1, \ell, \kappa))\} \tag{10}$$

Importantly, substituting the capital no-arbitrage condition before solving for the optimal degree of lockdown means that the government under commitment takes into account the reaction of investment to the anticipation of its policies. Define $V_\ell(\Gamma(\Omega_1, \ell, \kappa)) \equiv dV(\Gamma(\Omega_1, \ell, \kappa))/d\ell$ as the total derivative of the continuation value with respect to labor input. The first-order necessary condition associated with an interior solution to the problem of the government under commitment is simply

$$-V_\ell(\Gamma(\Omega_1, \ell, \kappa)) = A. \tag{11}$$

In choosing the degree of lockdown, the government weighs two opposing forces, as in Gourinchas (2020) and Hall et al. (2020). On one hand, it considers the future *health benefits* in terms of reduced mortality from inhibiting the disease spread, as captured by the marginal change in the continuation value $-V_\ell(\Gamma(\Omega_1, \ell, \kappa))$. On the other hand, it considers the *economic costs* captured by foregone marginal product of labor given by A. In turn, the economic costs are twofold. First, conditional on the level of capital, lockdown has a direct impact on output by limiting labor supply. Second, lockdown has an indirect impact on output by reducing the marginal product of capital which reduces investment. The government's ability to commit gives it the ability to take into account both of these factors, leading it to choose the optimal lockdown in anticipation of investors' reaction to the policy.

We also consider two potential corner solutions to the government's problem under commitment: complete lockdown and no lockdown. Under complete lockdown, $\ell = 0$ and

$$-V_\ell(\Gamma(\Omega_1, \ell, \kappa)) > A. \tag{12}$$

Conversely, under no lockdown, $\ell = 1$ and

$$-V_\ell(\Gamma(\Omega_1, \ell, \kappa)) < A. \tag{13}$$

4 Optimal Policy under Lack of Commitment

Under lack of commitment, the government takes capital k as given when choosing the lockdown policy at date $t = 1$. We can substitute for consumption c in equation (9) using equations (1), (2), and (4) to write the program for the the government under lack of commitment at date $t = 1$ as

$$\max_{\ell \in [0,1]} \left\{ (1-\alpha) k^{\alpha} \ell^{1-\alpha} + V\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right) \right\}. \tag{14}$$

Importantly, not substituting the capital no-arbitrage condition before solving for the optimal degree of lockdown means that the government under no commitment does not take into account the reaction of investment to the anticipation of its policies. The derivative of the government objective function with respect to ℓ is

$$(1-\alpha)^2 k^{\alpha} \ell^{-\alpha} + V_{\ell}\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right). \tag{15}$$

This expression makes clear that a government lacking commitment undervalues the economic cost of lockdown. This is because it takes capital decisions as sunk and does not internalize the impact of lockdown on ex ante investor expectations.[5] Investors take this lack of commitment into account when choosing investment. Therefore, the capital no-arbitrage condition applies with respect to the optimal behavior of government at the time of it choosing a lockdown policy. To see what this means, we substitute the capital no-arbitrage condition in equation (3), which accounts for optimal investor behavior, into equation (15) and rewrite the equilibrium derivative of the government objective function with respect to ℓ:

$$(1-\alpha) A + V_{\ell}\left(\Gamma\left(\Omega_1, \ell, \kappa\right)\right) \tag{16}$$

This derivative shows that in equilibrium, the marginal cost of lockdown for a government lacking commitment is $(1-\alpha) A$. This is below the marginal cost of lockdown for a government under commitment, which is equal to A. At the same time, the marginal benefit from lockdown is the same regardless of government commitment and given by $-V_{\ell}(\Gamma(\Omega_1, \ell, \kappa))$.

[5]Note that for there to be a commitment problem, it is necessary for the government to care about the consumption and health of domestic workers. Our insights would remain qualitatively unchanged if the government's weights on workers and investors were both positive.

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The FOC associated with an interior solution to the problem of the government under lack of commitment is simply

$$-V_\ell\left(\Gamma\left(\Omega_1,\ell,\kappa\right)\right)=\left(1-\alpha\right)A. \tag{17}$$

As previously, we also consider two potential corner solutions to the government's problem under lack of commitment: complete lockdown and no lockdown. Under complete lockdown, $\ell=0$ and

$$-V_\ell\left(\Gamma\left(\Omega_1,\ell,\kappa\right)\right)>\left(1-\alpha\right)A. \tag{18}$$

Conversely, under no lockdown, $\ell=1$ and

$$-V_\ell\left(\Gamma\left(\Omega_1,\ell,\kappa\right)\right)<\left(1-\alpha\right)A. \tag{19}$$

Denote by ℓ^c the optimal lockdown policy under full commitment and by ℓ^n the equilibrium lockdown under lack of commitment. Then we obtain the following result.

Proposition 1 (Time Inconsistency)**.** *Lockdown under no commitment is weakly larger than lockdown under full commitment: $\ell^n\leq\ell^c$. Moreover, lockdown under no commitment is strictly larger than lockdown under full commitment if either level of lockdown is interior: $\ell^n<\ell^c$ if $\ell^c\in(0,1)$ or $\ell^n\in(0,1)$.*

Proof. See Appendix A.1. □

Proposition 1 shows that an implication of lack of government commitment is that a suboptimal lockdown policy may be chosen. The reason for this is that, absent commitment, the government undervalues the economic cost of lockdown, leading to more lockdown and lower output than would be optimal from an ex ante perspective.

In the next proposition, we examine how the implications of lack of government commitment are impacted by the effectiveness of the lockdown technology with respect to limiting disease spread, as indexed by κ. We focus on cases in which the optimal policy under commitment involve some lockdown for some values of $\kappa\in(0,1)$. We then provide conditions under which the government under lack of commitment deviates from the commitment policy.

Proposition 2 (Effect of Lockdown Technology)**.** *Suppose that there exists a lockdown technology for which the optimal policy under commitment involves some lockdown, that is, $\ell^c<1$ for some $\kappa\in(0,1)$.*

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Then the following is true:

1. *If the lockdown technology has low effectiveness, then the policy under full commitment and under lack of commitment involves no lockdown. That is,* $\exists \underline{\kappa} \in (0,1)$ *such that* $\ell^c = \ell^n = 1$ *if* $\kappa \leq \underline{\kappa}$*.*

2. *If the lockdown technology has intermediate effectiveness, then the policy under full commitment is no lockdown and under lack of commitment is positive lockdown. That is,* $\exists \overline{\kappa} \in (\underline{\kappa}, 1]$ *such that* $\ell^c = 1 > \ell^n$ *if* $\kappa \in (\underline{\kappa}, \overline{\kappa})$*.*

Proof. See Appendix A.2. □

The following proposition considers policy under commitment and lack of commitment as a function of the initial number of susceptible individuals S_1.

Proposition 3 (Effect of Initial Health Status)**.** *Suppose that there exists a population share of susceptible individuals for which the optimal policy under commitment involves some lockdown, that is,* $\ell^c < 1$ *for some* $S_1 \in (0,1)$*. Then the following is true:*

1. *If the initial number of susceptible individuals is low, then the policy under full commitment and under lack of commitment involves no lockdown. That is,* $\exists \underline{S}_1 \in (0,1)$ *such that* $\ell^c = \ell^n = 1$ *if* $S_1 \leq \underline{S}_1$*.*

2. *If there is an intermediate number of susceptible individuals, then the policy under full commitment is no lockdown and under lack of commitment is positive lockdown. That is,* $\exists \overline{S}_1 \in (\underline{S}_1, 1]$ *such that* $\ell^c = 1 > \ell^n$ *if* $\kappa \in (\underline{S}_1, \overline{S}_1)$*.*

Proof. The proof is analogous to that of Proposition 2 and is thus omitted. □

If the lockdown technology is sufficiently ineffective at preventing disease (Proposition 2) or if the fraction of susceptible individuals is sufficiently low (Proposition 3), then there is no problem of lack of commitment. Both under commitment and under lack of commitment the economic cost of any lockdown dwarfs the mortality benefits, and having no lockdown is optimal. These results change if the lockdown technology has intermediate effectiveness. In this circumstance, while it is optimal for the government under commitment to not lockdown the economy, the government under lack of commitment which undervalues the cost of lockdown will prefer to lockdown the economy.[6]

[6]A natural question concerns comparative statics for $\kappa > \overline{\kappa}$ and $S_0 > \overline{S}_0$. Establishing these comparative statics would require additional assumptions beyond those made above.

5 Rules that Limit Future Lockdown

We have established that a government under lack of commitment may choose more severe lockdown than a government under full commitment. As a result, lack of commitment can lead to an economic contraction at date $t = 1$ that is deeper than is socially optimal.

In this environment, a credible lockdown policy plan can be socially optimal. Formally, suppose that rather than choosing a policy $\ell \in [0, 1]$, the policy decision ℓ is exogenously constrained to the optimum under commitment, $\ell = \ell^c$. Such a constraint on policy improves investor expectations of the future and can improve the efficiency of lockdown policy.

In principle, such a plan can depend on new information that arrives during a lockdown, such as estimates of disease mortality, the state of the economy, the likelihood of vaccine discovery, or the medical system's capacity. To capture this idea, suppose that a state variable $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$, with $\underline{\theta} < \overline{\theta}$, is realized before investment $k(\theta)$ is made at date $t = 0$ and then policy ℓ is chosen at date $t = 1$. Suppose that θ is drawn from a probability density function (pdf) $f(\theta)$ over $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$. Conditional on θ, social welfare can be written as[7]

$$c + V\left(\Gamma\left(\Omega_1, \ell, \kappa\right), \theta\right). \tag{20}$$

In this extended model, the optimal policies under commitment and no commitment depend on the realization of θ and are denoted by $\ell^c(\theta)$ and $\ell^n(\theta)$, respectively. An argument analogous to that in Proposition 1 implies that $\ell^c(\theta) \geq \ell^n(\theta)$. In other words, conditional on θ, the government lacking commitment chooses a weakly larger lockdown than the government under full commitment. If θ represents contractible information, then a credible plan that imposes the constraint $\ell = \ell^c(\theta)$ can increase social welfare since it forces the government without commitment to choose the policy under full commitment.

In practice, some of the information in θ may not be contractible, in which case a rigid plan can be too constraining, and flexibility is desirable. In this case, we can show that bounded discretion in the form of a rule $\underline{\ell} > 0$ that constrains the government to a policy choice $\ell \in [\underline{\ell}, 1]$ is socially desirable. Formally, let us suppose that $\ell^n(\theta)$ is a decreasing function of θ that is continuous in a neighborhood below $\overline{\theta}$. Therefore, higher values of θ are associated with more lockdown.

[7] While we introduce the state variable θ as an argument outside of the disease transition function $\Gamma(\cdot)$, this is without loss of generality and we could allow for θ to have a direct effect on disease spread by allowing it to index $\Gamma(\cdot)$.

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Moreover, let us suppose that the pdf $f(\theta)$ is strictly positive and is continuous in a neighborhood below $\overline{\theta}$. We can use analogous arguments as in the literature on commitment versus flexibility in policymaking (Amador et al., 2006; Athey et al., 2005; Halac and Yared, 2014, 2018) to show that rules that put a limit on lockdown can boost social welfare, even if the rule cannot depend explicitly on the realization of θ.[8]

Proposition 4 (Value of Rules)**.** *Consider an economy where lockdown under full commitment and under lack of commitment is never maximal, namely $\ell^c(\theta) \geq \ell^n(\theta) > 0$ for all θ, and where optimal lockdown under lack of commitment is sometimes interior, namely $\ell^n(\theta) < 1$ for some θ. Then a rule that imposes a lower bound $\underline{\ell}$ on labor supply strictly increases social welfare under lack of commitment.*

Proof. See Appendix A.3. □

Proposition 4 shows that the introduction of rules increases social welfare even if there is a value to flexibility. The intuition is that a government lacking commitment chooses more lockdown in the future than is socially desirable. As such, a marginally binding rule increases social welfare by raising investment and output at no cost of reduced policy flexibility. A key part of this argument is that extreme levels of future lockdown are assumed to never be optimal under commitment given current information. Thus, a rule that makes such extreme choices infeasible in the future can improve investor expectations and mitigate the economic costs of a lockdown. Our environment could be extended to one in which this assumption is violated, and extreme choices are sometimes optimal in the future even under commitment. In this environment, a limit on future lockdowns with an escape clause under extreme conditions could be optimal.[9]

6 Concluding Remarks

We have analyzed the value of government commitment in choosing a lockdown policy. A government would like to commit to limit the extent of future lockdown in order to support more optimistic investor expectations in the present. However, such a commitment is not credible since investment decisions are sunk when the government makes the lockdown decision. Our results suggest that welfare losses due to lack of commitment are more likely to arise in environments

[8]Because the function $V(\cdot)$ is not concave and the pdf $f(\cdot)$ can have a flexible structure, the following proposition does not follow directly from previous work and, instead, relies on a different theoretical argument.

[9]See Halac and Yared (forthcoming) for a discussion of threshold contracts with escape clauses.

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with greater capacity to limit disease spread through lockdown, such as urban areas in advanced economies. These problems may also arise early in a pandemic, when the size of the susceptible population is high and herd immunity has not yet developed. Our analysis highlights the value of lockdown to mitigate the health costs of pandemics, together with the importance of defining the limits of future lockdowns. Through their impact on business expectations, such limits can improve the efficiency of lockdown policy.

Our analysis leaves several interesting avenues for future research. First, while our environment focuses on a three-period environments, our results regarding the value of commitment has direct implications for the time consistency of optimal policy in an infinite horizon economy. In such an economy, optimal date 0 policy could be reevaluated at date 1 by a government with full commitment after date 1. Our analysis establishes conditions under which the government at date 1 prefers a more stringent lockdown than the date 0 optimal policy, thus making the optimal policy time-inconsistent in a fully dynamic model. Of course, a full characterization of the infinite horizon economy under lack of commitment would require the date 1 government to also anticipate lack of commitment by future governments. Characterizing these dynamic interactions is complex, and we leave this analysis for future work.

Second, we have evaluated the effect of rules that limit lockdowns assuming that governments adhere to such rules. In practice, rules may be broken and the private sector may be uncertain about the government's commitment to respecting them. In the context of capital taxation, Phelan (2006) and Dovis and Kirpalani (2019) show that this consideration leads the private sector to dynamically update its beliefs about a government's ability to commit. We conjecture that in our framework, this uncertainty could cause investors to react to lockdown extensions by becoming increasingly pessimistic about the government's ability to commit to lifting a future lockdown. This could lead to further declines in investment and economic activity in response to lockdown extensions.

Finally, our analysis ignores the availability of monetary and fiscal policy tools, as in Guerrieri et al. (2020). In our framework, these tools could not only mitigate the immediate economic costs of a pandemic, but also boost investment, thus counteracting future economic costs from underinvestment due to the government's lack of commitment. We leave the exploration of how optimal lockdown policy interacts with monetary and fiscal policy under lack of government commitment as an interesting subject of further research.

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Appendix

A Proofs

A.1 Proof of Proposition 1

Proof. To prove the first part of the statement, suppose by contradiction that $\ell^c < \ell^n$. The government under full commitment must weakly prefer choosing ℓ^c to ℓ^n, meaning

$$Al^c + V(\Gamma(\Omega_1, \ell^c, \kappa)) \geq Al^n + V(\Gamma(\Omega_1, \ell^n, \kappa)). \tag{21}$$

Moreover, the government under lack of commitment must weakly prefer choosing ℓ^n over ℓ^c, conditional on the level of capital k chosen by investors in anticipation of the lack of commitment:

$$(1-\alpha) k^\alpha [\ell^n]^{1-\alpha} + V(\Gamma(\Omega_1, \ell^n, \kappa)) \geq (1-\alpha) k^\alpha [\ell^c]^{1-\alpha} + V(\Gamma(\Omega_1, \ell^c, \kappa)). \tag{22}$$

Substitution of equation (3) into (22) implies that equation (22) can be rewritten as

$$(1-\alpha) Al^n + V(\Gamma(\Omega_1, \ell^n, \kappa)) \geq (1-\alpha) Al^n \left[\frac{\ell^c}{\ell^n}\right]^{1-\alpha} + V(\Gamma(\Omega_1, \ell^c, \kappa)) \tag{23}$$

Since $\ell^c < \ell^n$ and $\alpha \in (0,1)$, it follows that

$$\ell^n \left[\frac{\ell^c}{\ell^n}\right]^{1-\alpha} = \left[\frac{\ell^n}{\ell^c}\right]^\alpha \ell^c > \ell^c. \tag{24}$$

Substitution of (24) into (23) yields

$$(1-\alpha) Al^n + V(\Gamma(\Omega_1, \ell^n, \kappa)) > (1-\alpha) Al^c + V(\Gamma(\Omega_1, \ell^c, \kappa)). \tag{25}$$

Combining (21) and (25), we get

$$(1-\alpha) A(\ell^n - \ell^c) > A(\ell^n - \ell^c), \tag{26}$$

which is a contradiction. Therefore, $\ell^n \leq \ell^c$. To prove the second part of the statement, consider $\ell^c \in (0,1)$ or $\ell^n \in (0,1)$. Suppose by contradiction that $\ell^c = \ell^n \in (0,1)$. Since the optimum is

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interior, the FOC for the government under commitment is necessary for optimality:

$$A + V_\ell \left(\Gamma\left(\Omega_1, \ell^c, \kappa\right)\right) = 0. \tag{27}$$

Analogously, the FOC for the government under no commmitment following (16) is:

$$(1-\alpha)\, A + V_\ell \left(\Gamma\left(\Omega_1, \ell^n, \kappa\right)\right) = 0. \tag{28}$$

For equations (27) and (28) to simultaneously hold under $\ell^c = \ell^n$ would require

$$A = (1-\alpha)\, A, \tag{29}$$

which clearly represents a contradiction. We conclude that $\ell^n < \ell^c$. □

A.2 Proof of Proposition 2

Proof. The proof proceeds in three steps.

Proof of Step 1. We establish that there exists $\underline{\kappa}' \in (0,1)$ for which $l^c < 1$ and $l^n < 1$ are not solutions to the government's problem if $\kappa \leq \underline{\kappa}'$. Suppose that $\kappa = 0$. Then the optimal policy under full commitment and lack of commitment is no lockdown. To see this, the benefit of lockdown is given by the marginal continuation value, which by Assumption 1 satisfies $V_\ell(\Gamma(\Omega_1, \ell, 0)) = 0$ given $\kappa = 0$, while the cost of lockdown is given by the foregone economic output, which equals A for the government with commitment and $(1-\alpha)A$ for the government without commitment. Since the cost of lockdown is strictly positive with or without commitment, lockdown is never optimal. Now suppose that $\kappa = \varepsilon$ for $\varepsilon > 0$ arbitrarily small. We now show that under $\kappa = \varepsilon$ the optimal policies under both commitment and lack of commitment necessarily admit no lockdown. Consider first the case of a government with commitment. Suppose by way of contradiction that the optimal policy is $\ell^c < 1$ for some $\varepsilon_c > 0$. The FOC required for optimality of this policy is that

$$A + V_\ell \left(\Gamma\left(\Omega_1, \ell^c, \varepsilon_c\right)\right) \leq 0. \tag{30}$$

For any $\ell^c \in [0,1)$, the left hand side of (30) approaches $A > 0$ as $\varepsilon_c \to 0$ by Assumptions 1 and 2. However, this contradicts (30) for ε_c sufficiently small. This establishes that $\ell^c = 1$ is the unique

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solution for $\varepsilon_c > 0$ sufficiently small. Let $\bar{\varepsilon}_c > 0$ denote the highest value of ε_c for which inequality (30) is violated for all $\ell^c \in [0,1]$, and define $\bar{\varepsilon}_c = 1$ if it is never violated for any $\varepsilon_c \in [0,1]$ and $\ell^c \in [0,1]$. Now consider the case of lack of commitment. An exactly analogous argument, with A replaced by $(1-\alpha)A$ proves the claim that $\ell^n = 1$ is the unique solution for $\varepsilon_n > 0$ sufficiently small. Let $\bar{\varepsilon}_n > 0$ denote the highest value of ε_n for which the analog of inequality (30) for the government under no commitment (i.e., with A replaced by $(1-\alpha)A$) is violated for all $\ell^c \in [0,1]$, and define $\bar{\varepsilon}_n = 1$ if it is never violated for any $\varepsilon_n \in [0,1]$ and $\ell^n \in [0,1]$. By continuity, $\ell^c = \ell^n = 1$ is the unique solution if $\kappa \leq \underline{\kappa}'$ for $\underline{\kappa}' = \min\{\bar{\varepsilon}_c, \bar{\varepsilon}_n\} \in (0,1]$.

Proof of Step 2. We establish that there exists $\underline{\kappa} \in [\underline{\kappa}', 1)$ for which $l^c = 1$ and $l^n = 1$ are solutions to the government's problem if $\kappa \leq \underline{\kappa}$. Define $\underline{\kappa}$ as the highest value of κ such that for all $\kappa \leq \underline{\kappa}$ and all $\ell \in [0,1]$, the following condition holds

$$(1-\alpha) A + V(\Gamma(\Omega_1, 1, \kappa)) \geq (1-\alpha) A\ell^{1-\alpha} + V(\Gamma(\Omega_1, \ell, \kappa)). \tag{31}$$

The left hand side of (31) corresponds to equilibrium welfare for government under no commitment in an equilibrium under no lockdown, and the right hand side of (31) corresponds to the value of deviating to some ℓ. We begin by establishing that $\underline{\kappa} \geq \underline{\kappa}'$. This follows by part (i) since for $\kappa \leq \underline{\kappa}'$, the unique equilibrium under no commitment admits no lockdown, which means that (31) must hold. We now show that $\underline{\kappa} < 1$. The condition of the proposition states that the policy under full commitment admits some positive lockdown for some $\kappa \in (0,1)$. More specifically, it must be the case that under such a value of κ, the choice of $\ell^c < 1$ dominates choosing no lockdown, namely

$$A\ell^c + V(\Gamma(\Omega_1, \ell^c, \kappa)) \geq (1-\alpha) A + V(\Gamma(\Omega_1, 1, \kappa)). \tag{32}$$

Note that if (32) holds then (31) is violated for $\ell = \ell^c$. Suppose not and suppose that

$$(1-\alpha) A + V(\Gamma(\Omega_1, 1, \kappa)) \geq (1-\alpha) A [\ell^c]^{1-\alpha} + V(\Gamma(\Omega_1, \ell^c, \kappa)). \tag{33}$$

Combining equations (32) and (33) yields

$$(1-\alpha) A \left(1 - [\ell^c]^{1-\alpha}\right) > A(1-\ell^c), \tag{34}$$

which cannot hold since $\alpha \in (0,1)$ and $\ell^c < 1$. Therefore, by continuity of $V(\cdot)$ in Assumption 2, it follows that $\underline{\kappa} < 1$.

Proof of Step 3. We establish that there exists $\overline{\kappa} \in (\underline{\kappa}, 1)$ for which $l^c < 1$ and $l^n = 1$ are not solutions to the government's problem if $\kappa \in (\underline{\kappa}, \overline{\kappa})$. Suppose that $\kappa = \underline{\kappa} + \varepsilon$ for $\varepsilon > 0$ arbitrarily small. We can establish that $\ell^n < 1$. Suppose it were the case that $\ell^n = 1$. Because (31) is violated at $\kappa = \underline{\kappa} + \varepsilon$, then there exists some ℓ such that the government under lack of commitment can deviate and market itself strictly better off. Therefore, $\ell^n < 1$. Now consider the value of ℓ^c and suppose it were the case that $\ell^c < 1$. For the government under commitment to prefer $\ell^c < 1$ to no lockdown, it is necessary that

$$[V(\Gamma(\Omega_1, \ell^c, \underline{\kappa} + \varepsilon)) - V(\Gamma(\Omega_1, 1, \underline{\kappa} + \varepsilon))] > A(1 - \ell^c). \tag{35}$$

for some $\ell^c < 1$. Consider the left hand side of (35) as $\varepsilon \to 0$, holding ℓ^c fixed. It follows from the definition of $\underline{\kappa}$ in equation (31) that

$$(1-\alpha) A \left(1 - [\ell^c]^{1-\alpha}\right) \geq \lim_{\varepsilon \to 0} [V(\Gamma(\Omega_1, \ell^c, \underline{\kappa} + \varepsilon)) - V(\Gamma(\Omega_1, 1, \underline{\kappa} + \varepsilon))]. \tag{36}$$

Combining equations (35) and (36) implies that

$$(1-\alpha) A \left(1 - [\ell^c]^{1-\alpha}\right) > A(1 - \ell^c) \tag{37}$$

which is a contradiction. Therefore, $\ell^c = 1$. The existence of $\overline{\kappa}$ such that $\ell^c = 1 > \ell^n$ if $\kappa \in (\underline{\kappa}, \overline{\kappa})$ thus follows from continuity. □

A.3 Proof of Proposition 4

Proof. Consider a rule $\underline{\ell}(\varepsilon) = \ell^n(\overline{\theta} - \varepsilon)$ for $\varepsilon > 0$ arbitrarily small. We will establish that such a rule strictly increases social welfare. Let $\ell^n(\theta)$ denote the policy under no commitment in the absence of a rule and let $\ell^r(\theta, \varepsilon)$ denote the policy under no commitment subject to a rule. After introducing a rule, the change in social welfare conditional on $\theta < \overline{\theta} - \varepsilon$ is zero since the policy under no commitment is unchanged. The change in social welfare come from $\theta \in [\overline{\theta} - \varepsilon, \overline{\theta}]$ and

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equals

$$\int_{\overline{\theta}-\varepsilon}^{\overline{\theta}} \left[A\left(\ell^{r}\left(\theta,\varepsilon\right)-\ell^{n}\left(\theta\right)\right)+V\left(\Gamma\left(\Omega_{1},\ell^{r}\left(\theta,\varepsilon\right),\kappa\right),\theta\right)-V\left(\Gamma\left(\Omega_{1},\ell^{n}\left(\theta\right),\kappa\right),\theta\right)\right]f\left(\theta\right)d\theta. \tag{38}$$

We first establish that (38) is bounded from below by

$$\int_{\overline{\theta}-\varepsilon}^{\overline{\theta}} \left[A\left(\ell^{n}\left(\overline{\theta}-\varepsilon\right)-\ell^{n}\left(\theta\right)\right)+V\left(\Gamma\left(\Omega_{1},\ell^{n}\left(\overline{\theta}-\varepsilon\right),\kappa\right),\theta\right)-V\left(\Gamma\left(\Omega_{1},\ell^{n}\left(\theta\right),\kappa\right),\theta\right)\right]f\left(\theta\right)d\theta. \tag{39}$$

If for a given $\theta\in\left[\overline{\theta}-\varepsilon,\overline{\theta}\right]$ we have that $\ell^{r}\left(\theta,\varepsilon\right)=\ell^{n}\left(\overline{\theta}-\varepsilon\right)$, then

$$A\ell^{r}\left(\theta,\varepsilon\right)+V\left(\Gamma\left(\Omega_{1},\ell^{r}\left(\theta,\varepsilon\right),\kappa\right),\theta\right)=A\ell^{n}\left(\overline{\theta}-\varepsilon\right)+V\left(\Gamma\left(\Omega_{1},\ell^{n}\left(\overline{\theta}-\varepsilon\right),\kappa\right),\theta\right). \tag{40}$$

Now suppose that for a given $\theta\in\left[\overline{\theta}-\varepsilon,\overline{\theta}\right]$, $\ell^{r}\left(\theta,\varepsilon\right)>\ell^{n}\left(\overline{\theta}-\varepsilon\right)$. The government under no commitment must weakly prefers choosing $\ell^{r}\left(\theta,\varepsilon\right)$ in equilibrium to $\ell^{n}\left(\overline{\theta}-\varepsilon\right)<\ell^{r}\left(\theta,\varepsilon\right)$:

$$\begin{aligned}&\left(1-\alpha\right)A\ell^{r}\left(\theta,\varepsilon\right)+V\left(\Gamma\left(\Omega_{1},\ell^{r}\left(\theta,\varepsilon\right),\kappa\right),\theta\right)\\ &\geq\left(1-\alpha\right)A\ell^{r}\left(\theta,\varepsilon\right)\left(\frac{\ell^{n}\left(\overline{\theta}-\varepsilon\right)}{\ell^{r}\left(\theta,\varepsilon\right)}\right)^{1-\alpha}+V\left(\Gamma\left(\Omega_{1},\ell^{n}\left(\overline{\theta}-\varepsilon\right),\kappa\right),\theta\right).\end{aligned} \tag{41}$$

Since $\ell^{n}\left(\overline{\theta}-\varepsilon\right)<\ell^{r}\left(\theta,\varepsilon\right)$ and $\alpha\in\left(0,1\right)$, it follows that

$$\ell^{r}\left(\theta,\varepsilon\right)\left(\frac{\ell^{n}\left(\overline{\theta}-\varepsilon\right)}{\ell^{r}\left(\theta,\varepsilon\right)}\right)^{1-\alpha}=\ell^{n}\left(\overline{\theta}-\varepsilon\right)\left(\frac{\ell^{r}\left(\theta,\varepsilon\right)}{\ell^{n}\left(\overline{\theta}-\varepsilon\right)}\right)^{\alpha}>\ell^{n}\left(\overline{\theta}-\varepsilon\right). \tag{42}$$

Substitution of equation (42) into (41) implies that

$$A\ell^{r}\left(\theta,\varepsilon\right)+V\left(\Gamma\left(\Omega_{1},\ell^{r}\left(\theta,\varepsilon\right),\kappa\right),\theta\right)\geq A\ell^{n}\left(\overline{\theta}-\varepsilon\right)+V\left(\Gamma\left(\Omega_{1},\ell^{n}\left(\overline{\theta}-\varepsilon\right),\kappa\right),\theta\right). \tag{43}$$

Conditions (40) and (43) thus imply that the expression in equation (38) is bounded from below by (39).

Now consider the value of (39). We can show that it is positive for $\varepsilon>0$ arbitrarily small. Consider $\theta\in\left[\overline{\theta}-\varepsilon,\overline{\theta}\right]$. For a given $\varepsilon>0$, define $\overline{v}\left(\varepsilon\right)>0$ as the highest value $\overline{v}\left(\varepsilon\right)$ such that

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$\overline{v}(\varepsilon) < \overline{\theta} - \underline{\theta} - \varepsilon$ and also

$$A\left(\ell^{n}\left(\theta - v\right) - \ell^{n}\left(\theta\right)\right) + V\left(\Gamma\left(\Omega_{1}, \ell^{n}\left(\theta - v\right), \kappa\right), \theta\right) - V\left(\Gamma\left(\Omega_{1}, \ell^{n}\left(\theta\right), \kappa\right), \theta\right) > 0 \tag{44}$$

for all $v \in [0, \overline{v}(\varepsilon))$ and all $\theta \in \left[\overline{\theta} - \varepsilon, \overline{\theta}\right]$. To see why $\overline{v}(\varepsilon)$ exists, consider the first order condition that defines $\ell^{n}(\theta)$

$$(1-\alpha) A + V_{\ell}\left(\Gamma\left(\Omega_{1}, \ell^{n}\left(\theta\right), \kappa\right), \theta\right) = 0 \tag{45}$$

It follows that

$$A + V_{\ell}\left(\Gamma\left(\Omega_{1}, \ell^{n}\left(\theta\right), \kappa\right), \theta\right) > 0, \tag{46}$$

which means that social welfare is strictly increasing in ℓ in a neighborhood around $\ell^{n}(\theta)$. The existence of $\overline{v}(\varepsilon)$ follows from the fact that $\ell^{n}(\theta - v)$ is strictly decreasing in θ. Note that that $\overline{v}(\varepsilon) > \varepsilon$ if $\varepsilon = 0$. Moreover, by continuity, there exists some $\varepsilon > 0$ such that $\overline{v}(\varepsilon) > \varepsilon$. Thus, (44) holds for $v = \varepsilon - \left(\overline{\theta} - \theta\right) < \overline{v}(\varepsilon)$, which means that

$$\left[A\left(\ell^{n}\left(\overline{\theta} - \varepsilon\right) - \ell^{n}\left(\theta\right)\right) + V\left(\Gamma\left(\Omega_{1}, \ell^{n}\left(\overline{\theta} - \varepsilon\right), \kappa\right), \theta\right) - V\left(\Gamma\left(\Omega_{1}, \ell^{n}\left(\theta\right), \kappa\right), \theta\right)\right] > 0 \tag{47}$$

for all $\theta \in \left[\overline{\theta} - \varepsilon, \overline{\theta}\right]$. This means that (39) is strictly positive for $\varepsilon > 0$. Therefore, the perturbation strictly increase welfare. $\square$

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The impact of shutdown policies on unemployment during a pandemic[1]

Edward Kong[2] and Daniel Prinz[3]

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We use high-frequency Google search data, combined with data on the announcement dates of non-pharmaceutical interventions (NPIs) during the COVID-19 pandemic in U.S. states, to isolate the impact of NPIs on unemployment in an event-study framework. Exploiting the differential timing of the introduction of restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, and emergency declarations, we analyze how Google searches for claiming unemployment insurance (UI) varied from day to day and across states. We describe a set of assumptions under which proxy outcomes (e.g., Google searches) can be used to estimate the causal parameter of interest (e.g., share of UI claims caused by NPIs) when data on the outcome of interest (e.g., daily UI claims) are limited. Using this method, we quantify the share of overall growth in unemployment during the COVID-19 pandemic that was directly due to each of these NPIs. We find that between March 14 and 28, restaurant and bar limitations and non-essential business closures could explain 4.4% and 8.5% of UI claims respectively, while the other NPIs did not increase UI claims.

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2 MD/PhD Student, Harvard University and Harvard Medical School.
3 PhD Student, Harvard University.

1 Introduction

During a pandemic, governments may implement non-pharmaceutical interventions (NPIs) to slow the spread of disease. Examples of NPIs include shutting down businesses where social interactions take place, closing schools, ordering people to stay at home, and banning large gatherings. NPIs reduce the movement and social interactions of individuals during a pandemic (Dave et al., 2020; Friedson et al., 2020; Gupta et al., 2020) and slow disease spread (Flaxman et al., 2020), with varying degrees of effectiveness depending on the particular NPI. However, because many NPIs involve reductions in economic activity, there are concerns about the potential damage that NPIs may cause to the economy and labor markets. This led some elected officials to introduce NPIs later, introduce fewer NPIs overall, or consider the relaxation of NPI policies.

Identifying the impact of the implementation and the later relaxation of NPIs on economic outcomes such as employment is not straightforward. Pandemics may impact the economy through a number of channels. They decrease consumer demand for particular goods and services, as individuals avoid public places, which then translate into decreased labor demand. They may directly decrease labor demand if managers reduce worker density to avoid outbreaks at their firms and labor supply if workers choose to stay at home. These economic effects happen at the same time that NPIs are implemented. A further empirical challenge is that data on employment and unemployment is not readily available at the frequency at which policies change during pandemics. For example, data on U.S. unemployment insurance (UI) claims are released weekly, but during the COVID-19 pandemic, information on new cases, deaths, and the implementation of new NPIs changed daily.

In this paper, we present an empirical framework for estimating a key policy parameter: the *share* of the economic impact (as measured by UI claiming) *directly* caused by the NPIs themselves. We use high-frequency Google search data, combined with data on the exact dates of the announcement of NPIs during the COVID-19 pandemic in U.S. states, to isolate the impact of NPIs on UI claims in an event study framework. We consider six NPIs: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, and emergency declarations. Exploiting the differential timing of the introduction of these NPIs across U.S. states, we analyze how Google searches for claiming unemployment responded to each policy.

We find that the announcements of restaurant and bar limitations, non-essential business closures, and stay-at-home orders are associated with increases in the volume of Google searches for claiming

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UI on the day of the announcement as well as the following two days. At the same time, we find no such association for large-gatherings bans, school closures, and emergency declarations. The effect of stay-at-home orders disappears after controlling for restaurant and bar limitations and non-essential business closures, whereas the latter two policies have independent effects on Google searches that are robust to controlling for other policies.

We then introduce a method to translate our event study estimates into estimates of the share of UI claiming caused by each NPI. Importantly, while our method uses a proxy measure of UI claims (the volume of Google searches for "file for unemployment", first introduced and validated by Goldsmith-Pinkham and Sojourner, 2020), it does not rely directly on prior estimates of the relationship between the variable of interest (UI claims) and the proxy measure (Google searches). Instead, we require that the increase in Google searches caused by the NPIs is proportional to the increase in UI claims caused by the NPIs. Second, we assume that the overall increase in Google searches during the pandemic period can be mapped directly to the 10.2 million initial UI claims filed between March 14 and March 28. Under these assumptions, we estimate that the combined causal effect of these NPIs directly accounts for 12.8% of the UI claims filed during this period.

Estimating the causal impact of NPIs on the economy and the labor market is important for policy as governments need to decide whether to implement or relax particular NPIs during pandemics, taking into account both their effect on the spread of disease as well as their economic and labor market effects. We find that NPIs are heterogeneous in their effects; this heterogeneity is relevant for policy as it can inform trade-offs between the economic and public health impacts of policies when choosing which policies to implement or relax.

This paper makes several contributions. First, we provide estimates of the causal effect of NPI announcements on unemployment expectations. Second, we show how these can be translated into estimates of the contribution of NPIs to overall growth in UI claiming. Our method using high-frequency data on proxy outcomes to estimate policy effects could be useful beyond our particular setting. Third, this is the first study to simultaneously estimate the impacts of multiple NPI policies on UI claiming and to study variation in the magnitude of these effects.

Related Literature Our work contributes to the literature studying the impact of NPIs adopted during the COVID-19 pandemic on unemployment and other economic outcomes. Most closely related to our work, Baek et al. (2020) and Lin and Meissner (2020) use weekly UI claims data to study the

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effect of stay-at-home policies on UI claims. Baek et al. (2020) find a positive effect of stay-at-home orders, attributing 25% of the rise in UI claims between March 14, 2020 and April 4, 2020 to stay-at-home policies. In contrast, Lin and Meissner (2020) find that stay-at-home orders decrease UI claims.[1] Our paper extends this existing work on NPIs in several ways. First, we offer evidence on the causal effects of a broader set of six NPIs on unemployment. Second, we provide estimates using a daily outcome measure (the Google Trends data), which allows us to more precisely identify effects and better account for unobservable differences in the pandemic's progression across different states. Third, we are able to use more granular timing variation in NPI announcements to estimate the effects of multiple NPIs jointly, which corrects for correlation in NPI announcement dates and reveals that individual NPIs have smaller effects on UI claiming than single-NPI analyses may suggest.

We also contribute to broader empirical work on labor market during COVID-19 pandemic. Bartik et al. (2020*a*) and Kahn et al. (2020) study work hours and job postings respectively, and find that employee hours and job postings were reduced over the course of the pandemic. Dingel and Neiman (2020) provide estimates of the share of jobs can be performed from home, Mongey et al. (2020) use SafeGraph data to show how workers' ability to work from home affects their ability to practice social distancing. Coibion et al. (2020) find that job loss during the pandemic has been higher than implied by new UI claims and that many individuals who lost their jobs are not actively looking for work.[2] These empirical papers and ours complement a body of work that simulates the macroeconomic consequences of the pandemic and calibrates the effects of potential policies (Atkeson, 2020; Bethune and Korinek, 2020; Eichenbaum et al., 2020; Jordà et al., 2020; Glover et al., 2020; Guerrieri et al., 2020; Krueger et al., 2020; Ludvigson et al., 2020; Rampini, 2020). Our paper provides estimates of the labor-market effects of several of these policies and can be used to inform the parameter inputs of these models.

Lastly, we build on work that has used Google search data to study questions that are difficult to study with more traditional survey and administrative datasets. Our work is most closely related to Goldsmith-Pinkham and Sojourner (2020) who use Google search volumes to forecast UI claims during

[1]In a related historical paper, Correia et al. (2020) study the 1918 Flu Pandemic and find that early and aggressive implementation of NPIs were not associated with negative economic effects and may have been associated with faster economic growth after the pandemic.

[2]Further work has studied the the relationship between the COVID-19 pandemic and short-term aggregate economic activity (Lewis et al., 2020; Mulligan, 2020), consumption (Baker et al., 2020*b*), heterogeneity across firms (Bartik et al., 2020*b*; Hassan et al., 2020), and economic uncertainty (Baker et al., 2020*a*).

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the COVID-19 pandemic.[3] Our work is an example of how Google Trends data can be combined with policy variation to infer causal effects that are difficult to estimate using data from more traditional sources. In addition, we introduce a method that augments the utility of high-frequency proxies for estimating the causal effects of policies.

The remainder of this paper proceeds as follows. We provide background information on the COVID-19 pandemic and NPI responses to the pandemic in Section 2. We then describe our data in Section 3. We describe our conceptual framework in Section 4 and our empirical strategy in Section 5. We present our results in Section 6. In Section 7, we conclude with a brief discussion of the interpretation of our results.

2 Background

2.1 The COVID-19 Pandemic in the U.S.

In January 2020, coronavirus disease 2019 (COVID-19), an infectious disease caused by by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) spread to the United States. COVID-19 is a highly infectious disease: most studies suggest that its basic reproduction number (R0) is 2.2-2.7 (Du et al., 2020; Riou and Althaus, 2020; Wu et al., 2020); others report estimates as high as 5.7 (Sanche et al., 2020). Its symptoms include fever, cough, shortness of breath, difficulty breathing, chills, muscle pain, headache, sore throat, and new loss of taste or smell (Centers for Disease Control and Prevention, 2020*c*). COVID-19 can cause a wide spectrum of disease, including mild illness, moderate and severe pneumonia, respiratory failure, and death (Centers for Disease Control and Prevention, 2020*b*). To date, 1.19 million cases and 68,551 deaths have been reported in the U.S. (Centers for Disease Control and Prevention, 2020*a*).

2.2 Non-Pharmaceutical Interventions

Currently no vaccine or specific treatment exists for COVID-19 (Centers for Disease Control and Prevention, 2020*d*). U.S. states and cities have adopted NPIs to mitigate the spread of COVID-19. These include stay-at-home orders, mandatory quarantines for travelers, non-essential business closures, large gatherings bans, school closures, and restaurant and bar limitations. By April 20, 2020, all U.S. states with the exceptions of Arkansas, Iowa, Nebraska, North Dakota, South Dakota, and Wyoming have issued some form of a stay-at-home order. By the same time, all states with

[3] In earlier work by Baker and Fradkin (2017) estimate measures of job search intensity based on Google Trends and other data to study the consequences of UI policy changes.

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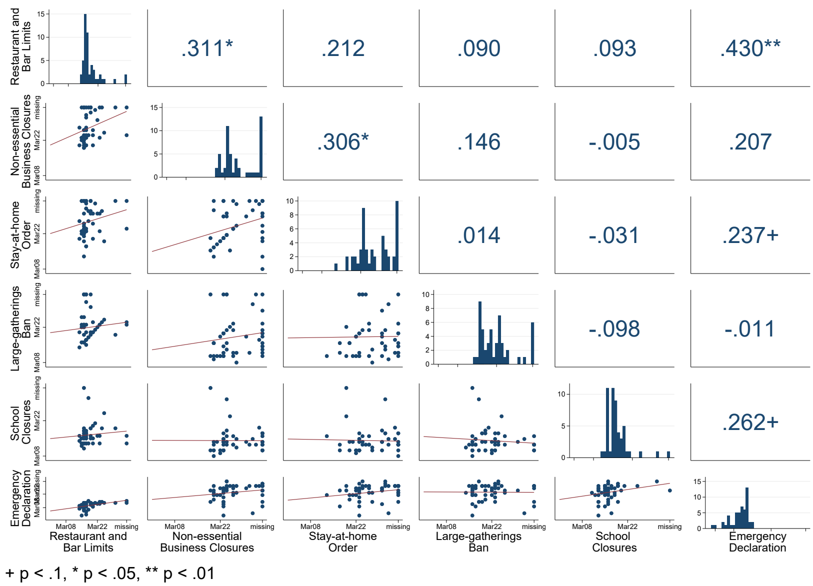
the exceptions of Arkansas, Minnesota, Nebraska, South Dakota, Texas, Utah, and Wyoming had implemented some form of non-essential business closures. Strict restaurant and bar limitations had been imposed in all states with the exception of South Dakota. All other states had closed restaurants and bars except for takeout and delivery, with the exceptions of Kansas and New Mexico which allowed limited on-site service and Oklahoma where restaurants and bars were only limited to takeout and delivery in affected counties (The Henry J. Kaiser Family Foundation, 2020).

Figure 1: Timing of NPIs



Note: Figure shows the distribution of the announcement dates of restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, and emergency declarations on the diagonal. The off-diagonal scatterplots show the cross-state pairwise relationship between the announcement dates for each pair of measures. The red lines are linear fits. The off-diagonal numbers are the corresponding correlation coefficient estimates. For more details, see Section 3.2.

Importantly for our analysis, while almost all states eventually implemented these NPIs, initial implementation was staggered. For example, restaurants and bars were limited to takeout and delivery in 35 states by March 18, while 4 states still had restaurants and bars operating normally a week later. Likewise, 7 states closed all non-essential businesses as early as March 20, whereas 16 states had not

closed non-essential businesses by April 1st. Figure 1 shows the distribution of announcement dates for each NPI over time and the pairwise correlation across states of these dates. While announcement dates are positively correlated, the correlation is weak in most cases. (Appendix Table A1 shows the announcement date for each state and each NPI. Appendix Figure A1 provides information about the geographic distribution of announcement dates in heatmap form.)

3 Data

We combine data on internet searches from Google Trends, data on NPI implementation dates from state announcements, as well as state economic data (e.g., industry composition) and data on the spread of COVID-19.

3.1 Google Search Data

We use data on Google searches for the term "file for unemployment" from February 1 to April 24, 2020.[4] We download these data from Google Trends, which releases data on relative search intensities by search term, day, and geographic location. Because Google only releases relative search volumes, throughout our analysis we will normalize search volumes such that the highest volume day in California during our time period is set to 100.[5] Because the Google Trends API draws a different sample of data for each request, we download and average 100 samples for each state to mitigate sampling variation. Appendix Figure A2 summarizes the overall evolution of Google searches for for claiming unemployment insurance during March and April, 2020.

3.2 NPI Timing Data

We use data released by The Henry J. Kaiser Family Foundation (2020) to identify which states have implemented each of the six NPIs we study: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, and emergency declarations. For each state and NPI, we identify the precise date on which the NPI was first announced. In cases where multiple announcements pertained to the same NPI, we use the first recorded announcement. For a list of all NPI introduction dates by state, see Table A1.

[4] 88% of internet searches in the U.S. happen on Google (Statcounter GlobalStats, 2020).

[5] Stephens-Davidowitz and Varian (2015) provide a detailed description of how Google Trends data can be accessed and used for social science research.

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3.3 Other Data

We use confirmed COVID-19 cases and deaths from Dong et al. (2020) and Johns Hopkins University (2020). Total initial UI claims filed at a national level between March 14 and March 28 are derived from weekly news releases from the U.S. Department of Labor (2020). Industry employment shares at the national and state levels are computed from the Quarterly Census of Employment and Wages (Bureau of Labor Statistics, 2020) and from the 2013-2017 American Community Survey (U.S. Census Bureau, 2020). We use data on industry-level unemployment growth from March 14-28 from three states: Massachusetts (Massachusetts Executive Office of Labor and Workforce Development, 2020), New York (New York State Department of Labor, 2020), and Washington (Washington State Employment Security Department, 2020).

4 Conceptual Framework

Our empirical analyses are built on a conceptual framework where firms internalize the information contained in NPI announcements about their optimal employment level and workers have rational expectations of firm layoff decisions. Changes in workers' expectations of their layoff probability then lead to a rapid response in Google search behavior, which is the proxy outcome we measure. This conceptual model predicts that Google searches by workers not only respond to actual layoffs but also shifts in their *expectations* of impending layoffs.[6]

Our model requires that firms internalize the information contained in NPI announcements. Policies like restaurant and bar limitations and non-essential business closures directly reduce affected firms' future demand. In the presence of layoff/re-hiring costs, this leads to a reduction in affected firms' *current* optimal employment level. For example, a retailer may not lay off workers if demand may rebound in the following month, but may be willing to incur the adjustment costs of re-hiring workers later if demand were assuredly low due to a non-essential business closure policy.[7]

Workers who are not immediately laid off are assumed to anticipate the employment responses of their employers. For example, a waiter who hears the announcement of restaurant and bar limitations would seek out information on claiming UI. If some affected workers delay their search behavior, we

[6]This focus of our model on worker and firm expectations helps to differentiate the effects of NPIs on layoffs from papers that show early reductions in hours and job postings (Bartik et al., 2020*a*; Kahn et al., 2020), outcomes that may be more responsive to short-run demand conditions.

[7]The importance of firms' demand expectations is magnified by the liquidity constraints faced by the typical small business: Bartik et al. (2020*b*) employ surveys of small businesses and find that 72% of business owners expect to re-open in December 2020 if the pandemic lasts 1 month, with this percentage dropping to 47% if the pandemic lasts 4 months.

may not be able to detect their responses depending on the length of our event study window.

One concern about this approach is that workers expectations' may not be correct: for example they under- or overestimate the change in their likelihood of unemployment when an NPI is announced and their internet search behavior may reflect such an under- or overreaction. This is only a problem for our approach to the extent that the response in internet search behavior around NPI announcements is biased in a way that is different from the bias associated with searches occurring for other reasons during our period. As long as workers are under- or over-reacting to NPIs and other economically relevant factors in the same way, our estimates remain unbiased.

5 Empirical Strategy

A characteristic of the economic downturn associated with the COVID-19 pandemic, and a common feature of many crises, is that the effects of particular policy responses are hard to isolate. We employ high-frequency proxy data from Google Trends to separately identify effects of policies released just days apart from each other and detect rapid changes in workers' behavior and expectations.

In addition to estimating causal effects of NPIs on Google searches, we also develop a new method to translate these estimates into causal effects on UI claims. In contrast to prior work using proxies for economic variables (e.g., Goldsmith-Pinkham and Sojourner, 2020; Baker and Fradkin, 2017), our method only requires one data point on UI claims: the total number of claims filed between March 14 and 28. This is because we do not directly estimate the relationship between Google searches and UI claims. Instead, we employ alternative assumptions to first estimate the *share* of UI claiming caused by NPIs, which we multiply by the total March 14-28 change in UI claims to obtain the effect in level terms. Our method allows for policy effect estimation using proxy data where data on the variable of interest are limited (because of low-frequency measurement, small samples, or measurement error) but where the researcher can assume that causal effects satisfy certain assumptions.

5.1 Single-Policy Event Study

To quantify the impact of a given NPI on search volume, our baseline specification below is an event study regression that exploits differential NPI announcement dates across different states. Our main specification is of the form:

$$S_{it} = \sum_{\tau=-7}^{6} \gamma_\tau \times 1\{r = \tau\} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{1}$$

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where S_{it} is Google search volume in state i and date t, r denotes the days relative to the date the policy was announced (which we define as day $r = 0$), and α_i and α_t are state and calendar date fixed effects. The coefficients of interest γ_τ estimate the differential increase in search volume for each day τ relative to the day prior to the announcement date ($r = -1$). We normalize $\gamma_{\tau=-1} = 0$ and cluster standard errors at the state level.

For periods $r > 6$ and $r < -7$, we assign $r = 6$ and $r = -7$ respectively. This follows from the assumption that the dynamic effects of the policy are constant 7 days after the policy announcement and prior to 7 days before the policy announcement. Estimation of the γ_τ coefficients for earlier pre-periods would rely only on comparisons between states that adopted the NPI early (the "treated" group for that pre-period) and states that adopted the NPI at least one week later (the "control" group for that pre-period). An analogous logic holds for later post-periods. Given that the NPIs were introduced at very similar times[8], states that adopted policies more than a week apart are likely unobservably different from each other. Moreover, separately identifying calendar date fixed effects and the γ_τ coefficients for these earlier and later periods relies on an increasingly sparse (and selected) set of "treated" and "control" states.[9]

5.2 Multiple-Policy Event Study

The standard event study approach described above estimates the effect of a single NPI on search volume. However, during the COVID-19 pandemic, many states announced multiple NPIs simultaneously or in close proximity to each other. Correlation among NPIs may lead the single-NPI event studies to overstate the impact of each NPI (Figure 1 shows the correlation patterns between the six NPIs we consider). However, running an event study that includes all possible policies may not be feasible due to potential collinearity. To address both of these issues, we first estimate single-policy event studies for each of the six NPIs we consider. To account for correlated NPI announcements, we then estimate a multiple-policy event study that includes the subset of NPIs that exhibited significant effects in the single-policy estimation. This specification takes the form:

$$S_{it} = \sum_{p \in \mathcal{P}} \sum_{\tau=-7}^{6} \eta_{p,\tau} \times 1\{r(p) = \tau\} + \alpha_i + \alpha_t + \nu_{it} \tag{2}$$

[8]The inter-quartile range of introduction dates is between 3 and 8 days for all of the policies we consider

[9]An alternative approach would be to drop data corresponding to $r < -7$ and $r > 6$, but while this "balances" the data in event time, the data becomes unbalanced in calendar time, certain calendar date fixed effects may no longer be separately identified from the γ_τ coefficients, and the reduction in sample size reduces statistical power.

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where S_{it} is Google search volume in state i and date t, $\mathcal{P}$ denotes the set of included policies, $r(p)$ denotes the days relative to the date that policy p was announced (which we define as day $r = 0$), and α_i, α_t are state and calendar date fixed effects respectively. The coefficients of interest $\eta_{p,\tau}$ estimate, for each policy p, the increase in search volume for each day τ relative to the day prior to the announcement date of each policy ($r(p) = -1$), controlling for the time-varying effects of the other policies in $\mathcal{P}$. We normalize $\eta_{p,\tau=-1} = 0$ for all policies p and cluster standard errors at the state level. Under the multiple-policy specification, we can estimate each policy's independent impact on search volume, controlling for the other policies that demonstrated an effect in the single-policy specification.

5.3 Robustness

We discuss potential concerns and assess the robustness of our results in a number of ways.

First, certain states had a large number of cases early on (e.g., California and Washington) or were particularly strongly hit by the pandemic (e.g., New York). To address the concern that our results are driven by these states, we re-estimate the event-study and the difference-in-differences specification excluding these three states.

Second, another concern is that our results may be driven by smaller states whose UI responses or economic trajectories may differ from larger states. To address this concern, we re-estimate our results weighting each state by its total employment.

Third, it is likely that NPI policy announcement dates are correlated with characteristics of the pandemic in each state. This would pose a problem to our identification strategy only if individuals modified their UI claiming behavior (and hence their Google search behavior) in response to their states' disease trajectory. To address this concern, we re-estimate our single-policy event-study specification (Equation 1) with additional controls for case growth and deaths at the state-calendar date level, both interacted with state dummies:

$$S_{it} = \sum_{\tau=-7}^{6} \tilde{\gamma}_\tau \times 1\{r = \tau\} + \tilde{\beta}_i \times \text{Case Growth}_{it} + \tilde{\delta}_i \times \text{Deaths}_{it} + \tilde{\alpha}_i + \tilde{\alpha}_t + \tilde{\varepsilon}_{it} \quad (3)$$

Case Growth$_{it}$ is defined as the additional cases in state i in calendar date t relative to the previous day and Deaths$_{it}$ is defined as the cumulative deaths in state i at calendar date t. Interacting both variables with state dummies allows the effects of case growth and deaths (captured by $\tilde{\beta}_i$ and $\tilde{\delta}_i$ respectively) to vary by state. This specification assesses whether our results are driven by differential

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case growth or deaths.

We also show that epidemiological outcomes are not changing rapidly around the exact timing of NPI announcements by replacing the outcome variable in our event study (Equation 1) with case growth and deaths.

Fourth, to further demonstrate that the NPI timing variation we use is not driven by the different epidemiological experiences of each state, we separate states into those that registered their first COVID-19 death early in the epidemic (on or before March 19) and those that registered their first COVID-19 death later (after March 19). We use March 19 as the cutoff date because it is the median date of the first COVID-19 death across states. We then estimate the event-study specification separately for both sets of states.

Fifth, one concern with event study approaches is that the same sets of states are used as "treated" and "control" states for various relative days. In Appendix C, we estimate an alternative difference-in-differences model, where we compare "treated" states that adopted their first NPI early vs. "control" states that did not announce any NPI during the timeframe we use for estimation.

Sixth, we assess whether an industry-specific NPI (restaurant and bar limitations) differentially affected states with a higher share of employment in food services. We present the methods and results for this case study in Appendix D.

5.4 Quantifying the Impact of Individual NPIs on UI Claims

We rely on the event study specifications described above to partition the evolution of search volume into the causal effects of the NPIs and an aggregate time trend. We assume that the number of UI claims in a given period is proportional to the *area* under the curve defined by search intensity over the same period.[10] We also assume that the Google search volume caused by factors other than the NPIs can be estimated by integrating the calendar date fixed effects in the event study. With these assumptions, the integral under the estimated NPI effect (given by the relative-time coefficients γ_τ in Equation 1 and $\delta_{p,\tau}$ in Equation 2) is proportional to the number of UI claims caused by the NPI. By comparing this integral to the integral under the time trend (α_t), we can isolate the direct causal effect of the NPI. In Appendix B, we provide a formal discussion of these assumptions and describe how they allow proxy data to be used to estimate causal effects.

[10] We do not require that the coefficient of proportionality be known or even estimated. Intuitively, the coefficient of proportionality cancels out in the numerator and denominator of the share expression we construct below. Moreover, the coefficient of proportionality is difficult to interpret, since over any requested time window, the Google Trends data are always normalized so that the maximum search intensity equals 100.

Consider the multiple-policy event study specification in Equation 2. Let I_p denote the integral under the event-study coefficients $\delta_{p,\tau}$ for a given NPI policy p and $\tau >= 0$. Let I_{α,t_1,t_2} denote the integral under the date fixed effects α_t between t_1 and t_2 (which estimate the direct pandemic effect). The share of UI claims between t_1 and t_2 caused by the NPI can be estimated as:

$$\text{Share of UI claims caused by NPI } p = \frac{I_p}{I_{\alpha,t1,t2} + \sum_p I_p}. \tag{4}$$

Because NPIs can have industry-specific impacts, another quantity of interest is the share of UI claims in a given industry that was caused by the NPI. We describe how this share can be computed in the case of restaurant and bar limitations in Appendix Section D.

Defining the appropriate time window $[t_1, t_2]$ is challenging and will affect estimation of the shares defined above. We estimate the above shares for our six policies of interest using a window of $t_1 =$ March 14, when the first states began announcing NPIs, through $t_2 =$ March 28, approximately the time that the final states began announcing NPIs (see Figure 1 and Table A1). This also allows us to simply utilize two periods worth of the weekly UI claims data, avoiding the need for interpolation. Given the short period in which most states announced their first NPIs, we can evaluate all six policies using the same denominator for Equation 4.

5.5 Identification

Our key identifying assumption is that the observed untreated outcomes of states that are not (yet) treated (states that implement their policy later) are a good counterfactual for the states implementing the policy on a given date. For example, this requires that states do not get an unobserved shock that impacts Google search behavior (e.g., new information on state-specific pandemic severity) at the time of the policy announcement. In support of this identifying assumption, we find flat pre-trends in each of our event studies (Figure 2), our results are robust to controls for epidemic severity (Figure 3), and epidemic severity does not change rapidly near NPI announcements (Appendix Figure A5).

Another source of bias would arise if workers anticipated the announcement and implementation of the NPIs. To the extent that anticipation led to consistently higher Google searches in the pre-period, our estimates of the causal policy effect will be biased toward zero. However, our results would still be policy-relevant: our estimates describe the effect of a policy *taking as given* firm and worker expectations. The policy-relevant treatment effect of the intervention accounts for the possibility that the policy results in a smaller increase in UI claims because firms had already laid off workers in

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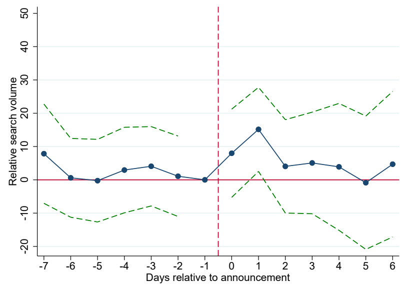
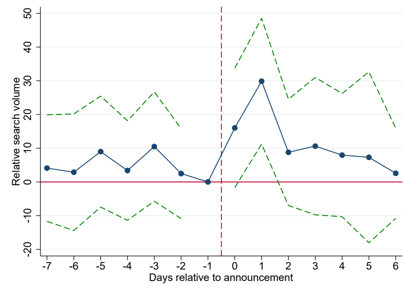
anticipation of the policy. That said, the pre-trends of our event studies (Figure 2) suggest little anticipatory effect in Google searches before the policies are actually announced.

Figure 2: Event Study Estimates

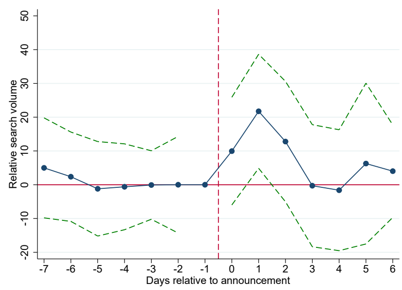
(a) Restaurant and Bar Limitations



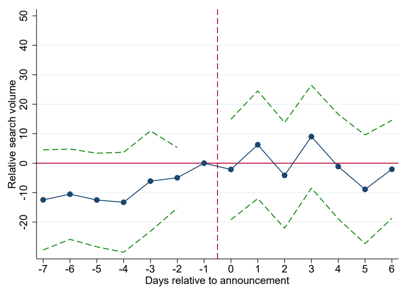
(b) Non-Essential Business Closures



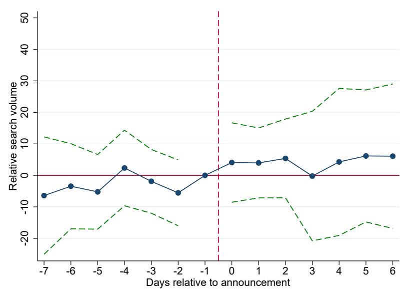
(c) Stay-at-Home Orders



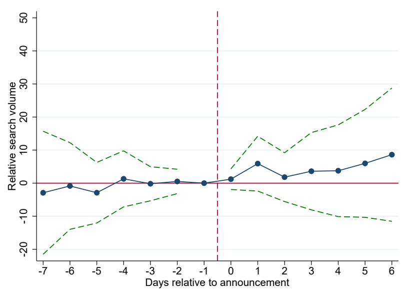
(d) Large-Gatherings Bans



(e) School Closures



(f) Emergency Declarations



Note: Figure shows event study estimates of the impact of the introduction of restaurant and bar limitations (Panel (a)), non-essential business closures (Panel (b)), stay-at-home orders (Panel (c)), large-gatherings bans (Panel (d)), school closures (Panel (e)), and emergency declarations (Panel (f)), based on Equation (1). The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Section 5.1.

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6 Results

6.1 Estimates from the Single-Policy Event Study

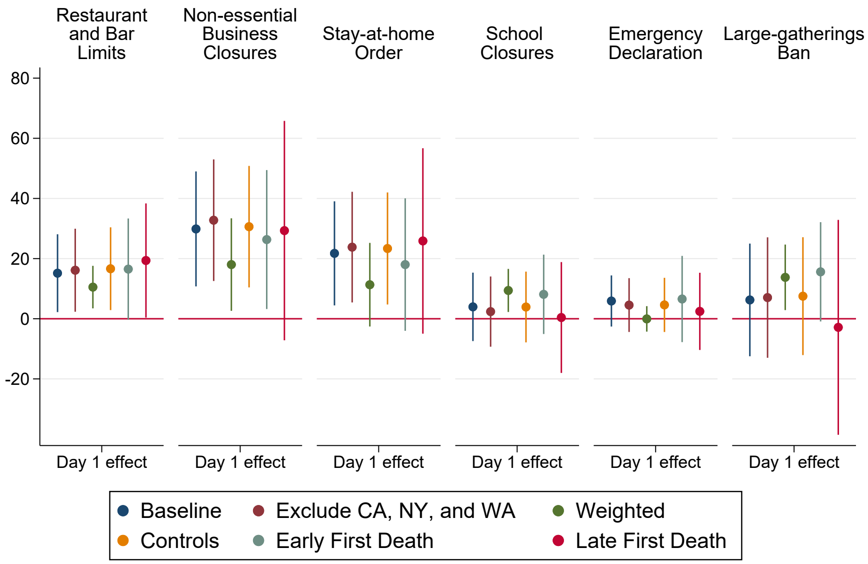
Figure 2 shows our event-study estimates for each of the NPIs. The first columns of Appendix Tables A2-A7 show the corresponding event study coefficients. Figure 2 suggests that there is no differential trend in Google search volume for UI claiming prior to the announcement of any of the NPIs. For restaurant and bar limitations, there is an approximately 15.2 unit (24.3%) average increase in Google search volume on relative day 1 (the first day following the announcement date). For non-essential business closures the, increase is 29.9 units (48%), and for stay-at-home orders it is 22.8 units (34.9%). Percentage increases are computed relative to the mean search volume over the March 14-28 period.[11] After these initial increases, search volumes return to their pre-announcement levels. This may reflect an "impulse response" effect of announcements: workers affected by the NPIs may search online intensively at first but then search less after they locate the appropriate resources for filing a UI claim. We see no comparable increase in search volume after the announcement of large-gatherings bans, school closures, and emergency declarations. Our interpretation is that these NPIs, announced in the same time frame, did not change unemployment expectations and did not directly increase UI claiming.

6.2 Estimates from the Multiple-Policy Event Study

Figure 4 and Table A8 report our event study results when we include multiple policies at the same time. Based on results reported in Section 6.1, we focus on the three NPIs that seem to have individual impacts: restaurant and bar limitations, essential business closures, and stay-at-home orders. Once we control for the presence and timing of the other policies, the impacts of restaurant limitations and non-essential business closures appear to be slightly smaller. Stay-at-home orders are no longer estimated to affect internet search volume because their timing is correlated with the timing of non-essential business closures. An insight from these results is that when estimating the contribution of individual policies, it is important to control for the presence and timing of other correlated policies.

[11] This is the most relevant normalization because it allows us to use a single period as a benchmark for different NPIs introduced at different times and also circumvents the issue that search volume for UI claiming is very low and sometimes not reported by Google in the preceding period.

Figure 3: Event Study Estimates: Robustness — Summary



Note: Figure summarizes the results of our event study estimates using alternative samples and alternative specifications, based on Equation 1. We show the coefficient estimate for the day after the announcement date (day 1) from our event study for each of the NPIs (restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, and emergency declarations). For each NPI, we show our baseline result (in navy), as well as alternative results (i) excluding California, New York, and Washington, three states hit hard and/early by the pandemic, (ii) weighting states by their total employment, (iii) controlling for case growth and the number of deaths, (iv) on the sample of states with early first deahts, (v) on the sample of states with late first deaths. For more details, see Section 5.3.

6.3 Robustness

To assess the robustness of our results, we estimate our event study on alternative samples and using alternative specifications. We estimate our results (i) excluding California, New York, and Washington, three states hit hard or early on by the pandemic, (ii) weighting states by their total employment, (iii) controlling for case growth and the number of deaths, (iv) on the sample of states with early first deaths, (v) on the sample of states with late first deaths. Figure 3 summarizes our results, showing coefficient estimates and standard errors for day 1 from the event study, the first full day after each announcement date. Our results are very similar under these different specifications and when

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estimated on alternative samples, although they are sometimes noisier on smaller samples. (Appendix Figures A3 and A4 show full event studies for each of the six policies and each of the alternative specifications and samples. Columns 2-6 of Appendix Tables A2-A7 show the corresponding event study coefficients.)

To examine whether the exact timing of the introduction of NPIs coincides with epidemiological events that potentially provide information to the public about the spread of the pandemic, Appendix Figure A5 shows the evolution of case growth and the number of deaths relative to the announcement of NPIs. We find no evidence that the announcement of NPIs is preceded or followed by jumps in these outcomes. (Appendix Tables A9 and A10 show the corresponding event study coefficients.) Note that this should not be taken as evidence that NPIs don't impact case growth or the number of deaths. Our estimates only show that controlling for overall time-trends, there is no *immediate* impact in our time frame; the effects of NPIs on cases and7 deaths would be expected to emerge later.

We present difference-in-differences estimates comparing "early adopters" (first NPI announced between March 13-17) with "late or never adopters" (after March 1 or never) in Appendix C. Figure C1 and Appendix Table C1 show that trends for early and late adopters are identical until the first NPI announcement, at which point the early adopter states experience a jump in search volume that is sustained through additional announcements by early adopter states. The overall differential increase in search volume in early adopter states is 13%. Importantly, late adopter states also have increasing search volume: this underscores the idea that most UI claiming is not the direct effect of NPI adoption.

In our case study of the Accommodation and Food Services industry, presented in Appendix D, we show that the effects of restaurant and bar limitations are driven by states with high food services employment. Figure D1 and Appendix Table D1 show the event study estimates separately for states with high (above-median) and low (below-median) food service employment shares. The point estimates suggest that the effect of restaurant and bar limitation announcements is larger for states with a high share of their residents employed in food service, though this difference is not statistically significant. We estimate that the Accommodation and Food Services industry accounts for about 25% (2.5 million) of all initial UI claims filed between March 14 and 28. However, the policy of restaurant and bar limitations can account for only 17.7% of this effect (about 440,000 claims).

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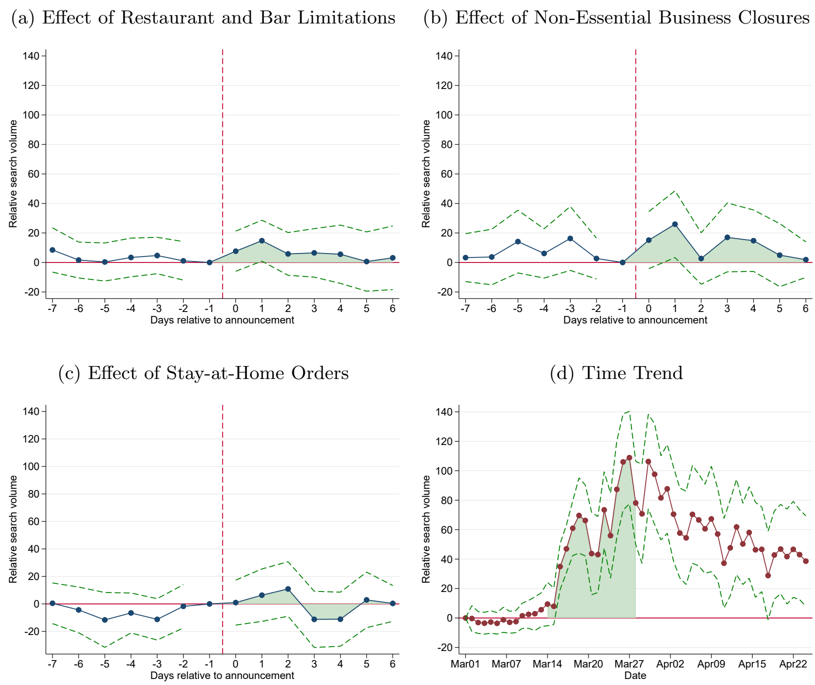
Figure 4: Dis-aggregating Unemployment Effects by Policy and Pandemic Causes



Note: Figure shows event study estimates of the impact of restaurant and bar limitations (Panel (a), non-essential business closures (Panel (b)), and stay-at-home orders (Panel (c)), based on Equation (2) which estimates the impact of the policies jointly. Panel (d) shows estimates of the overall time trend in UI search volume. The areas under the curves represent the share of the growth in UI claims that we attribute to the NPIs (Panels (a)-(c)) and other pandemic effects (Panel (d)). The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.2 and 5.4.

6.4 Estimates of NPI Impacts on UI Claims

We use the method outlined in Section 5.4 to compute the share and number of UI claims caused by the six NPIs. The results from our main specification (see Figure 2) suggest that only restaurant and bar limitations, non-essential business closures, and stay-at-home orders have statistically significant effects on search volume. To address the positive correlation between these policies (shown in Figure 1), we use the multiple-policy event study given by Equation 2 to estimate I_p, the area under the event study coefficients for each policy p, for the three policies above. Panels (a), (b), and (c) of Figure 4 graphically illustrate this calculation. Panel (d) shows $I_{\alpha,t1,t2})$, the area under the time fixed

effects. We obtain $I_p = 42.7$ for restaurant and bar limitations, $I_p = 82.9$ for non-essential business closures, and $I_p = -0.3$ for stay-at-home orders, and we compute $I_{\alpha,t1,t2} = 851.5$. These values imply that restaurant and bar limitations, non-essential business closures, and stay-at-home orders account for 4.4%, 8.5%, and 0.0% of all UI claims between March 14 and March 28, respectively. Under the single-policy event study design, we would have mistakenly inferred that restaurant and bar limitations, non-essential business closures, and stay-at-home orders account for 6.5%, 10.3%, and 6.5% of all UI claims from March 14-28. We conclude that the six NPIs we consider account for just under 13% of the rise in UI claims and that failing to control for multiple correlated NPI introductions will tend to inflate the estimated importance of individual NPIs.

7 Discussion

In March 2020, as the COVID-19 pandemic spread through the U.S. state governments issued emergency declarations, limited business operations, closed schools, and imposed social distancing measures. At the same time, unemployment insurance claims skyrocketed and reached their highest levels since 1982. In this paper, we present the first estimates of the combined and individual effects of six NPIs on UI claims. We disentangle the effects of multiple NPIs using high-frequency Google search data to proxy for UI claims, increasing our ability to leverage small differences in policy timing. We describe a method and set of assumptions that allows proxies to be used for policy evaluation when data on the outcome of interest are limited. With the increasing need to measure policy effects in real time, we hope that our method will complement new high-frequency sources of proxy data, such as SafeGraph data for measuring mobility, Google Trends data for measuring online search, and even high-frequency survey data where the outcomes of interest may need to be proxied using survey questions.

Our results imply that most of this increase in unemployment was *not* due to the NPIs that we consider. State-level restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, and emergency declarations account for less than 13% of the increase in UI claims from March 14-28, 2020. We find that restaurant and bar limitations and non-essential business closures account for 4.4% and 8.5% of the 10,174,000 UI claims filed during this period. On the other hand, large-gatherings bans, school closures, and emergency declarations did not significantly impact UI claims. Stay-at-home orders had significant effects when considered in isolation, but their effect disappears after controlling for non-essential business closures.

We caution against using our results to infer the impacts of relaxing these NPIs. At the time of

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introduction, the exact policy effects we estimate depend on pre-existing expectations and policies and this is also true when considering relaxations of these policies.

Our results can be combined with work on the effectiveness of NPIs on slowing disease spread to identify NPIs that are effective but "inexpensive" from the standpoint of unemployment. For example, Gupta et al. (2020) find that informational NPIs like emergency declarations and school closures had the largest effects on social distancing behavior, whereas we find that these two NPIs had no detectable short-term effects on unemployment.

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A Additional Figures and Tables

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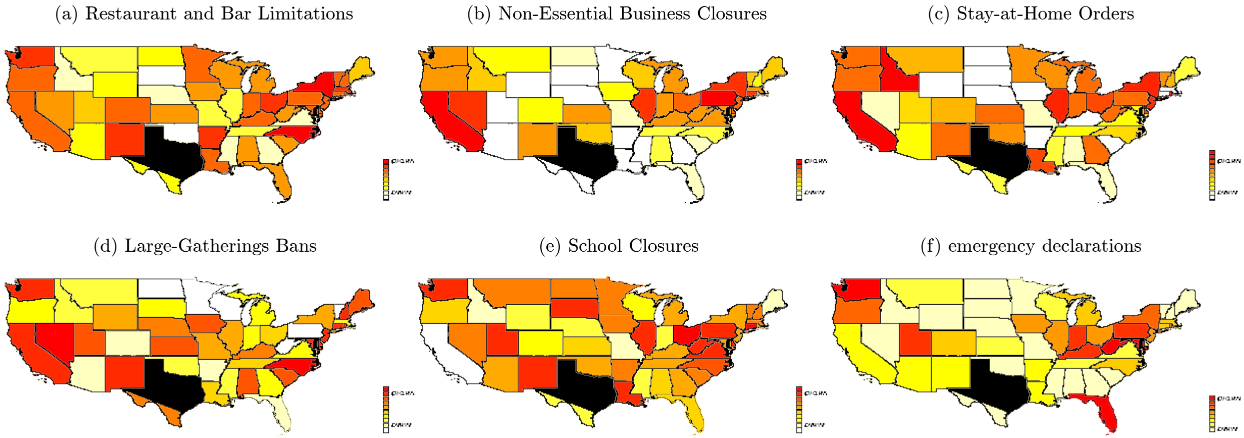
Appendix Figure A1: Geographic Distribution of NPI Adoption



(a) Restaurant and Bar Limitations

(b) Non-Essential Business Closures

(c) Stay-at-Home Orders

(d) Large-Gatherings Bans

(e) School Closures

(f) emergency declarations

Note: Figure shows heatmaps of the distribution of the announcement dates of restaurant and bar limitations (Panel (a)), non-essential business closures (Panel (b)), stay-at-home orders (Panel (c)), large-gatherings bans (Panel (d)), school closures (Panel (e)), and emergency declarations (Panel (f)) across states. Darker colors indicate an earlier announcement date, lighter colors indicate a later announcement date, and white indicates that the policy was not announced by April 3 in the state. For more details, see Section 3.2.

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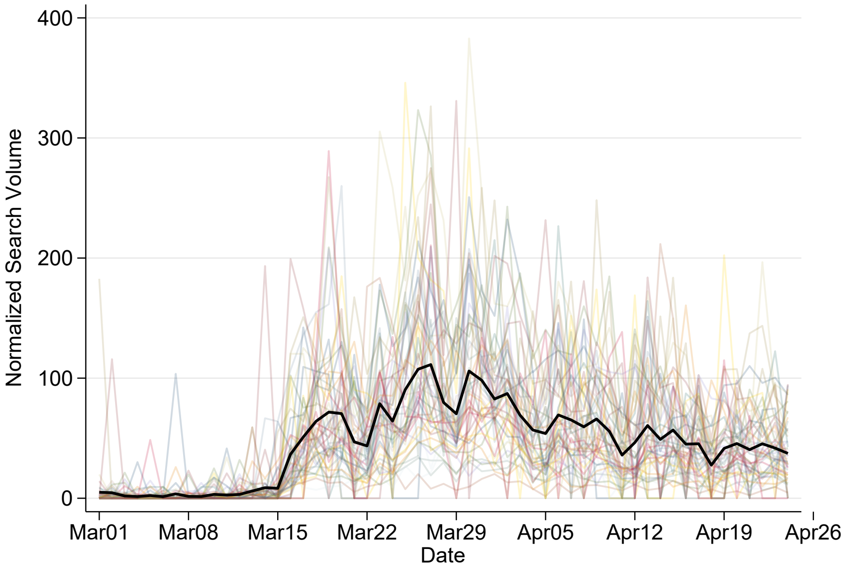
Appendix Figure A2: Evolution of Google Search Volume for Claiming Unemployment Insurance in March and April, 2020

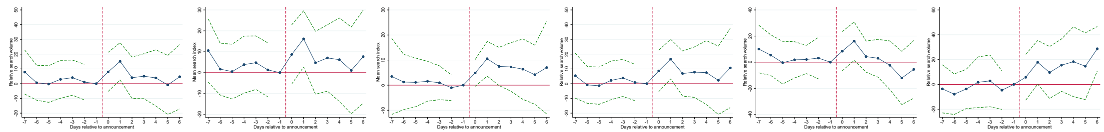


Note: Figure shows normalized Google search volumes for claiming unemployment insurance for U.S. states between March 01 and April 24, 2020. Each light colored line represents one state and the black line represents the national average. For more details, see Section 3.1.

Appendix Figure A3: Event Study Estimates: Robustness

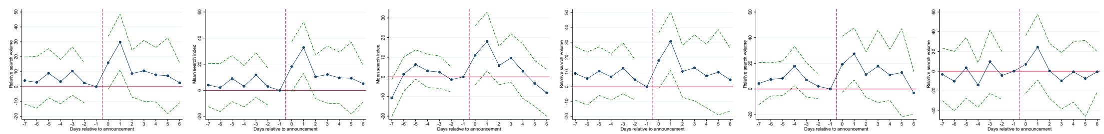
Restaurant and Bar Limitations

(a) Main Specification (b) Exclude CA, NY, and WA (c) Weighted (d) Controls (e) Early First Death (f) Late First Death



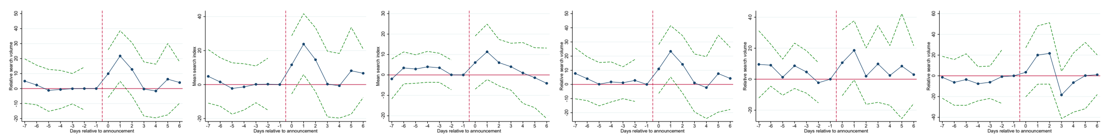
Non-Essential Business Closures

(g) Main Specification (h) Exclude CA, NY, and WA (i) Weighted (j) Controls (k) Early First Death (l) Late First Death



Stay-at-Home Orders

(m) Main Specification (n) Exclude CA, NY, and WA (o) Weighted (p) Controls (q) Early First Death (r) Late First Death



Note: Figure shows event study estimates of the impact of the introduction of restaurant and bar limitations (Panels (a)-(f)), non-essential business closures (Panels (g)-(l)), and stay at home orders (Panels (m)-(r)), based on Equation (1). Replicating Figure 2, Panels (a), (g), and (m) show our main specification. Panels (b), (h), and (n) show estimates excluding California, Washington, and New York. Panels (c), (i), and (o) show estimates weighted by total employment in the state. Panels (d), (j), and (p) show estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Panels (e), (k), and (q) show estimates limiting to the 26 states that registered their first COVID-19 death on or before March 19. Panels (f), (l), and (r) show estimates limiting to the 23 states that registered their first COVID-19 death after March 19. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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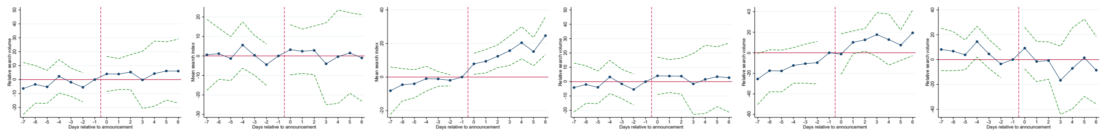
Appendix Figure A4: Event Study Estimates: Robustness

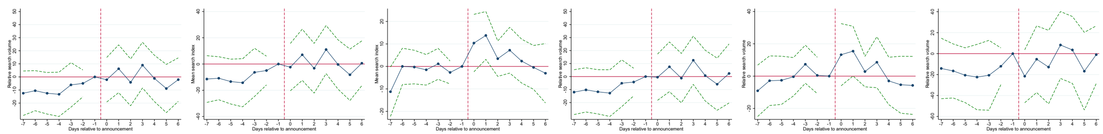
School Closures

(a) Main Specification (b) Exclude CA, NY, and WA (c) Weighted (d) Controls (e) Early First Death (f) Late First Death



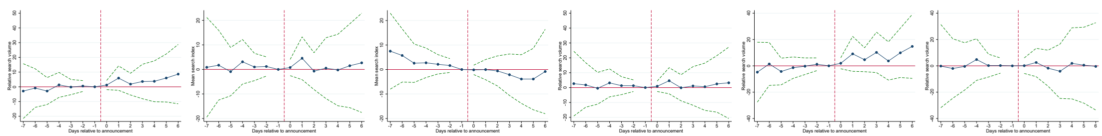
Large-Gatherings Bans

(g) Main Specification (h) Exclude CA, NY, and WA (i) Weighted (j) Controls (k) Early First Death (l) Late First Death



Health Emergencies

(m) Main Specification (n) Exclude CA, NY, and WA (o) Weighted (p) Controls (q) Early First Death (r) Late First Death



Note: Figure shows event study estimates of the impact of the introduction of school closures (Panels (a)-(f)), large-gatherings bans (Panels (g)-(l)), and emergency and public health emergency declarations (Panels (m)-(r)), based on Equation (1). Panels (a), (g), and (m) show our main specification. Panels (b), (h), and (n) show estimates excluding California, Washington, and New York. Panels (c), (i), and (o) show estimates weighted by total employment in the state. Panels (d), (j), and (p) show estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Panels (e), (k), and (q) show estimates limiting to the 26 states that registered their first COVID-19 death on or before March 19. Panels (f), (l), and (r) show estimates limiting to the 23 states that registered their first COVID-19 death after March 19. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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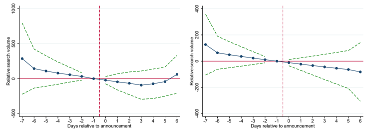
Appendix Figure A5: Event Study Estimates: Epidemiological Outcomes

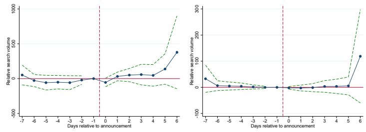
Restaurant and Bar Limitations

(a) Case Growth (b) Deaths



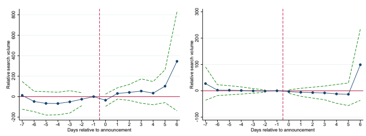
Non-Essential Business Closures

(c) Case Growth (d) Deaths



Stay-at-Home Orders

(e) Case Growth (f) Deaths



Note: Figure shows event study estimates of the relationship of the introduction of restaurant and bar limitations (Panels (a) and (b)), non-essential business closures (Panels (c) and (d)), and stay-at-home orders (Panels (e) and (f)) and epidemiological outcomes (case growth and deaths) based on Equation (1). Panels (a), (c), and (e) show estimates for case growth. Panels (b), (d), and (f) show estimates for deaths. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A1: NPI Adoption by State

State	State	Restaurant and Bar Limitation	Essential Business Closure	Stay-at-Home Order	Public Health Emegency	Large-Gatherings Ban	School Closure	First Case	First Death	Early First Death
AK	Alaska	3/17	3/20	3/17	3/11	3/20	3/13	3/13	3/25	
AL	Alabama	3/17	3/27	4/3	3/13	3/17	3/17	3/13	3/25	
AR	Arkansas	3/15			3/11	3/26	3/15	3/15	3/24	
AZ	Arizona	3/19		3/30	3/11	3/30	3/16	3/1	3/21	
CA	California	3/16	3/19	3/19	3/11	3/16		3/1	3/4	✓
CO	Colorado	3/16	3/26	3/26	3/10	3/26	3/18	3/6	3/13	✓
CT	Connecticut	3/16	3/20		3/10	3/16	3/11	3/10	3/18	✓
DC	District of Columbia	3/20	3/24	3/30	3/11	3/20	3/20	3/16	3/20	
DE	Delaware	3/16	3/22	3/22	3/12	3/16	3/13	3/11	3/26	
FL	Florida	3/17	4/1	4/1	3/1	4/1	3/17	3/2	3/8	✓
GA	Georgia	3/23		3/23	3/14	3/23	3/16	3/3	3/12	✓
HI	Hawaii	3/17		3/17	3/4	3/17	3/15	3/7	3/24	
IA	Iowa	3/17	3/26		3/9	3/17	3/15	3/9	3/25	
ID	Idaho	3/25	3/25	3/19	3/13	3/25	3/25	3/13	3/26	
IL	Illinois	3/20	3/20	3/20	3/9	3/20	3/13	3/1	3/17	✓
IN	Indiana	3/16	3/23	3/23	3/6	3/23	3/19	3/6	3/16	✓
KS	Kansas	3/17	3/23	3/23	3/12	3/17	3/17	3/8	3/13	✓
KY	Kentucky	3/16	3/23		3/6	3/19	3/16	3/6	3/16	✓
LA	Louisiana	3/16		3/22	3/11	3/22	3/13	3/11	3/14	✓
MA	Massachusetts	3/15	3/23		3/10	3/23	3/15	3/1	3/20	
MD	Maryland	3/16	3/23	3/30	3/5	3/16	3/16	3/6	3/19	✓
ME	Maine	3/18	3/24	3/31	3/15	3/18	3/31	3/12	3/27	
MI	Michigan	3/17	3/23	3/23	3/10	3/23	3/16	3/11	3/18	✓
MN	Minnesota	3/16		3/25	3/13		3/15	3/6	3/21	
MO	Missouri	3/21	4/3	4/3	3/13	3/21	3/21	3/8	3/18	✓
MS	Mississippi	3/24		3/31	3/14	3/24	3/19	3/12	3/19	✓
MT	Montana	3/20	3/26	3/26	3/12	3/24	3/15	3/13	3/27	
NC	North Carolina	3/14	3/27	3/27	3/10	3/14	3/14	3/3	3/25	
ND	North Dakota	3/19	4/2		3/13		3/15	3/12	3/27	
NE	Nebraska	3/30			3/13	3/19	3/19	3/6	3/28	
NH	New Hampshire	3/16	3/26	3/26	3/13	3/16	3/15	3/2	3/23	
NJ	New Jersey	3/16	3/21	3/21	3/9	3/16	3/16	3/5	3/10	✓
NM	New Mexico	3/15	3/23	3/23	3/11	3/16	3/13	3/11	3/25	
NV	Nevada	3/17	3/20	4/1	3/13	3/15	3/15	3/5	3/16	✓
NY	New York	3/14	3/20	3/20	3/7	3/20	3/16	3/2	3/14	✓
OH	Ohio	3/15	3/22	3/22	3/9	3/22	3/12	3/10	3/20	
OK	Oklahoma		3/24	3/24	3/15	3/24	3/16	3/7	3/19	✓
OR	Oregon	3/16	3/23	3/23	3/8	3/23	3/17	3/1	3/15	✓
PA	Pennsylvania	3/16	3/19	3/23	3/6		3/13	3/6	3/18	✓
RI	Rhode Island	3/16		3/13	3/9	3/16	3/18	3/1	3/28	
SC	South Carolina	3/17	3/31		3/13	3/17	3/15	3/7	3/16	✓
SD	South Dakota				3/13	3/23	3/13	3/12	3/11	✓
TN	Tennessee	3/22	3/30	3/30	3/12	3/22	3/16	3/5	3/20	
TX	Texas	3/19		3/31	3/13	3/19	3/19	3/5	3/17	✓
UT	Utah	3/18		3/27	3/6	3/18	3/13	3/7	3/22	
VA	Virginia	3/23	3/23	3/30	3/12	3/23	3/13	3/8	3/14	✓
VT	Vermont	3/16	3/24	3/24	3/13		3/15	3/8	3/19	✓
WA	Washington	3/15	3/23	3/23	2/29	3/16	3/13	3/1	3/1	✓
WI	Wisconsin	3/17	3/24	3/24	3/12		3/18	3/10	3/20	
WV	West Virginia	3/17	3/23	3/23	3/4		3/13	3/18	3/30	
WY	Wyoming	3/19			3/13	3/20	3/19	3/12	4/13	

Note: Table shows for each state: the day the state announced each NPI, the day the state registered its first death from COVID-19, the day the state registered its first confirmed case of COVID-19, and whether we categorize the state as a state with an early first death (first death by 3/19). The source of these data is The Henry J. Kaiser Family Foundation (2020). For more details, see Section 3.2.

Appendix Table A2: Event Study Estimates: Restaurant and Bar Limitations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-7	7.851	3.460	10.55	9.104	5.401	2.184	10.08	-7.012
	(7.603)	(7.727)	(7.708)	(8.014)	(7.771)	(5.847)	(9.080)	(8.122)
-6	0.603	1.256	1.688	4.081	-0.842	0.136	4.528	-9.131
	(6.039)	(5.618)	(6.326)	(6.222)	(6.350)	(4.818)	(8.371)	(7.994)
-5	-0.251	1.111	0.501	3.086	-1.376	0.166	-1.179	-4.694
	(6.329)	(4.953)	(6.687)	(5.716)	(6.445)	(4.341)	(8.735)	(7.515)
-4	2.941	1.545	3.843	3.566	2.216	0.846	1.209	0.946
	(6.549)	(4.053)	(6.964)	(4.636)	(6.682)	(3.678)	(7.551)	(10.17)
-3	4.077	0.955	4.756	1.958	3.893	0.530	1.970	2.713
	(6.080)	(3.445)	(6.533)	(4.010)	(6.403)	(3.527)	(6.114)	(10.74)
-2	1.080	-1.019	1.326	-1.019	0.781	-1.100	3.115	-5.240
	(6.165)	(2.601)	(6.572)	(3.088)	(6.293)	(2.618)	(8.535)	(7.878)
-1	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
0	7.979	4.873^{+}	8.682	6.146^{+}	8.638	5.827^{*}	8.043	7.231
	(6.760)	(2.725)	(7.234)	(3.278)	(7.167)	(2.900)	(7.921)	(10.08)
1	15.15^{*}	10.53^{**}	16.14^{*}	12.33^{**}	16.64^{*}	11.71^{**}	16.51^{+}	19.37^{*}
	(6.440)	(3.521)	(6.861)	(4.063)	(6.850)	(3.530)	(8.168)	(9.197)
2	4.043	7.468^{+}	4.722	8.895^{*}	6.859	9.097^{*}	4.318	13.56
	(7.154)	(3.884)	(7.676)	(4.242)	(7.781)	(3.808)	(7.234)	(11.27)
3	5.075	7.266	7.038	11.46^{*}	7.809	9.175^{+}	2.191	19.13^{+}
	(7.781)	(4.945)	(8.097)	(5.023)	(8.734)	(4.682)	(8.924)	(10.99)
4	3.899	6.379	6.193	9.383	7.507	9.203	-1.004	21.86
	(9.725)	(6.140)	(10.19)	(6.853)	(11.05)	(5.637)	(11.53)	(15.47)
5	-0.866	4.181	1.073	6.690	2.285	6.469	-13.01	18.81
	(10.21)	(6.013)	(10.58)	(6.248)	(11.82)	(5.857)	(14.00)	(14.14)
6	4.693	7.023	7.635	13.16	10.67	12.76	-3.455	33.22^{**}
	(11.15)	(9.444)	(11.34)	(9.893)	(13.72)	(8.580)	(16.30)	(11.50)
N	2805	2805	2640	2640	2244	2244	1144	1100
R^2	0.580	0.682	0.579	0.684	0.654	0.769	0.727	0.600
Employment Weights	No	Yes	No	Yes	No	Yes	No	No
Drop WA, CA, NY	No	No	Yes	Yes	No	No	No	No
Case Growth & Death Ctrls	No	No	No	No	Yes	Yes	No	No
Early or Late First Death	Both	Both	Both	Both	Both	Both	Early	Late

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the impact of the introduction of restaurant and bar limitations on search volume, based on Equations (1) and (3). Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Column (5) shows estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (6) shows estimates weighted by total employment in the state and including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (7) shows estimates for states with an early first death. Column (8) shows estimates for states with a late first death. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A3: Event Study Estimates: Non-Essential Business Closures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-7	4.100	-10.76*	4.111	-10.53+	8.973	-2.987	12.28	-0.695
	(8.058)	(4.817)	(8.446)	(5.486)	(9.166)	(6.411)	(10.85)	(14.00)
-6	2.879	1.328	2.143	1.393	5.542	5.795	13.16	-10.90
	(8.820)	(4.475)	(9.363)	(5.121)	(9.084)	(5.380)	(8.293)	(14.68)
-5	9.003	6.303	9.048	7.245+	10.57	10.50*	13.01+	1.390
	(8.393)	(3.800)	(8.965)	(4.238)	(8.314)	(4.424)	(7.275)	(14.61)
-4	3.377	3.076	3.174	2.343	6.702	6.623	21.83*	-11.65
	(7.535)	(4.350)	(8.061)	(4.833)	(7.984)	(4.737)	(8.297)	(12.21)
-3	10.49	2.387	11.77	5.027	12.47	5.559	9.937	10.70
	(8.269)	(4.191)	(8.772)	(4.634)	(8.744)	(4.572)	(7.209)	(17.64)
-2	2.486	-1.392	2.973	-0.881	4.778	0.697	5.198	-2.219
	(6.814)	(3.214)	(7.198)	(3.959)	(6.960)	(3.469)	(4.959)	(12.83)
-1	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
0	16.02+	11.04	18.26+	16.38+	17.64+	12.66	19.22	9.848
	(9.030)	(7.664)	(9.686)	(9.346)	(9.519)	(8.150)	(12.01)	(15.35)
1	29.87**	18.02*	32.77**	26.75**	30.62**	17.91*	26.34*	29.31
	(9.517)	(7.657)	(10.05)	(8.452)	(10.05)	(8.513)	(11.21)	(17.67)
2	8.786	5.755	10.45	11.44*	10.37	5.597	8.923	7.181
	(8.039)	(4.966)	(8.585)	(5.375)	(8.917)	(6.114)	(9.830)	(16.38)
3	10.62	9.611	12.13	14.71+	12.77	10.23	15.68	-1.005
	(10.39)	(6.302)	(11.18)	(8.125)	(11.30)	(7.471)	(15.55)	(15.50)
4	7.961	2.865	9.641	8.805	7.330	1.681	5.412	7.441
	(9.324)	(7.057)	(10.07)	(8.372)	(10.92)	(8.042)	(10.99)	(18.95)
5	7.297	-3.375	9.344	1.675	9.816	-3.160	7.924	5.644
	(12.94)	(5.965)	(14.00)	(7.676)	(14.65)	(6.969)	(18.16)	(24.37)
6	2.562	-8.106	5.120	-0.620	4.737	-8.246	-11.36	18.03
	(6.818)	(6.095)	(7.185)	(5.411)	(10.74)	(9.055)	(11.47)	(18.42)
N	2805	2805	2640	2640	2244	2244	1144	1100
R^2	0.582	0.694	0.581	0.696	0.656	0.776	0.732	0.601
Employment Weights	No	Yes	No	Yes	No	Yes	No	No
Drop WA, CA, NY	No	No	Yes	Yes	No	No	No	No
Case Growth & Death Ctrls	No	No	No	No	Yes	Yes	No	No
Early or Late First Death	Both	Both	Both	Both	Both	Both	Early	Late

Standard errors in parentheses
$^{+}\ p < .1$, $^{*}\ p < .05$, $^{**}\ p < .01$

Note: Table shows event study coefficients of the impact of non-essential business closures on search volume, based on Equations (1) and (3). Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Column (5) shows estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (6) shows estimates weighted by total employment in the state and including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (7) shows estimates for states with an early first death. Column (8) shows estimates for states with a late first death. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A4: Event Study Estimates: Stay-at-Home Orders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-7	4.995	-1.939	4.825	-0.944	7.740	2.906	16.35	-4.344
	(7.554)	(4.972)	(8.028)	(6.077)	(9.155)	(6.737)	(13.85)	(11.03)
-6	2.373	3.439	1.535	2.345	4.050	6.044	13.71	-8.111
	(6.748)	(3.992)	(7.280)	(4.389)	(7.897)	(5.364)	(9.157)	(12.35)
-5	-1.203	2.894	-2.294	0.938	0.148	5.608	5.136	-4.777
	(7.136)	(3.551)	(7.703)	(3.884)	(7.810)	(4.800)	(6.653)	(13.54)
-4	-0.608	3.976	-1.362	1.776	1.760	6.527	12.43	-7.109
	(6.486)	(3.856)	(6.954)	(4.439)	(7.224)	(4.383)	(8.944)	(9.226)
-3	-0.0792	3.492	0.133	4.768	1.186	6.618	7.506	-6.558
	(5.172)	(3.631)	(5.517)	(4.165)	(5.750)	(4.235)	(7.248)	(8.978)
-2	0.00188	0.0527	0.243	0.462	2.818	2.584	0.495	2.491
	(7.300)	(3.713)	(7.777)	(4.814)	(7.556)	(3.809)	(7.068)	(13.79)
-1	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
0	9.952	6.073	11.62	9.269	10.93	8.090	12.13	4.054
	(8.134)	(6.634)	(8.727)	(8.171)	(8.807)	(7.588)	(12.24)	(12.79)
1	21.75*	11.32	23.82*	17.02*	23.37*	11.96	18.02	25.87^{+}
	(8.616)	(6.920)	(9.145)	(8.371)	(9.272)	(7.896)	(10.69)	(14.94)
2	12.79	6.015	14.62	11.23^{+}	14.16	6.890	1.547	25.49
	(9.093)	(5.793)	(9.591)	(6.662)	(10.34)	(7.620)	(10.57)	(17.13)
3	-0.288	4.030	0.284	7.251	1.047	5.057	9.166	-13.79
	(9.220)	(5.865)	(9.859)	(7.838)	(10.44)	(7.564)	(13.90)	(13.66)
4	-1.622	0.969	-0.699	6.360	-2.242	1.433	-1.053	-3.126
	(9.134)	(7.588)	(9.705)	(9.095)	(11.16)	(9.495)	(11.31)	(18.03)
5	6.273	-1.361	8.126	4.206	7.615	-0.794	5.786	6.428
	(12.15)	(7.485)	(13.02)	(9.524)	(13.86)	(9.081)	(18.11)	(19.15)
6	4.021	-4.090	6.641	5.944	4.226	-3.490	-4.847	10.02
	(6.989)	(8.800)	(7.281)	(8.593)	(11.19)	(11.20)	(11.75)	(16.04)
N	2805	2805	2640	2640	2244	2244	1144	1100
R^2	0.581	0.685	0.580	0.685	0.656	0.770	0.728	0.604
Employment Weights	No	Yes	No	Yes	No	Yes	No	No
Drop WA, CA, NY	No	No	Yes	Yes	No	No	No	No
Case Growth & Death Ctrls	No	No	No	No	Yes	Yes	No	No
Early or Late First Death	Both	Both	Both	Both	Both	Both	Early	Late

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the impact of stay-at-home policies on search volume, based on Equations (1) and (3). Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Column (5) shows estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (6) shows estimates weighted by total employment in the state and including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (7) shows estimates for states with an early first death. Column (8) shows estimates for states with a late first death. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

Appendix Table A5: Event Study Estimates: Large-Gatherings Bans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-7	-12.46	-11.25^{+}	-11.46	-6.647	-11.97	-3.342	-4.629	-17.54
	(8.671)	(5.616)	(9.081)	(5.576)	(8.797)	(5.190)	(6.845)	(15.31)
-6	-10.53	0.0200	-10.85	2.791	-10.25	4.130	-0.843	-18.40
	(7.820)	(4.118)	(8.367)	(4.590)	(8.675)	(5.140)	(9.544)	(14.14)
-5	-12.50	-0.275	-13.38	0.851	-11.73	3.637	-0.482	-21.51
	(8.106)	(3.814)	(8.722)	(4.778)	(8.677)	(4.490)	(8.870)	(14.08)
-4	-13.28	-1.510	-14.29	-1.017	-12.74	1.581	1.323	-23.88
	(8.655)	(3.462)	(9.365)	(4.661)	(9.160)	(4.262)	(7.083)	(16.47)
-3	-6.089	1.163	-6.358	2.799	-5.126	3.971	8.627	-20.73
	(8.691)	(3.510)	(9.359)	(3.898)	(9.172)	(4.038)	(7.050)	(17.60)
-2	-4.952	-2.680	-4.964	-2.869	-4.205	-1.086	1.265	-11.79
	(5.239)	(2.605)	(5.591)	(3.173)	(5.424)	(2.801)	(5.724)	(9.423)
-1	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
0	-2.138	10.39	-2.377	12.85	-0.484	12.08^{+}	14.53	-20.46
	(8.699)	(6.518)	(9.203)	(7.872)	(9.072)	(6.666)	(10.10)	(13.39)
1	6.263	13.77*	7.052	18.94**	7.512	13.17*	15.61^{+}	-2.852
	(9.325)	(5.422)	(9.952)	(5.834)	(9.755)	(5.800)	(8.015)	(17.31)
2	-4.143	3.451	-3.239	8.308*	-1.210	3.553	2.887	-7.421
	(9.145)	(4.028)	(9.671)	(4.000)	(9.680)	(4.573)	(5.010)	(19.15)
3	9.016	7.220	11.03	13.55*	12.55	6.966	9.028	14.82
	(8.904)	(5.192)	(9.365)	(5.651)	(9.461)	(5.920)	(8.663)	(17.50)
4	-1.147	2.382	-0.355	4.799	0.747	0.246	-5.209	8.797
	(9.041)	(4.974)	(9.592)	(5.983)	(9.953)	(5.244)	(8.388)	(17.63)
5	-8.878	-0.435	-8.213	3.096	-5.882	-1.875	-6.801	-9.722
	(9.409)	(4.968)	(10.01)	(5.420)	(10.22)	(5.260)	(10.19)	(20.42)
6	-2.063	-3.026	0.607	5.954	2.385	-3.680	-4.885	6.729
	(8.494)	(6.734)	(8.703)	(5.060)	(11.58)	(9.079)	(13.03)	(18.97)
N	2805	2805	2640	2640	2244	2244	1144	1100
R^2	0.582	0.689	0.581	0.689	0.656	0.772	0.729	0.604
Employment Weights	No	Yes	No	Yes	No	Yes	No	No
Drop WA, CA, NY	No	No	Yes	Yes	No	No	No	No
Case Growth & Death Ctrls	No	No	No	No	Yes	Yes	No	No
Early or Late First Death	Both	Both	Both	Both	Both	Both	Early	Late

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the impact of large-gatherings bans on search volume, based on Equations (1) and (3). Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Column (5) shows estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (6) shows estimates weighted by total employment in the state and including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (7) shows estimates for states with an early first death. Column (8) shows estimates for states with a late first death. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A6: Event Study Estimates: School Closures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-7	-6.410	-8.142	0.574	-2.148	-4.109	-7.249	-20.12^{+}	8.108
	(9.505)	(7.219)	(9.278)	(11.37)	(8.692)	(5.556)	(11.18)	(8.874)
-6	-3.444	-4.556	1.149	0.0881	-1.996	-4.205	-14.05	6.763
	(6.896)	(4.908)	(6.695)	(7.417)	(6.681)	(4.115)	(9.804)	(8.904)
-5	-5.225	-4.008	-1.367	0.148	-3.947	-3.756	-14.83	3.837
	(6.042)	(4.275)	(5.756)	(6.240)	(5.783)	(3.687)	(9.995)	(6.329)
-4	2.357	-0.970	5.555	2.759	3.295	-0.871	-10.14	14.23*
	(6.124)	(3.771)	(6.062)	(5.332)	(5.892)	(3.288)	(8.591)	(6.410)
-3	-1.896	-1.120	0.298	1.713	-1.565	-1.378	-9.128	3.882
	(5.161)	(2.247)	(5.180)	(2.940)	(5.204)	(2.147)	(9.806)	(6.311)
-2	-5.542	-1.955	-4.490	-0.408	-5.443	-2.083	-8.761	-4.301
	(5.330)	(1.698)	(5.432)	(1.855)	(5.544)	(1.709)	(10.85)	(6.264)
-1	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
0	4.074	7.866*	3.180	6.783^{+}	4.058	7.629*	-2.195	10.00
	(6.430)	(3.193)	(6.552)	(3.599)	(6.646)	(3.543)	(10.51)	(9.049)
1	3.955	9.412*	2.384	8.336*	3.908	9.468*	8.124	0.415
	(5.664)	(3.565)	(5.800)	(4.030)	(5.859)	(4.027)	(6.407)	(8.929)
2	5.376	12.39**	2.853	10.03*	3.828	11.48**	9.756	-0.695
	(6.379)	(3.474)	(6.360)	(4.274)	(6.414)	(4.081)	(6.389)	(8.022)
3	-0.227	15.71**	-4.033	11.37^{+}	-1.617	14.72**	14.07	-15.79
	(10.48)	(4.487)	(10.71)	(5.736)	(10.84)	(5.353)	(12.25)	(14.92)
4	4.276	20.47**	-0.381	14.81*	1.610	19.19**	8.451	-7.344
	(11.91)	(4.889)	(12.22)	(6.501)	(12.14)	(5.482)	(14.10)	(17.70)
5	6.167	15.18**	1.502	9.611	3.454	13.79*	2.269	2.544
	(10.68)	(4.279)	(10.51)	(5.854)	(10.64)	(5.578)	(9.575)	(16.63)
6	6.086	24.65**	-1.028	17.39*	2.774	24.26**	13.06	-5.140
	(11.70)	(5.746)	(11.32)	(8.100)	(12.30)	(8.731)	(14.79)	(15.92)
N	2805	2805	2640	2640	2244	2244	1144	1100
R^2	0.579	0.696	0.577	0.683	0.653	0.774	0.728	0.598
Employment Weights	No	Yes	No	Yes	No	Yes	No	No
Drop WA, CA, NY	No	No	Yes	Yes	No	No	No	No
Case Growth & Death Ctrls	No	No	No	No	Yes	Yes	No	No
Early or Late First Death	Both	Both	Both	Both	Both	Both	Early	Late

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the impact of school closures on search volume, based on Equations (1) and (3). Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Column (5) shows estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (6) shows estimates weighted by total employment in the state and including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (7) shows estimates for states with an early first death. Column (8) shows estimates for states with a late first death. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A7: Event Study Estimates: Public Health Emergencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-7	-2.904	7.493	0.861	8.533	2.649	9.776	5.368	1.180
	(9.492)	(7.909)	(10.36)	(9.000)	(11.09)	(8.556)	(14.43)	(18.22)
-6	-0.847	5.734	1.724	6.616	1.766	6.600	6.582	-1.998
	(6.690)	(5.536)	(7.248)	(6.071)	(7.624)	(5.927)	(9.785)	(12.76)
-5	-2.891	2.576	-0.911	2.804	-0.455	3.661	0.895	-0.879
	(4.673)	(4.006)	(5.026)	(4.213)	(5.447)	(4.454)	(6.629)	(10.01)
-4	1.305	2.743	3.113	3.428	3.159	3.582	2.667	4.269
	(4.324)	(3.072)	(4.630)	(3.348)	(4.792)	(3.436)	(5.271)	(8.460)
-3	-0.176	2.130	0.995	2.553	1.302	2.679	2.597	0.206
	(2.630)	(2.012)	(2.842)	(2.184)	(3.080)	(2.286)	(4.040)	(4.976)
-2	0.528	1.622	1.205	2.118	1.258	1.854	2.681	0.264
	(1.882)	(1.444)	(1.993)	(1.585)	(1.995)	(1.536)	(2.704)	(3.116)
-1	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
0	1.208	-0.147	0.772	-0.0865	0.890	-0.199	1.244	0.219
	(1.593)	(0.978)	(1.692)	(1.280)	(1.790)	(1.347)	(2.449)	(3.230)
1	5.909	-0.0425	4.550	-0.413	4.605	-0.768	6.570	2.457
	(4.229)	(2.107)	(4.447)	(2.040)	(4.483)	(2.424)	(6.959)	(6.220)
2	1.819	-0.588	-0.704	-1.606	-0.122	-1.667	1.183	-2.289
	(3.762)	(3.135)	(3.830)	(3.125)	(4.466)	(3.547)	(5.753)	(7.911)
3	3.612	-2.133	0.518	-3.501	1.102	-3.408	5.331	-4.270
	(5.966)	(4.318)	(6.325)	(4.714)	(6.615)	(4.914)	(8.615)	(11.78)
4	3.752	-3.894	-0.237	-6.334	0.569	-5.815	-2.068	1.358
	(7.076)	(5.070)	(7.433)	(5.757)	(8.108)	(5.881)	(8.636)	(15.40)
5	5.984	-3.896	1.500	-5.621	2.484	-5.309	3.570	-0.0343
	(8.322)	(6.403)	(8.718)	(6.945)	(9.680)	(7.206)	(11.74)	(16.32)
6	8.619	-0.825	2.687	-1.906	3.217	-3.662	3.837	-0.277
	(10.28)	(8.787)	(10.32)	(7.514)	(12.24)	(9.126)	(15.96)	(18.88)
N	2805	2805	2640	2640	2244	2244	1144	1100
R^2	0.579	0.682	0.577	0.683	0.653	0.769	0.725	0.594
Employment Weights	No	Yes	No	Yes	No	Yes	No	No
Drop WA, CA, NY	No	No	Yes	Yes	No	No	No	No
Case Growth & Death Ctrls	No	No	No	No	Yes	Yes	No	No
Early or Late First Death	Both	Both	Both	Both	Both	Both	Early	Late

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the impact of emergency declarations on search volume, based on Equations (1) and (3). Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Column (5) shows estimates including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (6) shows estimates weighted by total employment in the state and including controls for case growth and number of deaths, both interacted with state dummies to allow the effect of case growth and deaths to vary by state. Column (7) shows estimates for states with an early first death. Column (8) shows estimates for states with a late first death. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A8: Event Study Estimates: Multiple-Policy Estimation

	(1) Restaurant and Bar Limitations	(2) Essential Business Closures	(3) Stay-at-Home Orders
-7	8.477	3.283	0.461
	(7.662)	(8.293)	(7.554)
-6	1.640	3.709	-4.368
	(6.211)	(9.605)	(8.478)
-5	0.324	14.16	-11.64
	(6.583)	(10.85)	(10.18)
-4	3.391	6.113	-6.584
	(6.688)	(8.528)	(7.410)
-3	4.714	16.27	-11.25
	(6.293)	(11.05)	(7.673)
-2	1.099	2.674	-1.767
	(6.660)	(7.072)	(8.041)
-1	0	0	0
	(.)	(.)	(.)
0	7.642	15.16	0.958
	(6.952)	(9.874)	(8.345)
1	14.77*	25.94*	6.354
	(7.077)	(11.54)	(9.731)
2	5.797	2.676	10.87
	(7.389)	(8.910)	(10.12)
3	6.501	17.01	-11.24
	(8.384)	(11.91)	(10.42)
4	5.587	14.77	-11.14
	(10.08)	(10.62)	(10.03)
5	0.638	4.978	2.905
	(10.25)	(10.91)	(10.31)
6	3.164	1.912	0.345
	(11.00)	(6.143)	(6.643)
N	2805	2805	2805
R^2	0.586	0.586	0.586

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the relationship between NPIs and search volume when we include multiple policies at the same time, based on Equation (2). Column (1) shows estimates for restaurant and bar limitations. Column (2) shows estimates for essential business closures. Column (3) shows estimates for stay-at-home orders. For more details, see Section 5.2.

Appendix Table A9: Event Study Estimates: Case Growth

	(1) Restaurant and Bar Limitations	(2) Essential Business Closures	(3) Stay-at-Home Orders	(4) Large-Gatherings Bans	(5) School Closures	(6) Public Health Emegencies
-7	286.6	51.78	12.48	149.3^{+}	617.8	-116.7
	(259.8)	(72.45)	(69.17)	(79.13)	(413.9)	(106.4)
-6	143.7	-27.57	-47.14	84.29^{+}	295.3	-83.14
	(141.9)	(44.22)	(50.74)	(42.90)	(204.3)	(69.36)
-5	108.9	-58.01	-65.79	68.56^{+}	244.6	-87.03
	(111.2)	(53.56)	(58.23)	(35.23)	(172.3)	(69.76)
-4	79.08	-51.75	-67.19	53.48^{+}	180.1	-74.12
	(81.40)	(49.27)	(56.28)	(26.92)	(129.6)	(60.58)
-3	56.37	-58.09	-50.79	33.16^{+}	131.6	-69.34
	(53.74)	(51.12)	(55.74)	(17.87)	(89.00)	(52.74)
-2	31.51	-20.74	-25.30	20.60*	65.11	-35.26
	(27.34)	(31.60)	(32.23)	(8.737)	(43.83)	(29.69)
-1	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
0	-21.58	-54.81^{+}	-35.08	-11.01	-57.03	-24.06
	(26.73)	(31.39)	(30.60)	(14.25)	(36.89)	(27.02)
1	-45.81	31.99	31.19	-28.04	-111.7	30.96
	(58.89)	(31.80)	(28.09)	(24.71)	(76.38)	(29.57)
2	-66.73	51.07	41.48	-28.62	-172.3	31.15
	(82.78)	(48.28)	(39.78)	(44.27)	(117.3)	(38.83)
3	-92.93	58.05	54.60	-22.50	-237.3	39.01
	(103.0)	(75.42)	(60.63)	(66.80)	(160.5)	(56.06)
4	-73.45	46.77	34.22	-45.03	-301.4	23.06
	(107.5)	(79.12)	(57.74)	(71.00)	(201.3)	(61.53)
5	-42.53	138.5	102.2	-45.51	-360.1	53.71
	(106.0)	(111.3)	(81.92)	(86.70)	(243.1)	(68.55)
6	60.70	377.7	345.3	-57.93	-582.9	116.4
	(138.2)	(267.0)	(246.9)	(138.9)	(381.4)	(147.9)
N	2244	2244	2244	2244	2244	2244
R^2	0.563	0.569	0.568	0.560	0.574	0.561

Standard errors in parentheses

$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the relationship between NPIs and case growth, based on Equation (1). Column (1) shows estimates for restaurant and bar limitations. Column (2) shows estimates for essential business closures. Column (3) shows estimates for stay-at-home orders. Column (4) shows estimates for large-gatherings bans. Column (5) shows estimates for school closures. Column (6) shows estimates for public health emegencies. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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Appendix Table A10: Event Study Estimates: Deaths

	(1) Restaurant and Bar Limitations	(2) Essential Business Closures	(3) Stay-at-Home Orders	(4) Large-Gatherings Bans	(5) School Closures	(6) Public Health Emegencies
-7	126.6	32.77	27.28	53.27^{+}	237.0	-32.13
	(118.5)	(26.54)	(32.18)	(28.38)	(178.4)	(26.03)
-6	63.85	6.345	2.352	30.29*	110.5	-19.34
	(64.34)	(9.547)	(10.54)	(14.25)	(86.57)	(13.67)
-5	49.09	4.964	2.018	25.06*	93.44	-16.65
	(50.66)	(7.833)	(8.807)	(11.71)	(73.10)	(11.59)
-4	36.02	4.129	1.154	18.84*	69.12	-13.10
	(37.85)	(6.353)	(6.944)	(8.743)	(54.67)	(9.215)
-3	23.30	1.460	-0.295	12.34*	50.37	-9.479
	(24.87)	(4.042)	(4.464)	(5.743)	(37.81)	(6.509)
-2	11.24	-0.247	-1.189	6.053*	24.98	-5.570
	(12.27)	(2.097)	(2.244)	(2.765)	(18.64)	(3.684)
-1	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
0	-11.45	-1.912	-3.143	-6.552^{+}	-21.24	4.114
	(12.19)	(2.499)	(3.296)	(3.264)	(16.57)	(3.492)
1	-22.62	-2.679	-5.708	-12.62*	-44.24	9.781
	(24.38)	(5.651)	(7.775)	(6.044)	(31.75)	(6.459)
2	-33.44	-1.132	-7.045	-19.08*	-67.90	14.93
	(36.65)	(7.871)	(10.53)	(9.107)	(49.33)	(10.45)
3	-44.09	3.478	-8.053	-24.91*	-91.95	20.32
	(49.20)	(11.33)	(13.30)	(12.26)	(66.80)	(14.30)
4	-54.11	3.764	-11.88	-31.00*	-115.1	25.06
	(61.39)	(13.99)	(18.23)	(15.35)	(83.80)	(17.32)
5	-63.79	5.460	-13.21	-36.03^{+}	-136.8	29.84
	(73.94)	(17.43)	(21.84)	(18.01)	(99.61)	(20.76)
6	-82.16	118.8	98.98	-47.85	-232.3	83.35
	(113.8)	(91.04)	(68.99)	(33.61)	(167.2)	(61.01)
N	2244	2244	2244	2244	2244	2244
R^2	0.345	0.345	0.345	0.343	0.350	0.344

Standard errors in parentheses

$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the relationship between NPIs and deaths, based on Equations (1) and (3). Column (1) shows estimates for restaurant and bar limitations. Column (2) shows estimates for essential business closures. Column (3) shows estimates for stay-at-home orders. Column (4) shows estimats for large-gatherings bans. Column (5) shows estimates for school closures. Column (6) shows estimates for public health emegencies. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level. For more details, see Sections 5.1 and 5.3.

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B Estimating Policy Effects Using Proxy Data

One important challenge of using proxy data to estimate policy effects is relating the causal effects of the policy on the proxy to the causal effect of the policy on the outcome of interest. One straightforward solution is to perform an initial estimation step that relates the outcome of interest to the proxy. Once this relationship is known, the causal impact of the policy on the proxy can be "fed through" the model relating the proxy and the outcome of interest to obtain the causal impact of the policy on the outcome of interest.

B.1 Method 1: Estimating Policy Effects Using Data on the Outcome of Interest

To formalize this first method, consider a data set with units $i \in I$ and time periods t. Denote the set of policies of interest by $\mathcal{P}$. Denote the dummy variable describing whether an individual policy $p \in \mathcal{P}$ is active by P_{it}, the outcome of interest by U_{it}, and the proxy variable by S_{it}. The objective is to explain the relative contribution of each policy p on U_{it}. For this example, we will focus on estimating how policies p affect the average time trend of U_{it} between t_1 and t_2:

$$\tilde{U} = \frac{1}{N_I} \sum_{i \in I} \sum_{t \in \{t_1, \ldots, t_2\}} U_{it}$$

First, assume that S_{it} is a *relevant* proxy for U_{it}. That is, variation in S_{it} predicts variation in U_{it}. Note that this assumption must hold for any method that uses proxy variables for outcomes of interest. This first method directly tests the relevance condition in Equation 5, while our method imposes relevance as an assumption (ideally verified in prior studies). Additionally, we assume $\tilde{U}$ is known and a causal effect γ_p of P_{it} on S_{it} can be obtained for each policy p. For example, in a linear regression:

$$S_{it} = \hat{\gamma}_p P_{it} + \omega_{it}$$

Then, the relationship between the proxy S_{it} and outcome of interest U_{it} is parameterized by $\theta_{U,S}$ and directly estimated. In the linear regression case, this is:

$$U_{it} = \hat{\theta}_{U,S} S_{it} + \zeta_{it} \tag{5}$$

Finally, parameters from the above regressions are combined to translate the causal effect of P_{it} on S_{it} into a causal effect of P_{it} on U_{it} by combining the above two relationships.In the linear case, this is simply:

$$\hat{\beta}_p = \hat{\theta}_{U,S} \times \hat{\gamma}_p$$

The share of $\tilde{U}$ explained by policy p is then simply

$$\pi_p \equiv \hat{\beta}_p / \tilde{U}.$$

This approach is valid for *any subset of policies* for which $\hat{\gamma}_p$ can be estimated, but requires compiling enough data on U_{it} to estimate $\hat{\theta}_{U,S}$. The precision of the $\hat{\beta}_p$ estimate depends on the ability of the estimated model in Equation 5 to predict U_{it}.

B.2 Method 2: Using Proxies to Estimate Policy Effects With Limited Outcome Data

In cases where data on U_{it} are limited, our alternative method allows for estimation of the share of $\tilde{U}$ when several additional assumptions hold.

Assumption 1: the effect of S_{it} on U_{it} must be proportional, that is, the relationship between the proxy and outcome has the form $U_{it} = \theta_{U,S} S_{it}$ for some $\theta_{U,S}$, which does not need to be estimated.

Assumption 2: the researcher must be able to specify *all* of the policies that affect $\tilde{U}$ and estimate causal effects γ_p for all of them. Given these assumptions, the *share* of $\tilde{U}$ caused by any policy $p \in \mathcal{P}$ can be estimated by:

$$\pi_p = \frac{\gamma_p}{\sum_{p \in \mathcal{P}} \gamma_p} \tag{6}$$

Note, the share of any subset of policies $\mathcal{P}_s \subseteq \mathcal{P}$ can be computed similarly as:

$$\pi_p = \frac{\sum_{p \in \mathcal{P}_s} \gamma_p}{\sum_{p \in \mathcal{P}} \gamma_p}. \tag{7}$$

Note that the expression for π_p no longer requires estimation of $\hat{\theta}_{U,S}$, and only depends on the γ_p parameters, which can be estimated using only data on the proxy variables S_{it} and the policies P_{it}. To recover the effect of p in units of U_{it}, we simply compute

$$\hat{\beta}_p = \pi_p \times \tilde{U}.$$

Hence, we have directly recovered the causal impact of p on U_{it}, without having to estimate the relationship between the proxy S_{it} and U_{it}.

This method uses the simple idea that the effect of a policy can be estimated as a *share* of a total known quantity of the outcome variable (e.g. total UI claims in a given period), if the researcher can account for all policies that would affect this total quantity. In our context, we define $\tilde{U}$ as the total UI claims between March 14 and March 28, and Assumption 2 is satisfied by defining the set of policies as the NPIs plus the direct effects of the pandemic. The causal effects of each NPI are estimated using an event-study approach, and the direct pandemic effects are estimated as the time trend in Google searches that remains after netting out the effect of the NPIs. For this interpretation to hold, this assumes that the only reason that Google search volume for "file for unemployment" was elevated from March 14 to March 28 relative to March 1st is due to direct pandemic effects. For more details, see Sections 5.1 and 5.2 above.

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C Difference-in-Differences

We also estimate a difference-in-differences event study specification where we compare "early adopters" and "late or never adopters" of NPIs. We label states as "early adopters" if they implemented their first NPI[12] within a week of the first state (March 13-17). We label states as "late adopters" if they implemented an NPI on or after March 18, or not at all. (See Figure 1, Appendix Figure A1, and Appendix Table A1 for details on when each state implemented its policies.) We estimate a regression of the form:

$$S_{it} = \sum_{\tau=March7}^{March21} \delta_\tau \times 1\{\text{Early Adopter, t=}\tau\} + \beta \times 1\{\text{Early Adopter}\} + \xi_t + \mu_{it}, \tag{8}$$

where the δ_τ coefficients describe the differential evolution of search volume in "early adopters" relative to "late adopters." We normalize $\delta_{\tau=March12} = 0$, so β captures the average difference in S_{it} between early and late adopters on March 12th. The ξ_t denote date fixed effects which control for the time trend in search behavior for the late adopters. We limit to the period of March 7 to March 17, which allows for 6 days where no states have implemented restaurant and bar limitations, followed by 5 days where the early adopters began implementing limitations but the late adopters did not. The late adopters are thus never treated during our estimation window. We also estimate a version of the difference-in-differences regression where we pool all dates before March 13 into a single pre-period and all dates on or after March 13 into a single post-period:

$$S_{it} = \alpha + \delta \times 1\{\text{Early Adopter}\} \times 1\{\text{Post}\} + \beta \times 1\{\text{Early Adopter}\} + \xi_t + \mu_{it}, \tag{9}$$

where the single δ coefficient measures the differential change between the pre-period and the post-period for the early adopters.

This difference-in-differences approach has some advantages and disadvantages relative to our main event study approach. It is a transparent approach that where control states are those that did not announce any NPI during the timeframe we use for estimation. On the other hand, these late-adopter states are more likely to be different on unobservable dimensions. We include this approach to offer additional evidence for our finding that NPIs increase search activity, but our quantitative estimates of UI claiming rely on our event study approach.

[12] Most states' first NPI was restaurant and bar limitations.

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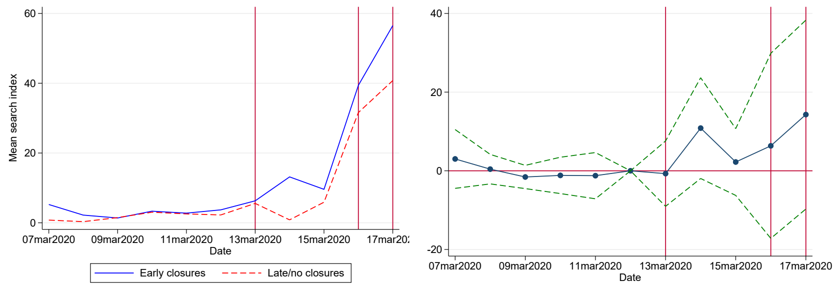
Appendix Figure C1: Difference-in-Differences Estimates — Early vs. Late Adopters

(a) Raw Data

(b) Coefficient Estimates



Note: Figure shows difference-in-differences estimates of the impact of NPI announcements, comparing "early adopters" (March 13-17) with "late or never adopters" (after March 17 or never). We divide states based on the announcement date of their first NPI they adopt. Panel (a) shows raw data and Panel (b) shows regression coefficients, based on Equation (9).

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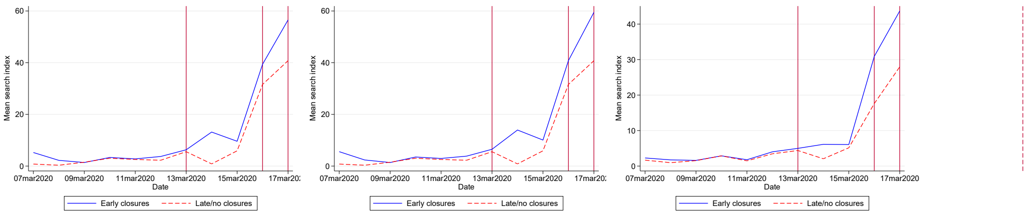
Appendix Figure C2: Difference-in-Differences Estimates — Early vs. Late Adopters: Robustness

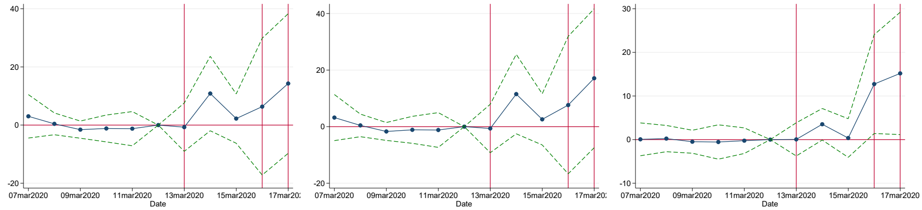
Raw Data

(a) Main Specification (b) Exclude CA, NY, WA (c) Weighted



Coefficient Estimates

(d) Main specification (e) Exclude CA, NY, WA (f) Weighted



Note: Figure shows difference-in-differences estimates of the impact of NPI announcements, comparing "early adopters" (March 13-17) with "late or never adopters" (after March 17 or never). We divide states based on the announcement date of their first NPI they adopt. Panels (a), (b), and (c) show raw data and Panels (d), (e), and (f) show regression coefficients, based on Equation (9). Panels (a) and (d) show our main specification. Panels (b) and (e) show estimates excluding California, Washington, and New York. Panels (c) and (f) show estimates weighted by total employment in the state.

Appendix Table C1: Difference-in-Differences Estimates — Early vs. Late Adopters

	(1)	(2)	(3)	(4)
Post March 12	14.20**	9.274**	14.20**	9.274**
	(3.333)	(2.017)	(3.335)	(2.018)
Early Closure States	-0.0781	-0.0655	0.0138	0.211
	(0.917)	(0.426)	(0.936)	(0.451)
Post X Early Closure	8.139+	6.987*	9.211+	9.029**
	(4.815)	(2.904)	(5.028)	(3.142)
Constant	2.737**	2.159**	2.737**	2.159**
	(0.817)	(0.304)	(0.817)	(0.304)
N	867	867	816	816
R^2	0.162	0.215	0.164	0.214
Employment Weights	No	Yes	No	Yes
Drop WA, CA, NY	No	No	Yes	Yes

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows difference-in-differences estimates of the impact of NPI announcements, comparing "early adopters" (March 13-17) with "late or never adopters" (after March 17 or never), based on Equation (9). We divide states based on the announcement date of their first NPI they adopt. Column (1) shows our main specification. Column (2) shows estimates weighted by total employment in the state. Column (3) shows estimates excluding California, Washington, and New York. Column (4) shows estimates weighted by total employment in the state and excluding California, Washington, and New York. Standard errors are clustered at the state level.

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D Case Study: Restaurant and Bar Limitations and Food Service Employment

Our empirical framework relies on the assumption that firms and individuals internalize how the information contained in NPI announcements affects firms' optimal labor-force size and individuals' employment probabilities. One test that could help validate this mechanism is to examine how Google searches change for individuals employed in industries directly affected by the NPI versus individuals employed in unaffected industries. In particular, we would like to assess whether the NPI of restaurant and bar limitations disproportionally affected employment expectations for food service workers. This is not possible to examine directly, since Google Trends data does not provide industry characteristics of searchers.[13] Instead, we implement this test by using variation in states' 2013-2017 employment shares in food service (measured using the American Community Survey and defined as the share of individuals employed in 2-digit NAICS code 72). We define high-food-service states as those with above-median employment in food service and run the following event-study specification:

$$S_{it} = \sum_{\tau=-7}^{6} \left(\hat{\gamma}_\tau \times 1\{r=\tau\} + \hat{\xi}_\tau \times 1\{r=\tau\} \times 1\{\text{High Food Service}\}\right) + \hat{\alpha}_i + \hat{\alpha}_t + \hat{\varepsilon}_{it} \tag{10}$$

where the $\hat{\gamma}_\tau$ coefficients now measure the response of Google search volume to restaurant and bar limitations for states with a below-median food service share and the sum $\hat{\gamma}_\tau + \hat{\xi}_\tau$ measures the response for states with an above-median food service share. We focus on the food service industry because it clearly corresponds to the policy of restaurant and bar limitations, which should have lowered firms' expected need for labor (e.g. waitstaff). Non-essential businesses would have been another candidate for an industry-level analysis, but definitions of "essential" were often unclear or varied across states. In lieu of a representative set of "non-essential" industry codes, we focus our attention on the food service industry.

D.1 Computing the industry-specific share of UI claims caused by an NPI

This section extends the method introduced in 5.4 to compute the industry-specific share of UI claims caused by a particular NPI. If the NPI p (here, restaurant and bar limitations) targets *only* industry s (here, Accommodation and Food Services) and $\rho_s \in [0,1]$ is the industry s share of the overall increase in UI claims, then the share of UI claims for s that was caused by the NPI can be estimated as:

$$\text{Share of UI claims in industry } s \text{ caused by NPI } p = \frac{I_p}{\rho_s \times (I_{\alpha,t1,t2} + \sum_p I_p)}. \tag{11}$$

D.2 Event-Study Results by Share of Food Service Employment

Figure D1 and Table D.3 report event study results separately for states with high (above-median) and low (below-median) food service employment shares, estimated from Equation 10. The point estimates suggest that the effect of restaurant and bar limitation announcement is larger for states with a high share of their residents employed in food service. However, we are not able to detect a statistically significant difference between the coefficients due to low statistical power.

D.3 Share of UI Claims in Accommodation and Food Services Caused by Restaurant and Bar Limitations

Finally, we calculate the number of UI claims filed as a result of restaurant and bar limitations as a share of the total UI claims filed in the Accommodation and Food Services industry between March 14 and March 28. This analysis assumes that restaurant and bar limitations only affected UI claiming in the Accommodation and Food Services industry.

First, we estimate the share of initial claims filed between March 14 and March 28 in the Accommodation and Food Services industry using data from three states (Massachusetts, New York, and Washington) that have released UI data by industry (Table D2).[14] We estimate the UI-claims-weighted average of this share to be 24.7% (about 2.5 million claims), where the weights we use are shown in Row 1 of Table D2.

[13]Search volumes for industry-specific terms such as "restaurant jobs" are too low to analyze at the state-day level

[14]Reliable national-level estimates of the contribution of individual industries to UI claims during the COVID-19 pandemic have not been released to date. Estimates using national-level data would differ if the Accommodation and Food Services share of new UI claims were different at the national level relative to Massachusetts, New York, and Washington.

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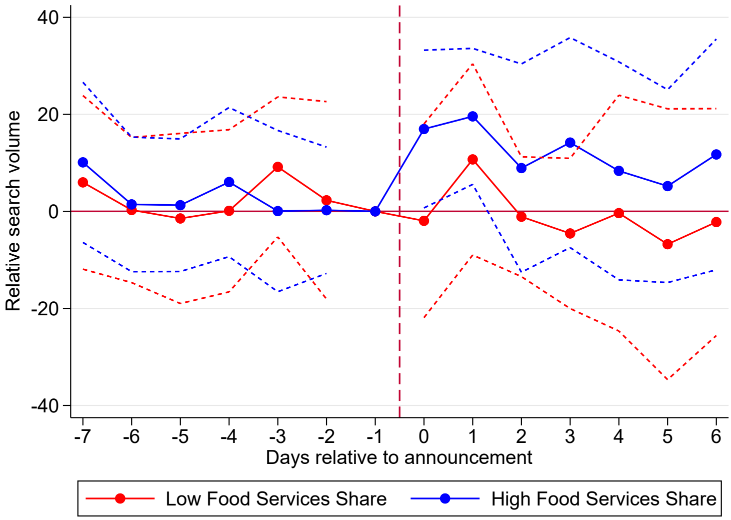
As we report in Section 6.2, we estimate that 4.4% of all UI claims between March 14 and March 28 were caused by restaurant and bar limitations (about 440,000 claims). Assuming that all of these claims occurred in Accommodation and Food Services, we conclude that 17.7% of the claims filed in Accommodation and Food Services were caused by restaurant and bar limitations.

Appendix Figure D1: Event Study Estimates by Share Employed in Food Service



Note: Figure shows event study estimates of the impact of the introduction of restaurant and bar limitations separately for states with below-median food service employment shares (in red) and above-median food service employment shares (in blue), based on Equation (10). The day prior to the announcement is normalized to zero and standard errors are clustered at the state level.

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Appendix Table D1: Event Study Estimates: Low vs. High Food-Service Share

	(1)	(2)
-7	5.984	10.107
	(-9.129)	(-8.422)
-6	0.284	1.445
	(-7.635)	(-7.075)
-5	-1.457	1.274
	(-8.948)	(-6.973)
-4	0.122	6.044
	(-8.526)	(-7.843)
-3	9.168	0.058
	(-7.363)	(-8.481)
-2	2.281	0.237
	(-10.384)	(-6.643)
-1	0	0
	0	0
0	-1.945	16.971*
	(-10.186)	(-8.296)
1	10.715	19.584**
	(-10.056)	(-7.154)
2	-1.101	8.924
	(-6.299)	(-10.955)
3	-4.549	14.185
	(-7.899)	(-11.044)
4	-0.356	8.351
	(-12.399)	(-11.464)
5	-6.77	5.206
	(-14.239)	(-10.143)
6	-2.2	11.738
	(-11.936)	(-12.133)
N	2,805	
R^2	0.583	

Standard errors in parentheses
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

Note: Table shows event study coefficients of the relationship between restaurant and bar limitations and Google search volume separately for states with a below-median share of employment in food service and for states with an above-median share of employment in food service, based on Equation (10). Column (1) shows estimates for states with a low food-service share. Column (2) shows estimates for states with a high food-service share. The day prior to the announcement is normalized to zero and standard errors are clustered at the state level.

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Appendix Table D2: Employment and unemployment statistics

	U.S.	Massachusetts	New York	Washington
Total UI Claims, March 14-28	10,174,000	328,967	449,778	291,854
UI Claims from Accommodation and Food Services		70,286	129,252	64,876
Share of UI Claims from Accommodation and Food Services, March 14-28		21.4%	28.7%	22.2%
Share Employed in Accommodation and Food Services	11.1%	10.1%	9.7%	10.0%

Note: Table shows employment and unemployment statistics for the U.S. and for three states (Massachusetts, New York, and Washington) for which industry-level unemployment claims are available. The source of national-level UI claims data is U.S. Department of Labor (2020). The source of Massachusetts UI claims data is Massachusetts Executive Office of Labor and Workforce Development (2020). The source of New York UI claims data is New York State Department of Labor (2020). The source of Washington UI claims data is Washington State Employment Security Department (2020). The source of national and state employment shares in the Food and Accommodation Services industry is Bureau of Labor Statistics (2020).

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Bowling together by bowling alone: Social capital and Covid-19[1]

Francesca Borgonovi[2] and Elodie Andrieu[3]

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The literature documents a strong positive association between social capital and health. However, because personal social interactions are implicated in the spread of viral infections, areas with high levels of social capital may be especially at risk during the COVID-19 pandemic. Social capital comprises not only a cognitive component (i.e. norms of reciprocity and trust) but also a relational component (i.e. social relationships and networks). We use data from counties in the United States to provide evidence on the extent to which community level responses such as reducing mobility to comply with social distancing advice and regulations are related with social capital. In line with predictions we find that individuals reduced mobility earlier and to a higher degree in counties with high levels of social capital than in counties with low levels of social capital.

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1 Francesca Borgonovi acknowledges support from the British Academy through its Global Professorship scheme. The views expressed reflect those of the authors and do not necessarily represent those of the British Academy. The authors would like to thank Mattia Sassi for help with the data.

2 British Academy Global Professor, University College London.
3 PhD student, King's College London.

Introduction

In Bowling Alone Putnam mapped the decline in social capital in the United States and traced such decline to changes in how individuals spend time at work, family and leisure. Rather than spending this time with others, negotiating a shared and common way forward, in communities with little social capital, individuals do and experience activities alone. By contrast, in communities with high levels of social capital, individuals do things together, from consequential things like being members of organisations, political parties and the church, to seemingly trivial things like having tea with one's neighbour, watching a sports game with others to going bowling (Putnam, 2000).

Many definitions of social capital exist (Coleman, 1998; Putnam, 1993; Fukuyama, 2000). Social capital reflects the resources and benefits that individuals and groups acquire through connections with others and involves both shared norms and values that promote cooperation as well as actual social relationships (Kawachi, Subramanian, & Kim, 2008). Attitudes and dispositions that promote interpersonal cooperation reflect the cognitive dimension of social capital while social connections reflect the relational dimension of social capital.

A vast literature indicates that the level of social capital a community possesses is consequential, i.e. otherwise similar communities experience different levels of economic development, crime rates and health depending on the social bonds that exist between its members (Kawachi, Kennedy, & Wilkinson, 1999; Kennedy, Kawachi, Prothrow-Stith, Lochner, & Gupta, 1998; Knack & Keefer, 1997; Longstaff, 2005; Sampson, Raudenbush, & Earls, 1997; Verba, Schlozman and Brady, 1995). In particular, research has identified a strong positive association between social capital and health. Robert Putnam suggested "*if you smoke and belong to no groups, it's a toss-up statistically whether you should stop smoking or start joining*" (Putman, 2000, p 331).

In the past decades, a large body of evidence has provided empirical support to Putnam's claim by showing a strong positive association between social capital and health (see Ehsan, Klaas, Bastianen, & Spini, 2019; Kawachi, Subramanian, & Kim, 2008; Rodgers, Valuev, Hswen, & Subramanian, 2019 for comprehensive reviews) and between social capital and health behaviours (Poortinga, 2006; Nieminen et al., 2013). Although most of the research is correlational in nature, some studies exploit longitudinal evidence and/or on natural experiments suggesting that associations may be causal (Rodgers et al., 2019). The majority of work on social capital and health status has examined the relationship between social capital and self-reported overall health, overall mortality/life expectancy and specific non-infectious health conditions such as cardiovascular diseases, obesity, diabetes and cancer. Few studies have been conducted in low-income countries where the health burden of communicable diseases remains high (Grootaert & Van Bastelaer, 2001) or have examined the contribution of social capital for infectious and communicable diseases and those that did, generally focused on sexually transmitted diseases (Frumence et al., 2014; Gregson et al., 2011; Mukoswa, Charalambous, & Nelson, 2017; Pronyk, et al., 2008; Semaan, et al., 2007).

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But what can be expected on the association between social capital and individuals' capacity to rapidly and profoundly changing their behaviours in order to halt the spread of the COVID-19 disease through social distancing? Are communities who bowl together in normal time better at bowling truly alone when COVID-19 required them to do so?

The epidemiological literature suggests that social interactions can foster the spread of infectious diseases (Béraud et al., 2015; Fumanelli, Ajelli, Manfredi, Vespignani, & Merler, 2012; Leung, Jit, Lau, & Wu, 2017; Mossong et al., 2008; Zhang et al., 2019). The fact that East Asia and Southern Europe were particularly hard hit by the COVID-19 pandemic has been related to the fact that countries in these regions have particularly high levels of social mixing across age groups within extended family units. Strong family ties, which are normally a protective factor for the elderly (Shor, Roelfs, & Yogev, 2013), might become risk factors during epidemics, particularly, when these are caused by pathogens like the SARS-CoV-2 virus, which has a marked age-related fatality profile (Chen et al., 2020; Jordan, Adab, & Cheng, 2020; Li et al., 2020; Oke & Heneghan, 2020; Zhou et al., 2020).

While patterns of family interactions are important, we argue that a closer examination of the social bonds that exist within a community is crucial. Social relations determine key factors that are important in shaping the course of the COVID-19 pandemic beyond disease susceptibility. In particular, social capital may be implicated in how and how fast governments respond to the spread of the disease, how communities react to government actions, and ultimately on the impact the disease will have on the physical and mental health of affected populations.

In this paper we examine data from US counties to identify how different communities responded to the threat posed by COVID-19 by changing one type of behaviour: reducing mobility.

Because COVID-19 is caused by a viral infection that can be passed on during an asymptomatic or peri-symptomatic phase (Bai et al., 2020), communities with high levels of interpersonal relations might be, other things being equal, more likely to experience sustained clusters of local infections and to do so earlier than other communities. However, beyond this initial phase, the evolution of the COVID-19 pandemic is determined by the extent to which communities are able to adopt behaviours that reduce transmission promptly and in a sustained way (Imperial College COVID-19 Response Team, 2020). Many national and local governments either suggested or mandated social distancing and shelter-in-place policies (Hartl et al., 2020). However, the effectiveness of such interventions depends on local communities following the advice of public health authorities or specific legislation. In the United States, government advice, regulations and information about shelter-in-place and social distancing occurred relatively late and were not uniformly implemented across the country[1]. The

[1] https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker and https://github.com/COVID19StatePolicy/SocialDistancing/blob/master/data/USstatesCov19distancingpolicy.csv

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government first announced school closures (with variation across states) on the 3rd of March 2020 when the cumulative number of diagnosed cases was in the United States was 81, public events were cancelled from March 12 2020, when the cumulative number of diagnosed cases was 1726 and only around March 17 2020 when the cumulative number of cases was 6154, public information campaigns were organised and people were advised to work from home if possible. A detailed timeline can be found in Annex Table A1.

Reducing interpersonal contacts by asking people to stay at home and to reduce their movements (Ainslie et al., 2020; Imai et al., 2020) and prohibiting large gatherings (Memish et al., 2019) are social distancing initiatives that have been widely implemented (Hale, et al., 2020). Such initiatives reduce mobility. We expect that communities with high levels of social capital will reduce mobility faster and more dramatically than communities with low levels of social capital, especially when reducing mobility are not yet legally mandated or enforced. Stronger actions in the early stages of the disease may be especially important, to halt the spread of the virus before cases start to rise exponentially (Dave, Friedson, Matsuzawa, & Sabia, 2020).

In the absence of vaccines or effective pharmacological treatments, communities will have to coexist with the health threat posed by COVID-19 for a prolonged period lasting hopefully months, and possibly years. We expect that communities with high levels of social capital will be better prepared to adapt to such 'new normal' by developing behaviours that keep transmission rates low and manageable for the local health infrastructure even in the absence of legal requirements prohibiting activities that entail health risks. We also expect that in communities with high levels of social capital more face masks and more tests will be made available because vertical social capital creates better conditions to mobilize resources and that in high social capital communities, local populations may be more willing and prepared to make use of protective devices and to adopt behaviours that reduce transmission. Data from Taiwan indicate that social capital was associated with the intention to receive vaccination against the flu, to wash hands more frequently, and with the intention to wear a face mask (Chuang, Huang, Tseng, Yen, & Yang, 2015). Similarly, in Sweden and the United States, social capital was associated with the intention to receive the vaccination against the H1N1 pandemic in 2009 (Rönnerstrand, 2013; 2014; 2016) as well as vaccination rates against H1N1 among pregnant women in the United States (Hernandez, Pullen, & Brauer, 2019). Furthermore, we expect that in communities with high levels of social capital local populations will be better at tracing contacts and monitoring the implementation and respect of social distancing. Finally, they may be better equipped at stepping up such initiatives as soon as transmissions started to increase.

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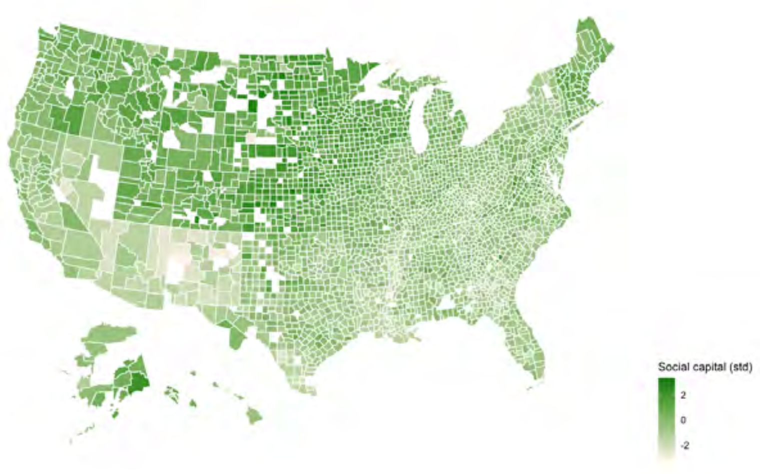
Data and methods

Social capital

County level social capital was acquired through "The geography of social capital" project. Data are available for 2,992 counties and cover 99.7 percent of the American population ($\mu = 0; \sigma = 1$). The social capital index that we use in our models is an aggregate index constructed using nine indicators: the number of registered non-religious non-profits per 1,000 people; the number of religious congregations per 1,000 people; an indicator reflecting the share who volunteered, who attended a public meeting, who report having worked with neighbours to fix/improve something, who served on a committee or as an officer, who attended a meeting where politics was discussed, and who took part in a demonstration in the past year; the average (over 2012 and 2016) of votes in the presidential election per citizen age 18+; mail-back response rates for the 2010 census; an indicator reflecting the share reporting at least some confidence in corporations, in the media, and in public schools; the share of births in past year to women who were unmarried; the share of women ages 35-44 who are currently married (and not separated) and the share of own children living in a single-parent family. A summary of data sources used to construct the social capital indicator are available in Annex Table A3. Details on the index construction and validation can be found at `https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america#toc-007-backlink`.

Figure 1: Social capital in US counties



Source: The geography of social capital in America.

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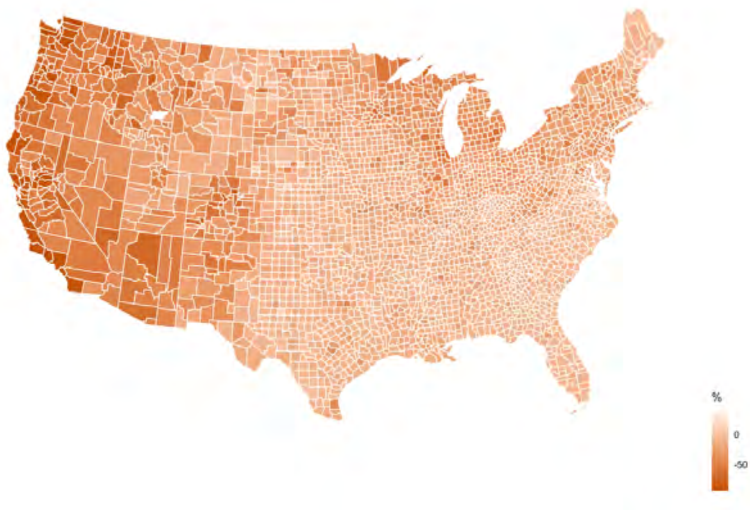
Mobility patterns

We identify mobility patterns at the county level using Cuebiq's Mobility Index (CMI)[2]. The CMI is a publicly accessible resource made available by Cuebiq and provides the level of movement for each week and in each county in the United States. The index is based on de-identified, geo-located information on smartphone users. The CMI for each county is the median of the aggregated movements of all users within a county. A detailed description of the Cuebiq dataset can be found at `https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights`. Data from Cuebiq has been used to map movements in Italian provinces prior to and following the implementation of restrictions to movement[3]. Our database contains movement from the first week in January 2020 until the week of 23 March. The CMI index reflects the percent change in mobility from one week compared to the previous week.

Figure 2: Mobility changes, March 23 week on week change



Source: Cuebiq mobility data.

We complement analyses based on Cuebiq data using data from the Community Mobility Reports developed by Google which cover mobility changes over the period 15 February 2020 to 11 April 2020[4]. Google data indicate the percent change in visits to the following categories: grocery and pharmacy (which includes places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies); parks (which

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[2]`https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights`

[3]`https://covid19mm.github.io/in-progress/2020/03/13/first-report-assessment.html`

[4]Google LLC "*Google COVID-19 Community Mobility Reports*", `https://www.google.com/covid19/mobility/`, accessed: 01-05-2020.

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includes local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens); transit stations (which includes public transport hubs such as subway, bus, and train stations); retail and recreation (which includes restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres); residential (places of residence) and work places. We conduct analyses using workplace mobility, mobility to groceries and pharmacies and mobility to retail and recreation. These are the three categories with sufficient data for a large number of counties and the ones that can best illustrate behavioural changes: workplace and groceries indicate necessities that, however, can be reorganized so that fewer mobility occurs in the case of groceries and pharmacy, retail and recreation, when activities are open, indicates especially high risk behaviour (mobility towards closed confined spaces). We present results only for recreational activities, but other tables can be requested from the authors.

The baseline for the calculation of the change in visits is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. Data are based on information from users who have opted-in to Location History for their Google Account, so the data represents a sample of Google map users. As with all samples, this may or may not represent the exact behaviour of the overall population.

Control variables

We introduce controls for the following county level characteristics: number of confirmed COVID-19 cases; economic orientation of the county, the economic, political and educational profile of residents; and population density.

The number of cumulative confirmed cases on March 8, 15 and 22 2020 from COVID-19 by county come from the USA Facts website[5] and data refer to the period 22 January 2020 – 23 March 2020. The USA Facts website provides aggregated data from the Center for Disease Control and Prevention (CDC), state- and local-level public health agencies. County-level data was confirmed by referencing state and local agencies directly.

We control for the economic orientation of the county's economy using data from the Economic Research Service of the USDA using the 2015 classification into one of the following six mutually exclusive categories of economic dependence: category 0 refers to non-specialized counties; category 1 comprises farming; category 2 comprises mining; category 3 comprises manufacturing; category 4 comprises federal/state government, and category 5 comprises recreation[6][7]. We introduce controls for the percentage of the population living in poverty using data from the U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program. Data refer to year 2018. We control for educational attainment using an indicator of the percentage of people in the county

[5] https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/

[6] https://www.ers.usda.gov/data-products/county-typology-codes/

[7] For definitions of the county typology codes, visit: https://www.ers.usda.gov/data-products/county-typology-codes/documentation/

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who have a bachelor or higher diploma. Data for education are based on a 5-yr average county-level estimates (2014-18) from the American Community Survey[8].

Moreover, we control for the population density in the county, computed following the US Census methodology using population estimates Data for 2018 from the June 2019 release of the Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin by the U.S. Census Bureau, Population Division[9] were used to calculate population density expressed in population per square mile[10]. Finally, we control for the percentage of votes cast that were in favour of Trump in the 2016 presidential elections. Data are scraped from results published by Townhall.com and are made publicly available on the Github platform[11].

Methods

First, we examine the relationship between social capital and changes in mobility in the week before announcements were made (i.e. the week starting on March 9). We report a series of models in which we introduce controls for the number of cumulative COVID-19 cases in the county up to March 8, as well as controls for county level socio-economic and demographic composition (educational attainment and poverty rates as well as the economic sector dependency of the county and its population density). We also include controls for the share of votes in the presidential elections of 2016 that went to Trump. Government actions and announcements can importantly guide behaviour and the fact the US administration dismissed the public health threat posed by coronavirus despite the surge in cases across the world until that week may have guided the behaviour of individuals in counties where there was a strong support for the current administration.

We then examine the relationship between social capital and the change in mobility in the 2 weeks following the announcements of restrictions by the US government (week starting on March 16 and week starting on March 23). We report a series of models in which we introduce controls for the number of cumulative COVID-19 cases in the county up to March 15 and March 22, as well as controls for country level socio-economic and demographic composition (educational attainment and poverty rates as well as the economic sector dependency of the county, and its population density).

We also include state fixed effects in addition to the county level controls.

[8] https://data.census.gov/cedsci/all?q=Educational\%20Attainment\%20in\%20the\%20United\%20States\&hidePreview=false\&tid=ACSST1Y2018.S1501

[9] https://www2.census.gov/programs-surveys/popest/technical-documentation/file-layouts/2010-2018/cc-est2018-alldata.pdf

[10] together with land area from the U.S. Census Bureau, Census of Population and Housing https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html#LND

[11] https://github.com/tonmcg/US_County_Level_Election_Results_08-16/blob/master/2016_US_County_Level_Presidential_Results.csv

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Results

Relationship between social capital and mobility

Tables 1 to 3 illustrate results on the association between social capital and mobility for three key weeks that mark the initial unfolding of the COVID-19 pandemic in the United States: the week starting on March 9, the week starting on March 16 and the week starting on March 23. For each week, results presented in models (1) and (3) were estimated using Cuebiq mobility data and reveal overall changes in mobility while results presented in models (2) and (4) were estimated using Google mobility data and reveal changes in mobility to retail and recreational activities.

Table 1 illustrates results on the association between social capital and mobility for the week starting on March 9 and therefore reveal associations in the week preceding announcements made by the US government on the importance of social distancing and the adoption of protective measures to limit the spread of COVID-19 (which occurred on March 17). Results suggest that, other things being equal, in the week starting on March 9 a small decline in mobility compared to the previous week was observed in the United States: on average mobility decreased by around 1.3% in the specification based on Cuebiq data and without state fixed effects. On the contrary, results show that mobility related to recreational activities increased relative to the baseline.

However, for both behavioural measures, a positive difference of one standard deviation in social capital was associated with an additional decline in mobility of around 0.4-1% points. In order words, in countries with higher levels of social capital mobility decreased more overall and decreased also when evaluating mobility to retail and recreation activities. In the specification including state level fixed effect, the coefficient on social capital is no longer significant but remains in the expected sign. A difference in social capital of one standard deviation corresponded in the behavioural change that can be observed when comparing counties with an additional 7-8 diagnosed cases of COVID-19. While this number seems small in hindsight and considering the rapid rise in case counts in the months that followed, by March 9 only 29 counties had at least 5 cases, 14 had at least 10 cases and 9 had at least 15 cases. Table 1 also suggests that in counties with a higher share of votes cast for Trump in the 2016 presidential election mobility was not reduced (and even increased) as much as in other counties.

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Table 1: Changes in mobility in the week starting on March 9 2020, Cuebiq and Google data

	Dependent variable: Mobility in the week of March 9			
	Overall mobility (week over week) change Controls	Recreational (change over baseline) Controls	Overall mobility (week over week) change Controls + FE	Recreational (change over baseline) Controls + FE
	(1)	(2)	(3)	(4)
Constant	−1.268***	7.170***	−0.167	10.856
	(0.114)	(0.243)	(0.495)	(7.278)
Social Capital	−0.378***	−1.015***	−0.221	−0.165
	(0.104)	(0.255)	(0.172)	(0.461)
N. of COVID confirmed	−0.057**	−0.132**	−0.035	−0.089
cases on March 8	(0.029)	(0.057)	(0.029)	(0.055)
Share of Republican votes	1.346**	8.501***	1.131	3.916**
in 2016 presidential elections	(0.628)	(1.440)	(0.767)	(1.808)
Population Density in	−0.087**	−0.249***	−0.073*	−0.257***
1000 people per sq. mile	(0.041)	(0.082)	(0.041)	(0.081)
% with a bachelor degree	0.031***	−0.198***	0.026**	−0.260***
	(0.012)	(0.026)	(0.013)	(0.029)
% in poverty	0.051***	0.048	0.045**	−0.001
	(0.018)	(0.044)	(0.020)	(0.047)
Economic dependency FE	✓	✓	✓	✓
State FE	*X*	*X*	✓	✓
Observations	2,960	2,215	2,960	2,215
R^2	0.024	0.182	0.095	0.258
Adjusted R^2	0.020	0.178	0.076	0.237
Residual Std. Error	3.888 (df=2948)	7.524 (df=2203)	3.775 (df=2900)	7.248 (df=2154)
F Statistic	6.497***	44.618***	5.141***	12.480***
	(df=11; 2948)	(df=11; 2203)	(df=59; 2900)	(df=60; 2154)

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. All specifications are un-weighted. Models (1) and (3) are based on Cuebiq data. Models (2) and (4) are based on Google data. Number of observations varies due to missing data at the county level. Dependent variable: mobility change in the week starting on March 9 (compared to the week starting on March 2 (week over week change) (1) and (3) and mobility change in the week starting on March 9 (relative to baseline), for recreational activities (2) and (4). Models control for the number of cases on March 8, the percentage of votes cast that were in favour of Trump in the 2016 presidential elections, the economic dependence of the county (reference category undifferentiated economic activity), population density (per 1000 people and mean centered), economic and educational profile of residents. Models (3) and (4) include state level fixed effects. All variables are mean centered and social capital is standardised (mean 0 and SD of 1).

Results for the week starting on March 16 cover the week in which the majority of COVID-19 topic-related announcements in the United States were made. Therefore, models presented in Table 2 capture how swiftly and readily health preserving behaviours were implemented by local communities following these national announcements when many economic activities were still open. Table 2 indicates that, on average, a decrease in mobility occurred following governmental advice on the usefulness of working from home when possible, the cancellation of public events and other restrictions. In the week starting on March 16 on average mobility was reduced by 16% compared to the previous week. The decline in mobility was progressive and even more pronounced the following week: Table 3 indicates that in the week starting on March 23 mobility was reduced, on average and additionally, by 21% compared to the week starting on March 16 (Table 3, model (1)). These changes in mobility are also observed in models including for state fixed effects, although coefficients are smaller (13%).

Tables 2 and 3 also suggest that mobility reductions were especially pronounced in counties with a higher level of social capital: a difference of one standard deviation in social capital was associated with an additional reduction of 0.6 to 1.3% points in mobility in the week starting on March 16 compared to the previous week (models without and with state fixed effects) and an additional reduction of 1.7 to 2.3% points in mobility in the week starting on March 23 (models without and with state fixed effects). Results are robust to the introduction of state fixed effects and of controls which may shape behaviour and be associated with social capital. These results reflect relationships when controlling for the number of cases diagnosed in the county on March 15 and March 22. The change in mobility associated with a difference of one SD in social capital in the week starting on March 16 is similar to the difference that can be observed with an additional 18 cases diagnosed with COVID-19 in the county up to March 15 and of 335 additional cases in the county up to March 22 in the week starting on March 23 (specification with controls and state fixed effects).

Reductions in mobility in the weeks starting on March 16 and on March 23 were pronounced with respect to mobility to retail and recreation compared to the baseline period (median mobility observed between January 3 and February 6): on average in the week starting on March 16 mobility directed at retail and recreation declined by around 14-20% (Table 2) depending on the specification and by 29-34% in the week starting on March 23rd (Table 3). Such reduction was especially marked in counties with high levels of social capital. A difference of one SD in social capital was associated with an additional decline of 2.5% points in the week starting on March 16. In the week starting on March 23 results remain statistically significant and quantitatively meaningful, yet coefficients are a bit less pronounced (-1.6%) when controls are introduced, suggesting that behaviour becomes less a matter of choice when restrictions are imposed by the government. Moreover, when adding state fixed effects (last model in Tables 2 and 3), results still suggest that counties with higher levels of social capital reduced mobility more relative to other counties. We obtain similar results when examining mobility to workplaces and grocery and pharmacy activities (available on request).

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Table 2: Changes in mobility in the week starting on March 16 2020, Cuebiq and Google data

	Dependent variable: Mobility in the week of March 16			
	Overall mobility (week over week) change Controls	Recreational (change over baseline) Controls	Overall mobility (week over week) change Controls + FE	Recreational (change over baseline) Controls + FE
	(1)	(2)	(3)	(4)
Constant	−15.696***	−20.178***	−13.434***	−13.882*
	(0.143)	(0.277)	(0.507)	(7.301)
Social Capital	−0.662***	−2.456***	−1.279***	−1.178***
	(0.131)	(0.291)	(0.176)	(0.456)
N. of COVID confirmed	−0.081***	−0.013	−0.071***	−0.013
cases on March 15	(0.008)	(0.015)	(0.007)	(0.013)
Share of Republican votes	9.970***	21.420***	7.411***	10.209***
in 2016 presidential elections	(0.789)	(1.647)	(0.786)	(1.798)
Population density	−0.507***	−0.400***	−0.434***	−0.313***
1000 people per sq. mile	(0.053)	(0.095)	(0.043)	(0.082)
% with a bachelor degree	−0.210***	−0.220***	−0.243***	−0.398***
	(0.015)	(0.030)	(0.013)	(0.029)
% in poverty	0.133***	0.348***	−0.012	0.110**
	(0.023)	(0.050)	(0.020)	(0.047)
Economic dependency FE	✓	✓	✓	✓
State FE	*X*	*X*	✓	✓
Observations	2,960	2,243	2,960	2,243
R^2	0.435	0.396	0.651	0.584
Adjusted R^2	0.433	0.393	0.644	0.572
Residual Std. Error	4.880 (df=2948)	8.660 (df=2231)	3.865 (df=2900)	7.271 (df=2182)
F Statistic	206.412***	133.113***	91.866***	50.997***
	(df=11; 2948)	(df=11; 2231)	(df=59; 2900)	(df=60; 2182)

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. All specifications are un-weighted. Number of observations varies due to missing data at the county level. Models (1) and (3) are based on Cuebiq data. Models (2) and (4) are based on Google data. Dependent variable: mobility change in the week starting on March 16 (compared to the week starting on March 9 (week over week change) (1) and (3) and mobility change in the week starting on March 16 (relative to baseline), for recreational activities (2) and (4). Models control for the number of cases on March 15, the percentage of votes cast that were in favour of Trump in the 2016 presidential elections, the economic dependence of the county (reference category undifferentiated economic activity), population density (per 1000 people and mean centered), economic and educational profile of residents. Models (3) and (4) include state level fixed effects. All variables are mean centered and social capital is standardised (mean 0 and SD of 1).

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Table 3: Changes in mobility in the week starting on March 23 2020, Cuebiq and Google data

	Dependent variable: Mobility in the week of March 23			
	Overall mobility (week over week) change Controls	Recreational (change over baseline) Controls	Overall mobility (week over week) change Controls + FE	Recreational (change over baseline) Controls + FE
	(1)	(2)	(3)	(4)
Constant	−20.996***	−33.602***	−13.097***	−29.061***
	(0.431)	(0.290)	(1.058)	(7.451)
Social Capital	−2.298***	−1.576***	−1.674***	−0.935**
	(0.394)	(0.305)	(0.368)	(0.462)
N. of COVID confirmed	−0.015***	−0.004*	−0.005***	−0.001
cases on March 22	(0.003)	(0.002)	(0.002)	(0.002)
Share of Republican votes	38.690***	28.411***	14.510***	15.351***
in 2016 presidential elections	(2.366)	(1.712)	(1.640)	(1.823)
Population density	0.227	−0.333**	−0.214*	−0.302***
1000 people per sq. mile	(0.208)	(0.133)	(0.117)	(0.110)
% with a bachelor degree	−0.201***	−0.181***	−0.499***	−0.368***
	(0.044)	(0.031)	(0.027)	(0.029)
% in poverty	0.298***	0.514***	−0.265***	0.180***
	(0.068)	(0.052)	(0.042)	(0.048)
Economic dependency FE	✓	✓	✓	✓
State FE	*X*	*X*	✓	✓
Observations	2,960	2,249	2,960	2,249
R^2	0.272	0.434	0.783	0.628
Adjusted R^2	0.270	0.431	0.779	0.618
Residual Std. Error	14.675 (df=2948)	9.053 (df=2237)	8.071 (df=2900)	7.420 (df=2188)
F Statistic	100.368***	155.962***	177.880***	61.594***
F Statistic	(df=11; 2948)	(df=11; 2237)	(df=59; 2900)	(df=60; 2188)

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. All specifications are un-weighted. Models (1) and (3) are based on Cuebiq data. Models (2) and (4) are based on Google data. Number of observations varies due to missing data at the county level. Dependent variable: mobility change in the week starting on March 23 (compared to the week starting on March 16 (week over week change) (1) and (3) and mobility change in the week starting on March 23 (relative to baseline), for recreational activities (2) and (4). Models control for the number of cases on March 22, the percentage of votes cast that were in favour of Trump in the 2016 presidential elections, the economic dependence of the county (reference category undifferentiated economic activity), population density (per 1000 people and mean centered), economic and educational profile of residents. Models (3) and (4) include state level fixed effects. All variables are mean centered and social capital is standardised (mean 0 and SD of 1).

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Limitations

The quality and properties of the data from Cuebiq and that have been made available by Google remain hard to assess given that the raw underlying data are not made public. In particular, we cannot assess the extent to which mobility patterns detected by Cuebiq and Google are representative of the overall patterns undertaken by populations in different counties. No information on the number of users or on the number of people who turned on their location history setting in Google is provided and no information can be identified on the extent to which the demographics of individuals used to construct Cuebiq mobility index or the Google mobility trends match the underlying demographics of underlying populations in different counties.

Cuebiq is a location intelligence company that analyses anonymous, aggregated location data to provide brands with consumer insights and, through its Data for Good initiative provides information on mobility patterns to researchers with the intention of improving community well-being. Cuebiq is GDPR-compliant and CCPA-compliant. Cuebiq collects location data in several ways, one of which is through a software development kit – an SDK. Cuebiq's SDK is embedded in mobile apps and collects first-party data from anonymous users who opted-in to the location data collection within partner apps. Users are allowed to opt out through several paths: app settings, device settings, TrustArc, and the Cuebiq App. Cuebiq partners with more than 220 mobile apps that include the proprietary Cuebiq SDK. The resulting data is aggregated and analysed for high-level, macro visitation trends, meaning the data collected does not contain any personally identifiable information. Brands and advertisers can access insights derived from Cuebiq's data using its artificial intelligence-driven business intelligence platform, Clara. Out of all apps that use data intelligence SDKs, around 1% have Cuebiq integrated, covering 6% of app downloads in that SDK segment. Only Radius Networks covers a higher percentage of app downloads in the SDK segment.

We only evaluate one type of behaviour, reduced mobility, rather than other forms of protective behaviours, such as wearing face masks, washing hands well and frequently, self-quarantining upon the development of symptoms or if one has entered into contact with a person with symptoms. Further research could attempt to identify alternative sources of mobility data, and/or alternative behavioural responses to confirm the validity of our initial study. We evaluate the relationship between social capital and mobility in the United States. Since countries around the world differ greatly in terms of social capital, political structure, health care system as well as existing mobility and behavioural patterns it would be important to evaluate if the results presented in our work were applicable to other contexts.

Finally, our results are descriptive and illustrate associations between the stocks of social capital in different US communities prior to the unfolding of the COVID-19 pandemic and how much different communities changed behaviour in the initial phases of the pandemic. Further research could attempt to identify the causal nature of such relations exploiting, if these existed, surges in local level cooperation as a function of externally driven

initiatives (rather than community led efforts which would, in themselves, be an expression of existing levels of social capital) and/or evaluate how behaviour was maintained in the long run.

Discussion and Implications

Our analyses suggest that in the very initial phases of the spread of infectious diseases such as COVID-19, communities that have a tight web of social relationships and strong norms of reciprocity may be better prepared and willing to change their behaviours to protect community members. Communities that ***'bowl together'*** in normal times, appear to be able to ***'bowl alone'*** when social distancing is needed to protect the community in general and its most vulnerable in particular. In the early phases of a highly infectious and deadly pandemic, governments may be reluctant and therefore may lose precious time to take action and enforce social distancing by curtailing personal freedoms through major restrictions on freedom of movement and freedom of association (on March 23 2020, only 9 state wide stay-at-home orders[12]). In such early phases, when government restrictions have not yet been imposed or in the immediate aftermath of such impositions, community level social capital appears to be especially important in promoting the adoption of difficult behavioural changes among the community.

Our work indicates that when legislation mandates that people adopt behaviours that reduce transmissions differences across communities will be reduced. However, in the absence of such legislation, the sense of community plays an important role. These findings may be especially important not only to evaluate what happened in the early phase of the COVID-19 pandemic in the US, but also to consider where efforts should be put as legal barriers to the SARS-CoV-2 virus are relaxed. Governments around the world are currently developing plans to relax some of the restrictions to movement that were implemented in February and March 2020 when the number of COVID-19 cases rapidly increased. Several analysts focus on medical factors, such as ICU capacity and personal protective equipment for medical professionals, such as face masks, availability of testing and contact tracing. Our work suggests that the stock of social capital in a community is an important factor that should also be considered. Reinforcing the social capital available in a community when this is present and supporting communities when social capital is lacking should be just as much of a priority as sourcing stocks of face masks or testing kits.

Restrictions to the freedom of movement and association, whether legally mandated or voluntarily enforced, are likely to have a profound impact on individuals' lives, health and well-being because they prevent people from exercising, they result in economic hardship, and isolation can lead to loneliness and poor mental health. Although our data do not allow to evaluate the extent to which community level social capital can buffer some of these negative unintended consequences, we believe that further research should attempt to evaluate these

[12]https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

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effects and focus on the later stages of the COVID-19 pandemic. Anecdotal evidence indicates that civil society organizations and local groups have already become active to devise innovative ways to ensure that lack of physical contact and physical separation does not lead to isolation. While certain individuals and communities can rely on established networks of social connections and on the availability of technological tools that enable them to leverage such connections, others may lack either social capital or technical aids or both. Supporting local aid groups and volunteering initiatives aimed at sustaining such individuals and communities should therefore become a priority as it is likely to have profound beneficial effects on both recipients and helpers (Borgonovi, 2008; Doré, Morris, Burr, Picard, & Ochsner, 2017)

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Annex A

Table A1: List of variables and sources

Data	Unit	Resource/website
Outcome variables:		
- Cuebiq's Mobility Index (CMI)	Week - over week - change	https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights
- Community Mobility by Google	% change from baseline	https://www.google.com/covid19/mobility/
Control variables:		
- Social capital	Std (mean 0 and SD of 1)	https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america\#toc-007-backlink
- Total population	Counts	https://www2.census.gov/programs-surveys/popest/technical-documentation/file-layouts/2010-2018/cc-est2018-alldata.pdf
- Number of cases	Counts	https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/
- Economic dependence of counties	Factor	https://www.ers.usda.gov/data-products/county-typology-codes/
- Poverty	Percentage	U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program
- Education	Percentage	https://data.census.gov/cedsci/all?q=Educational\%20Attainment\%20in\%20the\%20United\%20States\&hidePreview=false\&tid=ACSST1Y2018.S1501
- Density	Population per square mile	U.S. Census Bureau, Census of Population and Housing (https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html\#LND)
- Political	Percentage	https://github.com/tonmcg/US_County_Level_Election_Results_08-16/blob/master/2016_US_County_Level_Presidential_Results.csv

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Table A2: Descriptive Statistics

Variables	Mean	SD	Notes
Outcome variables:			
- Cuebiq's Mobility Index (CMI)	3.5	0.6	WoW change in analysis
- Community Mobility by Google			Indicative number
Control variables:			
- Social capital	0	1	Standardised
- Cases (COVID-19)	0	2	On March 8 2020
	1	11	On March 15 2020
	10	105	On March 22 2020
- Poverty	0.13 (US)	0.06	Mean centered in analysis
	0.15 (across counties)		
- Education	Bachelor +: 0.21 (US)	0.06	Mean centered in analysis
	Bachelor +: 0.22 (across counties)	0.09	
- Density	275	1789	Mean centered in analysis
- Political	0.47	0.16	Mean centered in analysis

Notes: Wow: Week over week change is used in the analysis.

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Table A3: Descriptive Statistics

Share of births in past year to women who were unmarried	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table S1301
Share of women ages 35-44 who are currently married (and not separated)	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B12002
Share of own children living in a single-parent family	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B09002
Registered non-religious non-profits per 1,000	IRS, Business Master File, 12/2015; ACS population estimates, 7/2015 (2015 vintage)	via National Center for Charitable Statistics American FactFinder Table PEPANNRES
Religious congregations per 1,000	U.S. Religion Census: Religious Congregations and Membership Study, 2010	via Association of Religious Data Archives, census conducted 2009-11
Share of adults who report having volunteered for a group in the past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share who report having attended a public meeting re. community affairs in past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share who report having worked with neighbors to fix/improve something in past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share of adults who served on a committee or as an officer of a group	Volunteer Supplement to the November 2013 Current Population Survey	
Share who attended a meeting where political issues were discussed in past year	Civic Engagement Supplement to the November 2008 Current Population Survey	
Share who took part in march/rally/protest/demonstration in past year	Civic Engagement Supplement to the November 2008 Current Population Survey	
Average (over 2012 and 2016) of votes in the presidential election per citizen age 18+	Election Administration and Voting Survey; ACS, 2012-2016, 5-year estimates	U.S. Election Assistance Commission; EAVS voting combined with American FactFinder Table B05003 estimates of citizens 18+; votes unavailable for Alaska counties, which we assign the statewide voting rate
Mail-back response rates for 2010 census	Census Bureau	via University of Michigan Population Studies Center, Institute for Social Research
Confidence in Institutions Sub-Index	Volunteer Supplement to the November 2013 Current Population Survey	Combination of share reporting at least some confidence in corporations, in the media, and in public schools

Source: Table 2. available online at `https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america#toc-005-backlink` accessed on May 3rd 2020.

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Change in mobility behavioural model:

Baseline (not presented):

$$\Delta M = c + \beta_1 SocialCapital_c + \beta_2 Cases_c + \epsilon c$$

Specification with controls:

$$\Delta M = c + \beta_1 SocialCapital_c + \beta_2 Cases_c + \beta Z_c \epsilon c$$

Specification with controls and state fixed effects:

$$\Delta M = c + \beta_1 SocialCapital_c + \beta_2 Cases_c + \beta Z_c + u_s \epsilon c$$

Where,

- $\Delta M$is the dependent variable, and reflects the change in mobility measured either by Cuebiq data or Google trends mobility for the 3 weeks of interest (weeks starting on March 9, 16 and 23 2020).
- $SocialCapital_c$ is the variable of interest at the county level (same for all specifications).
- $Cases_c$ is the number of cases for each county in the week prior (8th, 15th and 22nd of March 2020).
- u_s is the introduction of state level fixed effects.
- Z_c is a vector of controls at the county level, which we suspect to have an effect on the change of behaviour of communities (dependent variable). Those are the percentage of votes cast that were in favour of Trump in the 2016 presidential elections, the number of cases on March 8 or 15 or 22 2020 (depends on the model), economic dependence of the county (reference category undifferentiated economic activity), population density (per 1000 people), economic and educational profile of residents. All variables are mean centered and social capital is standardised (mean 0 and SD of 1).
- ϵ is random error, and subscript c refers to counties.

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Covid Economics Issue 17, 13 May 2020

Can the Covid bailouts save the economy?

Vadim Elenev,[1] Tim Landvoigt[2] and Stijn Van Nieuwerburgh[3]

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The Covid-19 crisis has led to a sharp deterioration in firm and bank balance sheets. The government has responded with a massive intervention in corporate credit markets. We study equilibrium dynamics of macroeconomic quantities and prices, and how they are affected by government intervention in the corporate debt markets. We find that the interventions should be highly effective at preventing a much deeper crisis by reducing corporate bankruptcies by about half, and short-circuiting the doom loop between corporate and financial sector fragility. The fiscal costs are high and will lead to rising interest rates on government debt. We propose a more effective intervention with lower fiscal cost. Finally, we study longer-run consequences for firm leverage and intermediary health when pandemics become the new normal.

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1 Assistant Professor of Finance, Johns Hopkins Carey Business School.
2 Assistant Professor of Finance, Wharton School, University of Pennsylvania and CEPR.
3 Earle W. Kazis and Benjamin Schore Professor of Real Estate and Professor of Finance, Columbia University Graduate School of Business and CEPR.

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1 Introduction

The global covid-19 pandemic has resulted in unprecedented decline in aggregate consumption, investment, and output in nearly every developed economy. Mandatory closures of non-essential businesses have cut off revenue streams and have brought many firms to the brink of insolvency. Firms pulled credit lines, raided cash reserves, and laid off or furloughed workers. In the wake of this economic collapse, the U.S. Congress authorized four rounds of bailouts worth \$3.8 trillion. The Federal Reserve has also launched a slew of programs aimed at keeping credit to businesses flowing. In this paper, we ask how effective the government's corporate loan programs are likely to be, and whether they will be able to prevent an unraveling of the economy in which corporate defaults bring down the financial intermediary sector. To this end, we compare an economy with and without the corporate sector bailout programs. Second, we ask what fiscal ramifications these programs have in the short and in the long run. Third, we propose an alternative corporate loan policy design that increases welfare and has lower fiscal cost. Finally, we study the long-run impact on non-financial and financial sector health from the realization that pandemics may be recurring events in the future.

We set up and solve a general equilibrium model, closely following Elenev, Landvoigt, and Van Nieuwerburgh (2020), henceforth ELVN. The model features a goods-producing corporate sector financed with debt and equity and an intermediary sector financed by deposits and equity. The household sector consists of shareholders and savers.

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Savers invest in safe assets, both bank deposits and government debt, and in risky corporate bonds. Banks intermediate between savers and non-financial firms. The model can produce severe financial crises whereby corporate defaults generate a wave of bank insolvencies, which in turn feed back on the real economy. The calibrated model matches many features of macro-economic quantity and price data.

We conceptualize the covid shock as a large decline in firm revenues in the non-financial corporate sector. The revenue shortfall makes it difficult for firms to pay their employees, make other fixed payments (e.g., rent) while also servicing their debt. We engineer this shock through an unexpected and large decline in the mean and an increase in the dispersion of firm productivity. In addition, the covid shock is accompanied by a decline in labor supply, capturing illness, child care duties, or worries about getting infected on the job. The shock is persistent in that the high-uncertainty regime is likely to last for at least another year.

Absent policy, the covid shock triggers a wave of corporate defaults. The corporate defaults in turn inflict losses on their lenders, principally the banks but also the households who directly hold corporate debt. The banking distress manifests itself in higher credit spreads. The higher cost of debt for firms and the uncertain economic outlook generate a large decline in corporate investment. A substantial share of banks fail and are bailed out by the government. The cost of these bank rescue operations adds to the already higher government spending and lower tax revenues that accompany a severe recession. The massive amount of new government debt that must be issued to fi-

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nance the primary deficit increases safe interest rates, all else equal. Higher safe interest rates in turn make servicing the debt more expensive for the government going forward. Higher safe rates also increase the cost of deposit funding for banks, hampering banks' recapitalization efforts. The mutually reinforcing spirals of firm distress, bank distress, and government bailouts create a macro-economic disaster. The non-linearity of the model solution is crucial to generate this behavior.

We then evaluate three government policies aimed at short-circuiting this doom loop and limiting the economic damage. The first one is a policy that buys risky corporate debt by issuing safe government debt. It is calibrated to the size of the primary and secondary market corporate credit facilities and the term asset lending facility (PMCCF+SMCCF+TALF). We call this intervention the corporate credit facility or CCF for short. At the time of this writing, the CCF plans to buy \$850 billion in corporate debt, or 8.9% of the outstanding stock (3.9% of GDP). The second one is a program in which banks make loans to non-financial firms. The loan principal is forgiven when loans are used to pay employees. The government provides a full credit guarantee to the banks. This policy captures the institutional reality of the Paycheck Protection Program (PPP). The PPP program has a size of \$671 billion or 3.1% of GDP. The third program also provides bank-originated bridge loans to non-financial firms. However, these loans are not forgivable, and they carry a modest interest rate of 3%. Moreover, banks must retain a fraction of the risk (5%) so that the government guarantee is partial (95%). This program reflects the de-

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tails of the Main Street Lending Program (MSLP), which has a size of \$600 billion or 2.8% of GDP. The main policy We consider the combination of all three programs to be the counterpart to the real world intervention.

The main take-away is that the bridge loan programs (PPP and MSLP) are successful at preventing the bulk of firm bankruptcies. This prevents the pandemic from spilling over into a banking crisis. Stronger banks are able to continue making loans, suffering merely a severe recession rather than a meltdown. Credit spreads still rise but not as much as they would absent policy. Facing a modestly higher cost of debt, firms borrow and invest less. However, investment shrinks by much less than it otherwise would. Preventing bank defaults prevents government bailouts and the associated fiscal outlay. This cost reduction is offset by the direct costs of the programs. The PPP provides debt forgiveness and therefore has a much higher direct cost than the MSLP, which contains no forgiveness. Relative to the no-pandemic situation, government deficits still balloon. Since savers must absorb the extra debt that the government is issuing in bad times, the require a higher interest rate. Government debt increases substantially and takes 20 years to come back down to pre-pandemic levels. In sharp contrast, the CCF is much less effective. It lowers credit spreads thereby boosting investment compared to the do-nothing situation. However, the program has only minor effects on firm defaults. And the program still has fiscal implications since the government must issue Treasury debt to buy the corporate debt. This increases safe rates, which increases the cost of deposit funding for

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banks and contributes to their fragility. A program that combines all three of the PPP, MSLF, and CCF increases societal welfare by 6.6% in consumption equivalent units compared to a do-nothing scenario.

Since the loans are given to all firms without conditionality, the PPP wastes resources on firms that do not need the aid. We contrast the actual government programs with a hypothetical policy that conditions on need. Both which firms receive credit and how much credit they obtain depends on firm-level productivity. Obviously, the information requirements imposed on the government to implement this conditional bridge loan program (CBL) are more stringent. We find that a much smaller-sized program is needed to prevent a lot more bankruptcies. The CBL program increases welfare by 7% compared to a do-nothing scenario.

Finally, we turn to the longer-term implications. We solve a model where the pandemic not only creates a massive unanticipated shock, as described above, but also creates an "awakening" to the possibility that pandemics may be recurring events forever after. This is in the spirit of Kozlowski, Veldkamp, and Venkateswaran (2020), who emphasize the long-run impact on beliefs ("scarring"). We model a new pandemic state of the world which happens with small probability from now onwards. While this awakening has only minor implications during the pandemic shock, it leads to a transition to a different long-run economy with less corporate debt and a smaller but more robust financial sector.

Related Literature Our paper contributes to two strands of the literature. The first one is a new literature that has sprung up in re-

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sponse to the covid pandemic. The focus of this literature has been on understanding the interaction of the spread of the disease and the macro-economy.[1] This literature merges simple models of individual consumption and labor supply with epidemiological models to predict how behavior affects the spread of the disease and to study the effect of social distancing and re-opening policies. Early contributions are . This literature has not contemplated the role of firms and financial intermediaries and government intervention in this market. Faria-e-Castro (2020) provides a DSGE model to analyse different types of fiscal policies to help stabilize household income. It finds that UI benefits are the most effective stabilization tool for borrowing households, while saving households favour unconditional transfers. Liquidity assistance programs are effective if the policy objective is to stabilize employment in the affected sector.

A second branch of the literature studied government interventions in the wake of the Great Financial Crisis. In contrast with the current crisis, most of these interventions were aimed at stabilizing the financial sector. TARP provided equity injections, the GSEs were bailed out, FDIC guarantees on bank debt, and a myriad of Federal Reserve commitments worth \$6.7 trillion (TALF, TSL, CPFF, etc.) provided liquidity to the banking and mortgage sectors. Blinder and

[1] An incomplete list of references to this fast-growing literature is Atkeson (2020), Eichenbaum, Rebelo, and Trabandt (2020), von Thadden (2020), Krueger, Uhlig, and Xie (2020a,b), Kaplan, Moll, and Violante (2020), Hagedorn and Mitman (2020), Rampini (2020), Brotherhood, Kircher, Santos, and Tertilt (2020), Bethune and Korinek (2020), Guerrieri, Lorenzoni, Straub, and Werning (2020), Ludvigson, Ng, and Ma (2020), Alvarez, Argente, and Lippi (2020), Jones, Philippon, and Venkateswaran (2020), Glover, Heathcote, Krueger, and Rios-Rull (2020), Greenstone and Nigam (2020), Kozlowski, Veldkamp, and Venkateswaran (2020), Farboodi, Jarosch, and Shimer (2020), and Xiao (2020).

Zandi (2015) provide a retrospective. The only direct interventions in the non-financial sector were the auto sector bailouts. Of the $84 billion of TARP money committed, the cost of the auto bailouts was ultimately $17 billion. A large literature studies the micro- and macro-prudential policy response to the financial crisis. Elenev, Landvoigt, and Van Nieuwerburgh (2020) provides references and studies the effect of tighter bank capital requirements.

While some are sanguine about the government's ability to spend trillions more (Blanchard, 2019), for example on covid bailouts, Jiang, Lustig, Van Nieuwerburgh, and Xiaolan (2020) warn of higher yields on government debt. We investigate the fiscal implications of the covid bailouts. The model predicts that they will lead to higher interest rates in the short run and require higher tax rates to bring the debt back down.

The rest of the paper is organized as follows. Section 2 discusses the evolution of credit spreads and the institutional detail of the corporate lending programs introduced during the covid pandemic up until April 30. Section 3 provides a summary of the ELVN model. Section 3.2 discusses how we adapt the model and calibration to both model the covid shock and the policies aimed to fight it. Section 4 discusses the main results. Section 5 studies the new normal economy with recurrent pandemics. Section 6 concludes.

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2 Institutional Background

2.1 Credit Market Disruption

Credit Spreads A first sign of trouble in the corporate sector showed up in the prices of corporate bonds. Figure 1 shows the ICE BofA US AAA, BBB, and High Yield index option-adjusted spreads between January 1, 2020 and April 27, 2020. The time series measures the spread for corporate debt over a duration-adjusted safe yield (swap rate). Naturally, credit spread are lower for the safest firms (AAA), intermediate for the lowest-rated investment-grade firms (BBB), and highest for the firms rated below investment grade (High Yield). The AAA spread went from 0.56% on February 18, before the covid crisis began in the U.S., to a peak value of 2.35% on Friday March 20 and remained very high on Monday March 23 at 2.18%. The BBB spread increased from 1.31% on February 18 to 4.88% on March 23. The HY spread went from 3.61% on February 18 to 10.87% on March 23. For comparison, the only other two peaks of comparable magnitude in the HY index were October 2011 (European debt crisis, 8.98%) and February 2016 (Chinese equity market crash, 8.87%). On both occasions, the BBB spread remained below 3.25% and the AAA spread below 1%. To find a widespread spike like the one in the covid pandemic, we have to go back to the Great Financial Crisis. On December 15, 2008, the HY index peaked at 21.8%, the BBB index was at 8.02%, and the AAA spread was 3.85%.

The policy interventions of March 23 and April 9, 2020, discussed

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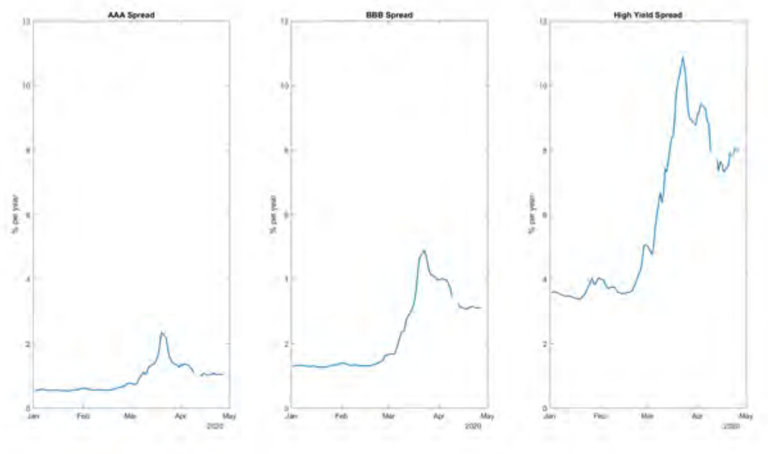
Figure 1: High Yield Bond Spread



The left panel plots the ICE BofA AAA U.S. corporate index option-adjusted spread. The middle panel plots the ICE BofA BBB U.S. corporate index option-adjusted spread. The right panel plots the ICE BofA High Yield U.S. corporate index option-adjusted spread. The data are daily for January 1, 2020 until April 27, 2020. Source: FRED.

in detail below, have partially closed credit spreads. The high yield spread tapered back off to 7.35% by April 14. The BBB spread was at 3.11%, and the AAA spread at 1.00%. Since then, spreads have been stable, with the HY spread drifting up slightly to 8.01% on April 27. In sum, the HY spread has stabilized at nearly twice the pre-pandemic level of two months earlier. BBB and AAA spreads have also doubled.

CLO Prices Over the past five years, many corporate loans have been sold to special purpose vehicles who issue collateralized loan obligations to bond market investors. CLO tranches have various credit ratings. The CLO market, which was already subject to credit deterioration issues in 2019 and early 2020, has been particularly hard

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Table 1: CLO Bond Prices

Rating	Transport	Hotel, Gaming, Leis.	Bev., Food, Tobacco	Retail, Cons. Serv.
Overall	**-16.77%**	**-21.98%**	**-14.64%**	**-17.94%**
BBB-	-9.30%	-10.53%		
BB+	-6.73%	-8.58%	-5.05%	-5.70%
BB	-8.06%	-11.36%	-4.70%	-5.48%
BB-	-11.91%	-12.83%	-8.37%	-8.70%
B+	-18.94%	-18.76%	-9.09%	-13.03%
B	-12.85%	-20.24%	-12.95%	-17.84%
B-	-17.85%	-25.39%	-15.94%	-16.88%
CCC+	-17.74%	-29.43%	-14.89%	-22.53%
CCC	-18.14%	-42.00%	-19.43%	-26.14%
CCC-	-6.98%	–	-23.87%	-22.95%
CC	–	–	-2.37%	-20.41%
C	-11.11%	–	–	–
D	-90.62%	-91.57%	-30.00%	-28.44%

Source: Trepp. Price changes between January 31, 2020 and April 6, 2020.

hit by the pandemic. Table 1 shows price changes in CLO tranches between January 31 and April 6, 2020. The average CLO bond lost around 15% in value, with much larger losses in lower-rated tranches and in industries that were affected more strongly by the pandemic.

Treasury Yields and Sovereign CDS Spreads Figure 2 shows U.S. Treasury yields of maturities 1, 5, and 10-years in the left panel and U.S. sovereign CDS spreads of maturities 1-, 5-, and 10-years in the right panel. Ten-year Treasury yields decline from 1.55% on February 18 to 0.54% on March 9. This corresponds to a 10.5% increase in bond prices in 14 business days. We interpret this sharp decline in interest rates as a combination of (i) lower growth expectations (Gormsen and Koijen, 2020), (ii) precautionary savings/flight-to-safety as the market woke up to the possibility of a severe crisis.

In the following seven trading days, there is a sharp reversal and 10-year interest rates doubles from 0.54% to 1.18% on March 18, a 6.1% drop in the bond price. We believe this sharp decline in interest rates is

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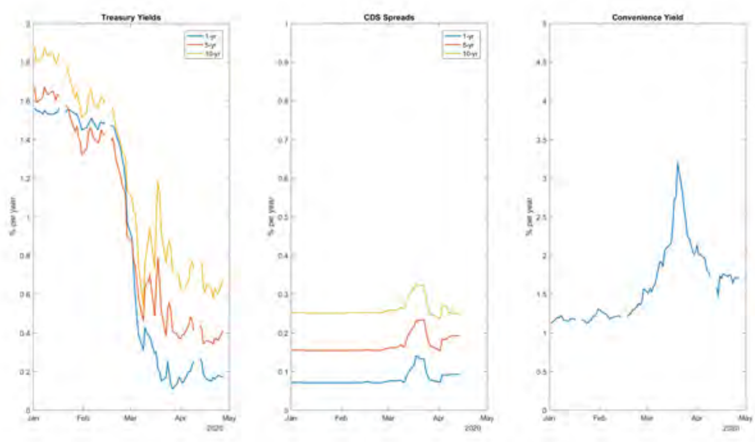
due to a combination of (i) expectations of large bailouts which need to be absorbed by savers, (ii) increased credit risk of the U.S. government, and (iii) distressed selling of safe assets to meet margin calls in other parts of investors' portfolios. Indeed, we see a 5-7bps jump in CDS spreads between March 9 and 18. Just prior to the peak in interest rates, in an emergency meeting on Sunday March 15, the Fed lowered the policy rate from 1.25% to 0.25% and announced a $700bn Treasury and Agency purchase program. This followed an earlier rate cut by 50 bps on March 3. On March 23, the Fed announced that the QE program would be unlimited in size. The intervention was successful in propping up government bond prices and 10-year yields fell back down to around 65 bps by April 27, a 5.2% increase in bond prices from March 18. U.S. sovereign CDS spreads also normalized to pre-crisis levels. Investors –so far– seem quite sanguine about the massive expansion in government debt, projected to be 21% of GDP in 2020, fueled by a 19% of GDP primary deficit. This debt expansion would push the U.S. federal debt held by the public above 100% in 2020 and above 107% of GDP in 2021, exceeding the previous 1947 record.

It is quite likely that the U.S. benefited from its privileged status as global safe haven asset during the covid crisis. A standard measure of the convenience yield advocated by Krishnamurthy and Vissing-Jorgensen (2012)), the spread between the AAA-rated corporate bond yield and the 10-year Treasury, increased substantially in March, peaking on March 20, before settling back down to a level 50 bps above its pre-crisis level. The AAA-corporate spread reflects of course all interventions by the Fed in both the Treasury and corporate bond markets,

and disentangling them is a difficult task. Suffice to say that the underlying safe rate, without convenience, is higher than the Treasury bond yield and has not fallen as much as the Treasury yields.

Figure 2: High Yield Bond Spread



The left panel plots the U.S. Treasury Bond constant-maturity yields on bonds of maturities 1, 5, and 10 years. The middle panel plots the U.S. sovereign CDS spread of maturities 1, 5, and 10 years. The right panel plots the Moody's AAA-rated corporate bond yield minus the 10-year constant maturity Treasury yield. The data are daily for January 1, 2020 until April 27, 2020. Source: FRED and Datastream.

2.2 Policy Response

2.2.1 Institutional Details

Chronology Both Central Banks and Treasury departments around the world have mounted massive responses to the crisis. We focus on the United States. Most relevant for our purposes are several new government programs that provide bridge loans to the corporate sector as part of the $2.2 trillion CARES Act passed on March 27, 2020.

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The Fed is using its balance sheet to lever up the equity commitments made by the Treasury. The Fed first announced the establishment of these programs on March 23. On April 9, the Fed clarified how much leverage it would provide to each of the facilities to scale up the aid to corporations. The Fed announcement amounted to a $2.3 trillion relief package. On April 23, Congress approved a new $484 billion rescue package, which included $321 billion in additional money for the paycheck protection program defined below. On April 30, the modalities of the MSLP were announced.

Program Details

1. Credit facilities for large firms

   – The Primary Market Corporate Credit Facility (PMCCF) is for new bonds and loans with maturities up to four years, issued by non-financial companies that are investment-grade (or were as of March 22). Interest rates are issuer-specific and informed by market conditions, plus a 100 bps facility fee. Loans may be syndicated, in which case the PMCCF participates under the same terms as the other syndicate partners.

   – The Secondary Market Corporate Credit Facility (SMCCF) provides liquidity for outstanding corporate bonds with (mostly) investment grade ratings. The Facility also may purchase U.S.-listed ETFs whose investment objective is to provide broad exposure to the market for U.S. corporate

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bonds. Bonds are bought at fair market value. The ETF purchases allow for non-IG bond purchases, for example, through a HY credit index.

- The Term Asset-Backed Securities Loan Facility (TALF) enables the issuance of asset-backed securities backed by student loans, auto loans, credit card loans, loans guaranteed by the Small Business Administration (SBA), existing commercial mortgage-backed securities (CMBS) and collateralized loan obligations (CLO). TALF only purchases AAA-rated tranches.
- These three programs support up to $850 billion in credit backed by $85 billion in credit protection provided by the Treasury. The PMCCF, SMCCF, and TALF receive $50bn, $25bn, and $10bn in equity from the Treasury, respectively. Loans from the Fed to these facilities provide leverage of 10-to-1 to the Treasury funds. In the case of the SMCCF, the leverage from Treasury depends on the instrument: 10x for IG corp bonds, 7x for IG ETF and FA, and 3x for HY ETF.

2. The Main Street Lending Program targets small and mid-sized businesses (below 15,000 employees or with 2019 revenues of $5 billion or less). Banks originate these loans, retain a portion and sell the remainder to the facility. Principal and interest on these four-year loans are deferred for 1 year. The facility's size is $600 billion in loans, backed by $75 billion in equity from the Treasury. As announced on April 30, there are three facilities

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that differ in the details of the loan features and banks' risk retention requirements. Firms may only participate in one of the three programs and only if they have not also participated in the PMCCF and have not received other direct support under the CARES Act. all loans carry an interest rate of LIBOR + 300bps.

- The Main Street New Loan Facility (MSNLF): loan made on or after 4/24/2020; banks retain 5% share; minimum loan size \$0.5 mi; maximum loan size \$25 mi as long as the total debt after the loan remains below 4 times 2019 EBITDA; amortizes 1/3 in years 2, 3, and 4; is not junior to any existing firm debt.
- The Main Street Priority Loan Facility (MSPLF): loan made after 4/24/2020; banks retain 15% share; minimum loan size \$0.5 mi; maximum loan size \$25 mi as long as the total debt after the loan remains below 6 times 2019 EBITDA; amortizes 15% in years 2 and 3, and 70% in year 4; is senior to all other corporate debt except mortgage debt.
- The Main Street Expanded Loan Facility (MSELF): upsized tranche upsized after 4/24/2020 on a loan made before 4/24/2020 with at least 18 months remaining maturity; banks retain 5% share; minimum loan size \$10 mi; maximum loan size \$200 mi as long as the total debt after the loan remains below 6 times 2019 EBITDA and the loan amount is less than 35% of existing corporate debt that is pari passu with the loan; amortizes 15% in years 2 and

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3, and 70% in year 4; is senior or pari passu to all other corporate debt except mortgage debt.

3. The Small Business Administration's Paycheck Protection Program (PPP) targets small companies with fewer than 500 employees. Initially, up to $350 billion in loans made by banks are guaranteed by the Small Business Administration. The money ran out within days. The April 23 top-up increased the size of the program to $671 billion. The loan principal is up to 2.5 months of payroll, with a maximum of $10 million. The loan maturity is two years and the interest rate is 1%. The CARES Act provides for forgiveness of up to the full principal amount of qualifying PPP loans. The amount of loan forgiveness depends on the total amount of payroll costs, payments of interest on mortgage obligations, rent payments on leases, and utility payments over the eight-week period following the date of the loan. However, not more than 25 percent of the loan forgiveness amount may be attributable to non-payroll costs. The Fed provides term financing to banks, collateralized by PPP loans up to their face value.

2.2.2 Mapping to the Model

To map this intricate set of interventions into our model, we consider three programs: bond purchases, forgivable bridge loans, regular bridge loans.

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CCF = Corporate Bond Purchases First, we model a government purchase program of corporate bonds. It is calibrated to the combined size of the PMCCF, SMCCF, and TALF, which is \$850 billion. According to S&P Global, the size of the U.S. corporate bond market is \$9,300 billion as of January 2019. Of this, \$7,144 billion is bonds issued by non-financial corporations, of which \$4717.6 is rated investment grade. The size of the corporate loan market, the C&I loans held by all U.S. commercial banks, is \$2,360 billion at the end of 2019. Since the model has only one type of debt, we scale the \$850 billion purchases by the size of the overall non-financial corporate debt market of \$9504 (\$7144+\$2360). This generates a purchase share of 8.9% of the overall corporate debt market. This program is \$850/\$21,729=3.9% of 2019 GDP. The model roughly matches the share of GDP since it roughly matches the ratio of the corporate bond market to GDP.

PPP = Forgivable Bridge Loans The second type of program is modeled after the PPP. Banks make loans to non-financial firms that are 100% guaranteed by the government and that are 100% forgiven. There is no risk retention requirement for the banks. We abstract from the fact that the PPP loans target small firms. In reality, several larger firms ended up receiving these loans as well. The SBA PPP loans feature debt forgiveness to the extent that firms use them to keep employees on the payroll. For example, the part of the loan that is used to pay rent is not forgiven. We suspect that the vast majority of firms who obtained PPP loans will enjoy full debt forgiveness since

money is fungible and firms can always "use the proceeds to make payroll." The forgiveness is modeled as a -100% interest rate earned by the government. We abstract from the 1% interest rate banks earn on the loans. The size of the PPP program is \$671 billion, which is 3.1% of 2019 GDP. For simplicity, these are one-period loans. In the model, firms can refinance these loans after a year in the regular long-term corporate debt market.

MSLP = Regular Bridge Loans The third policy is modeled after the MSLP. Firms receive bridge loans from banks. Banks have a 5% risk retention; the government bears 95% of the default risk. Banks earn an interest rate of 3% on the bridge loans. For simplicity, these are one-period loans, which can be refinanced in the regular debt market. The size of this program is \$600 billion or 2.8% of 2019 GDP.

Combo We also study the combination of these three programs.

3 The Model

In the interest of space, we only summarize the model setup here, and refer the reader to ELVN for a formal treatment.

3.1 Summary

Setup The model features two groups of households: borrowers and savers. Both have Epstein-Zin preferences. Savers are more pa-

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tient than borrowers. Borrowers are the shareholders of both goods-producing firms, called producers, and financial intermediaries, called banks. Borrowers and savers inelastically supply their one unit of labor.

A continuum of producers combine capital and labor using a Cobb-Douglas production technology to make output. Production is subject to aggregate, persistent TFP shocks and to idiosyncratic i.i.d. productivity shocks. The cross-sectional dispersion of the idiosyncratic productivity shock constitutes a second aggregate persistent shock. The latter can be thought of as an uncertainty or capital misallocation shock. Producers are funded with long-term debt, issued to both banks and savers, and equity, issued to borrowers. Interest expenses are tax deductible. Each producers must pay its employees and service its debt after aggregate and idiosyncratic productivity shocks are realized but before new equity or debt can be raised. Firms with negative profits default (liquidity default). Lenders seize the collateral of defaulted firms and liquidate the firms, suffering a loss in the process (some of which is a deadweight loss). Shareholders replace liquidated firms with new ones. The model leads to fractional default; the default rate is higher in periods of high uncertainty. Firms are subject to a standard collateral constraint.

Financial intermediaries, or banks for short, are profit-maximizing firms that buy the debt of non-financial firms. They fund these corporate loans with deposits that they issue to savers and with equity capital that they raise from borrowers. Bank debt enjoys government guarantees (e.g., deposit insurance). Banks are subject to a standard

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regulatory capital constraint (to limit moral hazard associated with deposit insurance). Banks make optimal default decisions (strategic default), trading off preserving franchise value versus shifting their debt onto the government. Banks are hit with idiosyncratic profit shocks, resulting in fractional default. Defaulted banks are taken over by the government and liquidated, subject to a loss (some of which is a deadweight loss). Shareholders replace liquidated banks with new ones.

We make assumptions that imply aggregation into a representative producer and a representative bank, allowing us to focus on incomplete risk-sharing between savers, borrowers, firms, and banks.

The government follows a set of mostly exogenous spending and tax rules. Only spending on bank bailouts and on government debt service are endogenously determined. The government issues one-period risk-free debt chosen to satisfy the government budget constraint.

Savers do not directly hold corporate equity to capture the reality of limited participation in equity markets. However, they invest in risk-free assets (bank and government debt), and risky corporate debt issued by firms. Unlike banks, savers incur holding costs when they buy corporate debt. This cost creates a comparative disadvantage for saver ownership of corporate debt, and provides a role for intermediaries in transforming long-term risky debt into short-term safe debt.

Figure 3 illustrates the balance sheets of the model's agents and their interactions.

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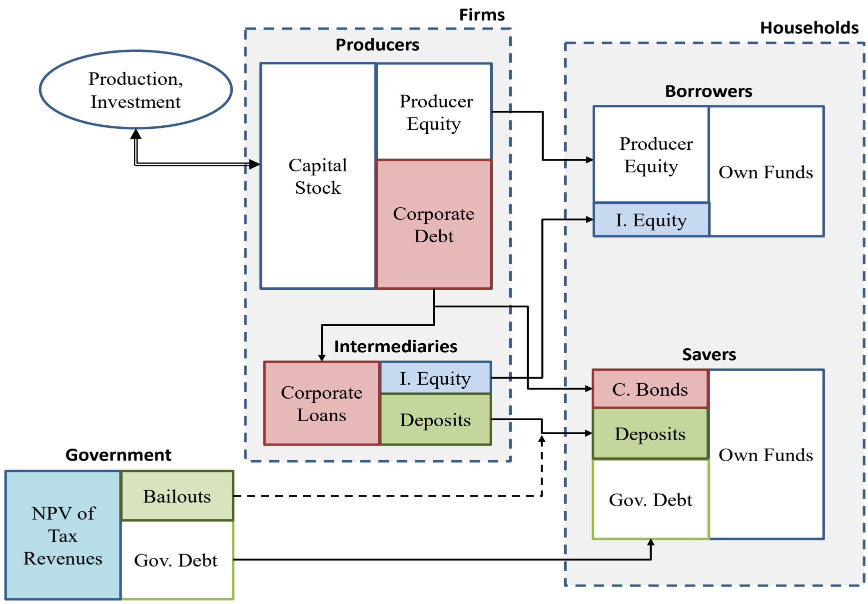
Figure 3: Overview of Balance Sheets of Model Agents



Equilibrium Given a sequence of aggregate productivity and uncertainty shocks, idiosyncratic productivity shocks, and idiosyncratic intermediary profit shocks, and given a government policy, a competitive equilibrium is a consumption and capital investment choice for borrowers; a debt issuance, equity issuance, capital demand, and labor demand, for producers; a debt issuance, equity issuance, and loan supply decision for financial intermediaries; a consumption and financial investment choice of short-term safe debt and long-term risky debt for savers; and a price vector, such that given the prices, borrowers and savers maximize life-time utility, producers and intermediaries maximize shareholder value, the government satisfies its budget constraint, and markets clear. The markets the must clear are the markets for: risk-free bonds (deposits and government debt), risky corporate debt,

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physical capital, labor, and goods. Goods market clearing states that total output (GDP) equals the sum of aggregate consumption, discretionary government spending, investment (including capital adjustment costs), bank equity adjustment costs, and aggregate deadweight losses from corporate and intermediary bankruptcies.

Welfare In order to compare economies that differ in their policy parameter vector Θ, we must take a stance on how to weigh borrower and saver households. We compute an ex-ante measure of welfare based on compensating variation similar to Alvarez and Jermann (2005). Consider the equilibrium of two different economies $k = 0, 1$, characterized by policy vectors Θ^0 and Θ^1, and denote expected lifetime utility at time 0 for agent j in economy k by $\bar{V}^{j,k} = \mathrm{E}_0[V_1^j(\cdot;\, \Theta^k)]$. Denote the time-0 price of the consumption stream of agent j in economy k by:

$$\bar{P}^{j,k} = \mathrm{E}_0\left[\sum_{t=0}^{\infty} \mathcal{M}_{t,t+1}^{j,k} C_{t+1}^{j,k}\right],$$

where $\mathcal{M}_{t,t+1}^{j,k}$ is the SDF of agent j in economy k. The percentage welfare gain for agent j from living in economy Θ^1 relative to economy Θ^0, in expectation, is:

$$\Delta\bar{V}^j = \frac{\bar{V}^{j,1}}{\bar{V}^{j,0}} - 1.$$

Since the value functions are expressed in consumption units, we can multiply these welfare gains with the time-0 prices of consumption

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streams in the Θ^0 economy and add up:

$$\mathcal{W}^{cev} = \Delta\bar{V}^B \bar{P}^{B,0} + \Delta\bar{V}^S \bar{P}^{S,0}.$$

This measure is the minimum one-time wealth transfer in the Θ^0 economy (the benchmark) required to make agents at least as well off as in the Θ^1 economy (the alternative). If this number is positive, a transfer scheme can be implemented to make the alternative economy a Pareto improvement. If this number is negative, such a scheme cannot be implemented because it would require a bigger transfer to one agent than the other is willing to give up.

Solution Each agent's problem depends on the wealth of others; the entire wealth distribution is a state variable. Each agent must forecast how that state variable evolves, including the bankruptcy decisions of borrowers and intermediaries. We solve the model using projection-based numerical methods. A detailed description of the globally non-linear algorithm can be found in Appendix B of Elenev, Landvoigt, and Van Nieuwerburgh (2020).

3.2 Covid Crisis

This section discusses how we model the covid pandemic shock, covid-related government policies, and how we adjust the calibration relative to ELVN.

3.2.1 Covid Shock

Firms production function is given by

$$y_t^i = Z_t^A \omega_t^i \left(k_t^i\right)^{1-\alpha} (l_t^i)^\alpha$$

The model features two aggregate shocks: aggregate TFP shocks Z_t^A and shocks to the cross-sectional dispersion of firm-level productivity shocks which we call uncertainty shocks. Firm-level productivity shocks are denoted by $\omega_i \sim \Gamma_\omega(\mu_\omega, \sigma_\omega^2)$, where Γ_ω denotes the cdf, parameterized by two parameters, a mean μ_ω and a variance σ_ω^2. The cross-sectional variance σ_ω^2 follows a two-state Markov chain fluctuating between a low and a high-uncertainty regime. Aggregate TFP shocks follow an independent 5-state Markov chain.

The covid shock is modeled as the combination of four ingredients. The first aspect of the covid shock is a transition from the low- ($\sigma_{\omega,L}^2$) to the high-uncertainty regime ($\sigma_{\omega,H}^2$). Because of persistence in σ_ω^2, the economy is likely to remain in the high uncertainty state with probabilities dictated by the Markov chain.

Second, we assume that the productivity dispersion is unexpectedly high for one period: $\sigma_{\omega,covid}^2 > \sigma_{\omega,H}^2 > \sigma_{\omega,L}^2$. This is modeled as a one-period MIT shock. The rise of VIX to an all-time high serves as motivation for this assumption. More broadly, the notion of increased firm productivity dispersion captures capital misallocation. During covid, some firms (like cruise companies and airlines) saw much greater reductions in revenues than others, while some even say significant

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increases in revenue (Amazon, Netflix, Zoom).

The third aspect of the covid shock is a decline in average firm productivity μ_ω, leading to a decline in average firm revenue. We model this as an unexpected change (MIT shock); agents believe that $\mu_\omega = 1$. A decline in average firm productivity has the same effect as a decline in aggregate TFP, except that TFP is persistent and TFP fluctuations are anticipated. We think the unexpected and pervasive nature of revenue drops in the cross-section of firms is well captured by the unanticipated one-year drop in μ_ω.

Fourth, we assume a reduction in labor supply. In the model, labor is supplied inelastically by both borrower ($\overline{L}^B$) and savers ($\overline{L}^S$) households. We assume a symmetric drop in labor supply. This captures government-mandated closure of non-essential businesses, forcing many workers to stay at home. It also captures inability to work due to covid-related illness and child care duties. The decline in labor supply further lowers production, since labor demand $\int l_t^i di$ must equal labor supply in equilibrium.

3.2.2 How Corporate Bankruptcies Work

The decision problem of producers within each period has the following timing:

1. The aggregate productivity shock is realized. Given capital k_t and outstanding debt a_t^P, producers choose labor inputs l_t^j, $j \in \{B, S\}$. Further, producers pay a fixed cost of production to operate (rents, insurance, etc.) ς is the fixed cost that is

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proportional in capital k_t.

2. Idiosyncratic productivity shocks are realized. Production occurs. Producers that cannot service their debt from current profits default and shut down.

3. Failed producers are replaced by new producers such that the total mass of producers remains unchanged. All producers pay a dividend, issue new debt, and buy capital for next period.

The flow profit at stage 2 before taxes is

$$\pi_t = \omega_t Z_t k_t^{1-\alpha} l_t^{\alpha} - \sum_j w_t^j l_t^j - a_t^P - \varsigma k_t, \tag{1}$$

Producers with $\pi_t < 0$ are in default and are seized and resolved by their creditors. This implies a default threshold

$$\omega_t^* = \frac{a_t^P + \varsigma k_t + \sum_j w_t^j l_t^j}{Z_t k_t^{1-\alpha} l_t^{\alpha}}, \tag{2}$$

such that producers with low idiosyncratic shocks $\omega_t < \omega_t^*$ default. Firms that do not have enough revenue to service their debt and pay their employees default. The crucial friction that generates defaults is a timing assumption that corporations must service their debt before they can raise new equity or debt.

Lenders (banks and savers) seize the firms that default, pay the employees, and liquidate the firm. Liquidation means that they earn a fraction $(1-\zeta^P)$ of this period's output plus the non-depreciated value of the capital stock. A fraction ζ^P is a bankruptcy cost, of which a

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fraction η^P is a deadweight loss to society and the remainder a transfer payment to households. By inflicting losses on their lenders, corporate defaults cause financial intermediary fragility. Banks' net worth will go down because of the losses they suffer, as well as because of the lower equilibrium valuation of corporate loans. Lower corporate bond prices (higher yields) reflects both higher default risk and a higher default risk premium. For some banks, the losses will be so severe that they (optimally choose to) default. Defaulting banks are bailed out by the government; any equity is wiped out, depositors are made whole (deposit insurance), and the government incurs bankruptcy costs ζ^F (a fraction η^F of which are deadweight losses to society). The government in turn needs to raise new debt on the Treasury market to finance these bank bailouts. The increase in safe asset supply increases equilibrium interest rates on safe assets, ceteris paribus. Since deposits are also safe assets, the bailout-induced increase in the safe rate increases the cost of deposit funding. The higher cost of funding hampers bank recapitalization and aggravates the financial fragility. This negative feedback loop can lead to severe financial crises in our non-linear model. When banks become fragile, credit to the real economy becomes scarce and expensive. Corporate investment tanks. This lowers capital formation and output in all future periods, adding persistence to the crisis.

3.2.3 Government Policies

Government policies' aim will aim to stave off ar at least weaken corporate defaults and thereby prevent the vicious cycle between corporate

and banking fragility which chokes off investment and economic activity. We consider four policies, motivated by the discussion in section 2.2.

CCF = Corporate Bond Purchases The corporate bond purchase policy has the government buying long-term risky corporate debt from both banks and savers in proportion to their holdings and at market prices. The government issues short-term government debt to finance these purchases. Treasury debt is held by the saver in equilibrium.

PPP= Forgivable Bridge Loans We consider a bridge loan program that closely reflects the Payroll Protection Program. Each firm receives an equal-size bridge loan from private lenders. The size of the loan is dictated by the total size of the program. The firm receives the loan in stage 2 of its problem, after production but before defaults and trading in financial markets. The loan must be repaid at the end of the period, in stage 3 of the firm's intra-period problem. At that point, firms can refinance the debt on the regular long-term corporate debt market. Since the firm receives the bridge loan before defaulting and the size of the loan is a multiple $\bar{A}^{brU}$ of the firm's wage bill, the default threshold becomes:

$$\omega_t^{*,brU} = \frac{\varsigma k_t + (1 - \bar{A}^{brU}) \sum_j w_t^j l_t^j + a_t^P}{Z_t k_t^{1-\alpha} l_t^{\alpha}}. \tag{3}$$

Producers with low idiosyncratic productivity $\omega_t < \omega_t^{*,brU}$ default. This is a smaller fraction since the policy lowers the default threshold

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compared to the no-policy case ($\omega_t^{*,brU} < \omega_t^*$). Thus the bridge loans help a mass of firms prevent default and the concomitant losses. It also avoids the deadweight losses to society associated with these defaults. Some firms with low productivity still default, notwithstanding the bridge loan program. The remaining losses are born by banks and the government depending on the extent of government guarantees. A policy parameter I_{br} measures the share of the losses born by the government, ranging from 0 (no guarantees for bridge loans) to 1 (full guarantees). In the PPP, $I_{br} = 1$.

Firms pay an interest rate $r^{br} = 1\%$ to banks on the bridge loans. After this interest payment, the loans are forgiven by the government. To capture the debt forgiveness aspect of the PPP, the bridge loans carry a $r^{gov} = -100\%$ interest rate relative to the government (i.e., the effective interest rate faced by firms is $r^{br} + r^{gov} = -99\%$).

MSLP= Regular Bridge Loans The third policy modeled after the MSLP is similar to the PPP, except for two features. First, there is partial risk retention by banks: $I_{br} < 1$. Second, the principal is not forgiven ($r^{gov} = 0$) and the interest rate paid to banks is higher: $r^{br} = 3\%$.

CBL=Conditional Bridge Loans As a fourth, hypothetical, policy we consider a conditional bridge loan program. The government can target firms that are most likely to default if they do not receive a bridge loan. Specifically, a firm of productivity ω_t receives a bank loan of size $\bar{A}^{brC}(1-\omega_t)\sum_j w_t^j l_t^j$ in stage 2 of the firm problem. The

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conditionality operates both on the extensive and intensive margins. First, only firms with $\omega_t < \omega_t^*$ receive bridge loans. Second, the loan size is larger the lower the firm's productivity.

This bridge loan program changes the default threshold from ω_t^* to $\omega_t^{*,brC}$:

$$\omega_t^{*,brC} = \frac{\varsigma k_t + (1 - \bar{A}^{brC}) \sum_j w_t^j l_t^j + a_t^P}{Z_t k_t^{1-\alpha} l_t^\alpha - \bar{A}^{brC} \sum_j w_t^j l_t^j}. \tag{4}$$

All other aspects of the program are the same as for the regular bridge loan program. In particular, we consider a program configuration that is the average of PPP and MSLP: a debt forgiveness of 50% of the principal ($r^{gov} = -50\%$), and interest payments to banks of $r^{br} = 2\%$ of the principal. The conditional bridge loan will generally be more effective, on a per-dollar-basis, in preventing firms from defaulting than the PPP. Hence, we do not fix the size of the CBL program, but rather compute what fraction of GDP the government must spend to achieve the same reduction in the firm default rate as in the PPP.

The CBL policy imposes strong information requirements on the government: It must observe each firm's productivity. In reality, there is an issue of asymmetric information —firms know more about their drop in revenue than the government— as well as moral hazard —firms have an incentive to overstate their need. Imperfect verification on the part of the government, especially in an episode of scarce time and resources, makes these frictions potentially important. We view the cost difference between the PPP and the CBL programs as an estimate of the extra costs of imperfect information or enforcement.

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3.3 Calibration

The model is calibrated at annual frequency and matches a large number of moments related to the macro economy, credit markets, non-financial and financial sector leverage ratios, default rates, loss rates, as well as a number of fiscal policy targets. We refer the reader to ELVN. We leave the calibration mostly unchanged, only changing the following aspects.

The first change we make is the nature of the covid shock, as discussed above. This introduces the possibility of a drop in mean productivity μ_ω. Government discretionary spending, transfer spending, and income tax rates depend on $Z^A\mu_\omega$, so that declines in μ_ω lead to symmetric declines in tax revenue as declines in Z^A. ELVN held $\mu_\omega = 1$ so that this does not really represent a change in calibration.

Second, we set the inter-temporal elasticity of substitution of the saver to a value of 2, higher than the value of 1 we use in ELVN. The higher saver EIS dampens the response of the safe interest rate to changes in the supply of safe assets by lowering the price elasticity of demand of the saver.

Third, we change is the maximum bank leverage ratio. Prior to the covid crisis, banks faced strict minimum bank equity capital requirements of 12% (maximum leverage of $\xi = .88$). ELVN choose a 6% minimum bank equity capital ($\xi = .94$) since they calibrate to the pre-GFC crisis data. This higher capital requirement reflects the changes made by the Dodd-Frank Act and Basel agreements after the GFC. The stronger capitalization before the covid crisis helps dampen

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the impact of the covid shock.

Fourth, we introduce a small default penalty for banks in the period of the covid shock, $\rho = 0.04$. We simultaneously change the cross-sectional dispersion of bank idiosyncratic profit shocks to $\sigma_\varepsilon = 0.05$. A greater value of σ_ε makes bank failures less sensitive to fluctuations in the franchise value of banks, but also leads to more bank failures ceteris paribus. The two parameters jointly control the mean of the bank default rate and its sensitivity to bank value. This parameter change is modeled as a one-period MIT shock. We continue to match the unconditional bank failure rate from historical FDIC data, as in ELVN. The default penalty can be motivated by government-provided moral suasion that banks who take bailout money need to stay afloat, or by a range of unmodeled government policies such as higher unemployment insurance, checks mailed to households, or quantitative easing that help de-risk the banks' balance sheets. The higher dispersion of bank idiosyncratic shocks can be motivated by the increased dispersion of profitability/losses on the part of banks' balance sheet unrelated to corporate loans, e.g., household mortgages.

4 Results

Figures 4, 5, 6, and 7 summarize our main results. Each graph plots the impact of the covid shock in the year in which it hits the economy. We focus on the first five bars labeled "One-time pandemic." The first (blue) bar shows the effect onf te economy without any policy response. The other bars respond to the four actual government policies: forgiv-

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Figure 4: Policy Responses to Covid Crisis: Non-financial Firms

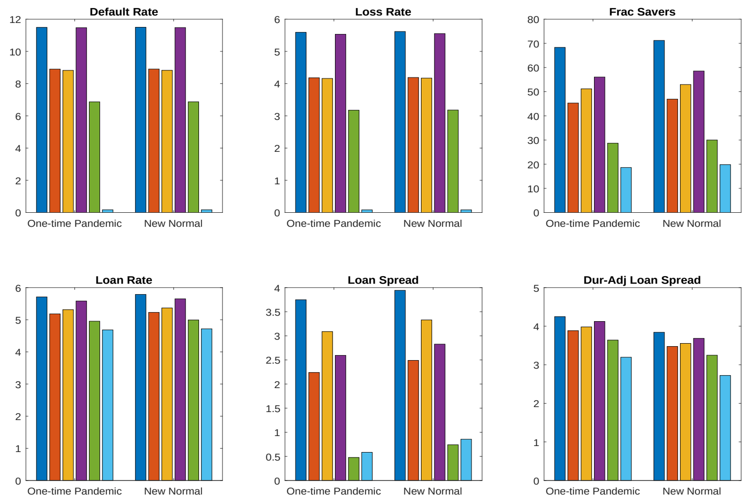
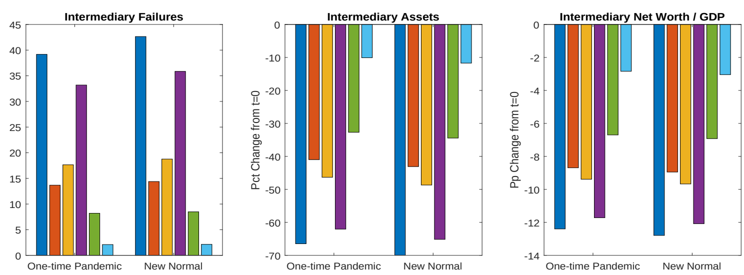


Figure 5: Policy Responses to Covid Crisis: Financial Intermediaries



able bridge loans (PPP, orange), regular bridge loans (MSLP, yellow), corporate bond purchases (CCF, purple), and the combination of all three (Combo, green). The last bar is for the hypothetical conditional bridge loan program (CBL, black).

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Figure 6: Policy Responses to Covid Crisis: Macroeconomy

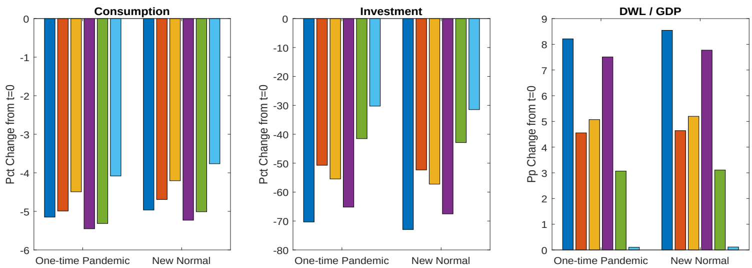
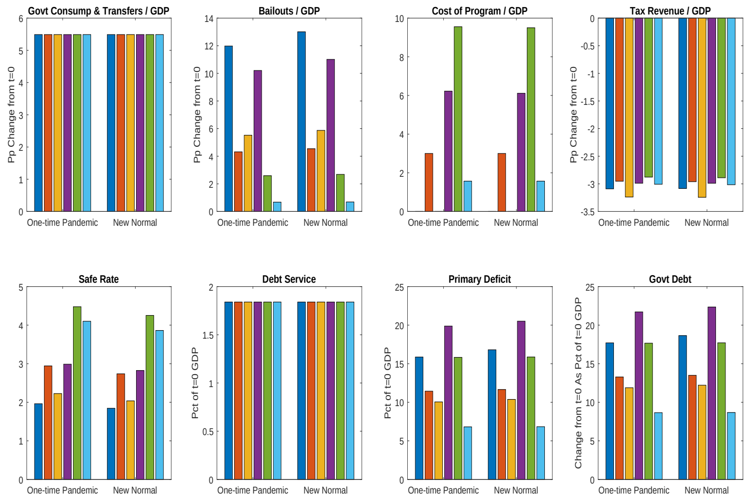


Figure 7: Policy Responses to Covid Crisis: Fiscal Policy



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4.1 Do Nothing

We first consider a (counter-factual) scenario in which the government does nothing new in response to the covid crisis. It continues its usual counter-cyclical spending and pro-cyclical taxation policies, as well as its bank bailout policies. It issues short-term government debt to plug any hole in the deficit.

In the absence of policy, corporate defaults and loan losses skyrocket

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in response to the covid shock. The default rate in the non-financial sector goes from its normal level of 2.2% per year to 11.5%, a fivefold increase. The loss rate also increases by a factor of five to 5.6%.

These loan losses trigger credit disintermediation: the fraction of corporate debt held by savers (banks) rises (falls) sharply from 15% (85%) before the crisis to 68% (32%). The loan losses not only cause a smaller but also a weaker banking sector. Financial fragility manifests itself in an increase in the bank failure rate—nearly 40% of the banks become insolvent—and a decline in aggregate intermediary net worth, as shown in Figure 5. Higher credit spreads are a manifestation of the increased scarcity of banks' resources; they reflect not only a higher amount of credit risk but also a higher price of credit risk. The increase in the credit spread can be seen most clearly in the last panel of Figure 4 which plots a duration-adjusted loan spreads, as Figure 1 did for the data.

Faced with higher costs of debt, firms reduce investment. As shown in Figure 6, investment falls by 70%. Both firm and bank defaults create a surge in deadweight losses, which reduces resources available for investment or consumption. Aggregate consumption falls by 5.15%.

The economic downturn and the concomitant bank bailouts trigger a massive increase in the primary deficit which swells to 17% of $t = 0$ pre-covid GDP (short: GDP0) in the period of the shock. Government consumption (discretionary and transfer spending) is 5.5% points of GDP0 higher de to automatic stabilization programs (e.g., unemployment insurance, food stamps, etc.) and tax revenue falls by 3% points as a share of GDP0. However, the main spending increase comes from

bailing out the banking sector to the tune of 12% of GDP0. Adding the interest service on the debt leads to a total of 19.2% of new debt that must be raised relative to current GDP, or equivalently 17.7% of GDP0. The one-year Treasury rate falls to 2% from a level of 2.7% before the crisis.

In sum, absent policy, the economy suffers a large decline in macroeconomic activity, a rise in corporate defaults, a rise in bank defaults and loss in intermediary capacity, and a spike in credit spreads which feeds back on the real economy and discourages investment. The decline in economic activity depresses real interest rates, but the effect is offset by an increase in government debt due to counter-cyclical deficits, higher debt service, and bank bailouts. Can covid policy improve on this disastrous outcome?

4.2 PPP

The PPP policy (orange bars) provides forgivable bridge loans to all firms. The loans make a substantial dent in non-financial corporate defaults which fall by 2.6% points, a 23% reduction. This is enough to eliminate 2/3 of all bank bankruptcies. The fall in intermediary assets and net worth is substantially smaller. The reduced financial distress lowers the increase in the corporate loan rate. The intervention helps "close credit spreads." The forgivable loans put cash in firms' pockets which, combined with the lower loan rates, substantially reduce the fall in investment. Instead of falling by 70%, investment falls by 50%. Deadweight losses are half as large as in the do-nothing scenario.

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Because PPP loans are forgivable, the direct effect of the policy is to add 3% of GDP to the deficit. The policy also results in a 100 bps higher safe rate of interest which will cause higher debt service costs in the future. However, the policy saves about 7.6% of GDP0 in bank bailouts that do not occur. All told, the primary deficit shrinks to 11.3% of GDP0. The increase in debt is 13.3% of GDP0 which is 4.4% points lower than in the do nothing scenario. The government is saving money by spending money. The higher safe rate encourages saving over consumption. This helps explain why the fall in consumption is still -5.0% despite the sharp reduction in lost resources due to bankruptcies.

4.3 MSLP

Next we consider the MSLP (yellow bars), which gives regular bridge loans to firms with a 3% interest rate and 5% bank risk retention (95% government guarantee). The program has the same size (3% of GDP) as the PPP. Even though the loans are not forgivable so that the average successful at reducing firm defaults. Bank defaults are also lower (17.7%), but not quite as low as in the PPP (13.7%) because banks now share in some of the losses through the risk retention feature of the MSLP bridge loans. Because there is more residual financial fragility, credit spreads and interest rates on corporate loans remain somewhat more elevated than in the PPP. Corporate investment falls by 55%, a bit more than in the PPP.

The MSLP program is not expensive to the government since there is no debt forgiveness feature, and since most firms end up being able

to pay back the loan. Yet, the program still eliminates most bank bankruptcies, and saves much of the cost of bank bailouts. The primary deficit is about 10% of GDP0. The government must issue less new debt, 11.9% of GDP0. Lower new debt issuance helps keep the interest rate low, which in turn reduces the debt service going forward and the additional debt that needs to be issued. The safe rate of 2.2% is below the 2.7% pre-pandemic level. The lower safe interest rate discourages saving and results in a smaller drop in aggregate consumption of -4.5%.

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4.4 Bond Purchases

A large bond purchasing program of 8.9% of the stock of corporate debt (purple bars) is not very effective at mitigating the crisis. Loan losses are not reduced. More surprisingly, loan rates are not lowered much, only 13 basis points compared to the do nothing scenario. While the loan spread goes down, the effect is largely offset by an increase in the safe rate. Therefore, it is no surprise that the fall in investment is not very different compared to the no policy scenario. Similarly, the policy does not help much in terms of countering financial fragility. Bank bailouts are reduced, but by much less than under the other policies.

In order to finance the corporate debt purchases, the government must issue 8.9% of GDP worth of additional Treasuries. The primary deficit including the bond purchases, is 19.6% of GDP0. The corporate bond purchases substantially increase safe interest rates. The price

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effects on the debt imply that the government debt increases by 21.7% of GDP0, 4% points more than under no policy. The higher safe interest rates discourage consumption, which falls by 5.45%. Higher safe rates also increase the cost of funding for banks. This hampers their recapitalization and amplifies their financial fragility.

4.5 Combination Policy

The government is combining the three previous policies in reality. The results from the combo policy are plotted in the green bars. They are the model's closes prediction for what will happen by the end of 2020 after all policies have been fully rolled out. The three policies are a potent cocktail to fight the economic fallout from the pandemic. The policy combo lowers corporate defaults and losses by 40% compared to no policy. Bank bankruptcies are reduced by 80%, and bank net worth losses are only half as large as under no policy. Credit spreads are greatly reduced, a place where the policy combination is more than the sum of the parts. Safe rates go up, which offsets some but not all of the effect of lower spreads on the corporate loan rate. Facing a lower cost of debt, investment falls by 40% compared to 70% under no policy. Higher safe rates, which double compared to pre-pandemic levels, also mean a much larger debt service going forward. The primary deficit of 15.6% of GDP0 is essentially the same as under no policy. The government spends on policy measures what it would have spent on higher bank bailouts instead. Aggregate consumption falls by 5.3%, which is a bit more than under no policy and a reflection of the higher

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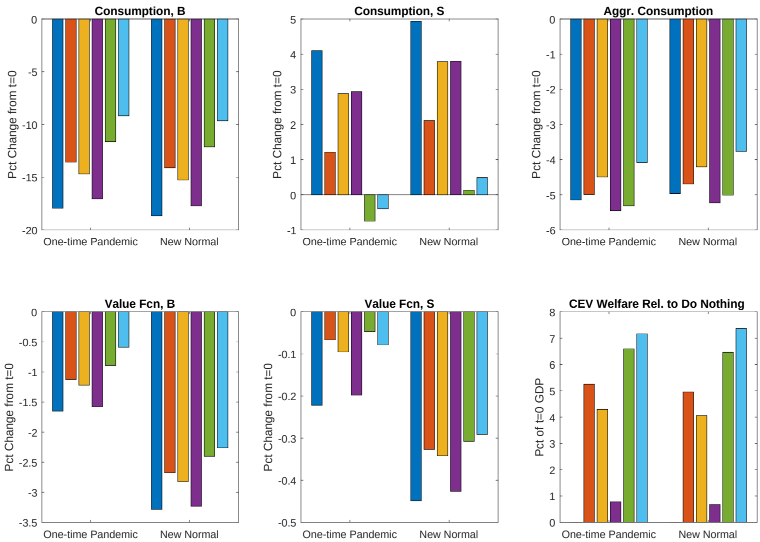
safe interest rates.

Figure 8 summarizes the welfare effects of the various policies. The bottom row shows the change in value functions of borrowers and savers, relative to pre-pandemic period. The value function summarizes the expected, risk-adjusted discounted value of the current and all future consumption impacts. The bottom right panel shows a measure of how much permanent consumption the economy would be willing to give up to adopt each of the policies relative to a no-policy alternative. The CEV welfare measure aggregates the value functions of the two groups of households by their respective values of a dollar of consumption in the covid state; recall the welfare discussion in Section 3.1. All three legs of the policy combo are valuable, with the PPP being the most valuable, followed by the MSLP, and CCF as a distant third. Combined, they increase aggregate welfare by 6.5% of permanent consumption. The top row of Figure 8 shows the first-period consumption response to the covid shock for each of the two agents. Borrowers, who are the shareholders of non-financial and financial firms, are substantially worse off. Savers consume slightly more in the first period but, as we know from their value functions, are still worse off due to the risk in consumption. Borrowers most prefer the policies that provide the greatest relief to the firms they own. Savers slightly prefer policies with larger fiscal cost because the larger fiscal expansion increases their wealth.

Figure 8: Policy Responses to Covid Crisis: Welfare



4.6 Contingent Bridge Loans

The last policy we analyze assumes that banks make productivity-contingent loans (light blue bars). The loans are forgivable and 100% guaranteed by the government, just like the PPP loans. It is an alternative to the policies enacted, albeit a somewhat idealistic one given the informational requirements it imposes on the (banks who implement it on behalf of the) government. Nevertheless, the experiment is instructive. This policy eliminates nearly all corporate default. It also eliminates all bank default and most of the credit disintermediation. Bank net worth only falls by 2.8% of GDP rather than 12.4% under no policy. Since firms face a lower cost of debt under this policy than under the combo policy, investment falls by only 30%, the least among all experiments.

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The size of this program is endogenous, and calibrated to eliminate all defaults. The cost ends up being 1.6% of GDP. The lower direct fiscal outlay helps stem the rise in the primary deficit and the additional debt that needs to be raised. The primary deficit in the year of the covid shock is 6.7% of GDP. Only 6.8% of GDP0's worth of new Treasury debt must be issued, 10% points less than under the combo policy. Interest rates rise by 30 bps less than in the combo policy. Hence, this program is not only more effective at eliminating corporate defaults and improving the health of the banking sector, it also is cheaper for the government and results in smaller declines in aggregate investment and consumption (-4.1%).

Welfare is 0.5% higher in the CBL scenario than in the combo policy. We conclude that the real-life combo is not far off from a policy that, at first sight, seems much more efficient but also much harder to implement.

4.7 Long-run Consequences

So far, we have analyzed only the first period of the covid shock. Figure 9 shows the long-run response of the macro-economic aggregates over 25 years. The model generates a very large cumulative loss in GDP, consumption, and investment of 19%, 22%, and 41% under the combo policy. The long-run cumulative loss in aggregate consumption is almost four times as large as the one-year loss, even though the covid shock is assumed to fully dissipate (even as a future possibility) after one year. The fall in investment is mostly a one-year phenomenon but

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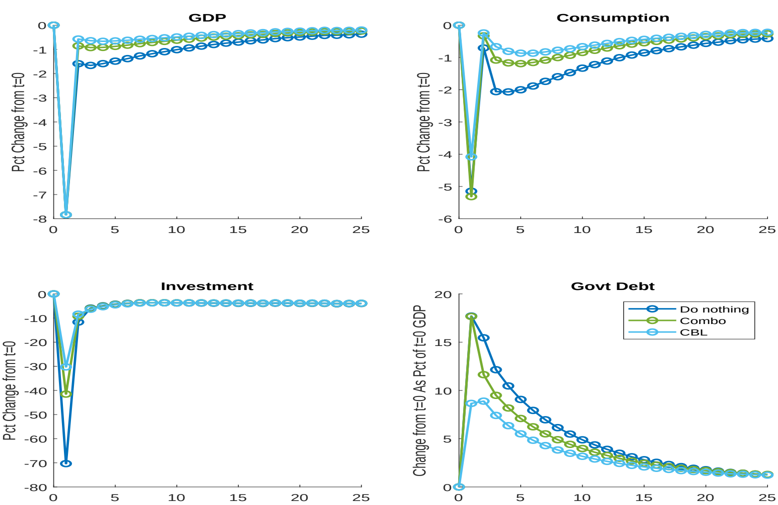
it persistently depresses the stock of capital and hence the output-producing capacity of the economy. There is persistence also through the high-uncertainty regime which is likely to last for another year (in expectation). Intermediary recapitalization also takes time and lends persistence to the crisis. The model produces a V-shaped recovery but with a long tail of modestly depressed economy activity. The CBL program would mitigate 5% points of cumulative consumption losses.

Figure 9: Policy Responses to Covid Crisis: Long-run



The last panel of Figure 9 shows the evolution of government debt, and suggests it will take a very long time to return the government debt back to pre-pandemic levels. Interestingly, even though the combo policy leads to the same-size initial expansion of debt, the debt is paid back faster than under no policy. This is due to the better health of the financial system along the transition path under the combo policy.

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5 New Normal

We now consider an extension of the model where the pandemic causes the realization that an economic shock like the pandemic could reoccur in the future, an awakening to a new normal. Formally, we include the pandemic state (low μ_ω, high $\sigma_{\omega,covid}$, low labor supply) as an extra state of the world that occurs with low but not zero probability, $p_{covid} = 1\%$. The pandemic shock is now not only an MIT shock in the first period, but also a change in beliefs from $p_{covid} = 0\%$ to $p_{covid} = 1\%$ going forward.

The second set of bars in Figures 4, 5, 6, and 7 report on the economy's responses to the covid shock in this "new normal" economy. The results are very similar to the responses in the economy that does not undergo the awakening. Simply put, the shock is so large that it swamps the effect of the change in beliefs.

However, the long-run looks different. Table 2 compares the steady state of the benchmark economy to that of the new normal economy. Firm leverage adjust downward endogenously due to the higher risk. This makes the economy safer, but also shrinks the size of the intermediary sector. With less credit extended to the non-financial sector, the economy shrinks permanently. Further, investment and consumption growth are much more volatile. Both borrowers and savers are worse off. While borrower consumption volatility increases by over 20%, mean borrower consumption only falls by 5bp. For borrowers, the reduction in GDP is partly offset by the expansion in equity financing of firms, which results in borrowers capturing a larger share of aggregate

Table 2: Long-Run Effects of a Pandemic State

	Baseline	**Pandemic**
	Borrowers	
1. Mkt value capital/ Y	214.8	213.9
2. Book val corp debt/ Y	75.4	71.7
3. Book corp leverage	35.1	33.5
4. % producer constr binds	0.1	0.0
5. Default rate	1.90	1.96
6. Loss-given-default rate	48.7	46.5
7. Loss Rate	0.91	0.89
	Intermediaries	
8. Mkt val assets / Y	65.2	61.2
9. Mkt fin leverage	87.7	87.8
10. % intermed constr binds	73.0	86.1
11. Bankruptcies	0.01	0.48
12. Wealth I / Y	8.3	7.7
13. Franchise Value	6.8	7.8
	Savers	
14. Deposits/GDP	58.5	55.0
15. Government debt/GDP	71.2	72.7
16. Corp Debt Share S	15.5	16.4
	Prices	
17. Risk-free rate	2.21	2.20
18. Corporate bond rate	4.18	4.21
19. Credit spread	1.98	2.00
20. Excess return on corp. bonds	1.08	1.13
	Welfare	
		% change to baseline
21. Value function, B	0.263	-0.04
22. Value function, S	0.373	-0.24
23. DWL/GDP	0.612	9.34
	Size of the Economy	
24. GDP	0.986	-0.29
25. Capital stock	2.118	-0.68
26. Aggr. Consumption	0.633	-0.28
27. Consumption, B	0.262	-0.05
28. Consumption, S	0.371	-0.45
	Volatility	
29. Investment gr	9.20	61.54
30. Consumption gr	2.25	8.26
31. Consumption gr, B	2.74	20.73
32. Consumption gr, S	3.88	-5.04
33. Aggr. welfare* $\mathcal{W}^{cev}$		-5.11

*: Aggregate welfare is percentage of baseline GDP; see text.

income. Saver consumption declines by 0.45%, more than GDP. All told, households would be willing to pay 5% of baseline GDP to avoid the transition to the economy with infrequently occurring pandemics.

6 Conclusion

The covid pandemic poses severe challenges for the economy of most developed countries. We focus on the health of the corporate sector and its ramifications for the health of the financial sector and the macro-economy. Absent policy intervention, a negative feedback loop between corporate default and financial intermediary weakness creates a macro-economic disaster. The Payroll Protection Program and Main Street Lending Program are effective at breaking the vicious cycle. They avoid most corporate bankruptcies and their financial sector and macro-economic fallout. In contrast, the corporate credit facility that buys corporate bonds is much less effective. Combined, the programs provide a potent cocktail that prevents 8.5% in cumulative output losses and creates huge welfare benefits compared to a do-nothing scenario. The interventions do have long-run fiscal implications, as well as effects for the long-run size of the non-financial and financial sectors.

Much work remains to be done. One could augment the model with a monetary sector and study how conventional and non-conventional monetary interventions interact with the corporate lending policies analyzed here. One could augment the model with an epidemiological block that captures the spread of the disease, introduce firms that pro-

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duce different types of goods (social and private consumption) which are differentially affected, and endogenize labor supply. As the government programs are fully rolled out, it will be important to study their effectiveness using firm- and bank-level data. Our model can serve as a useful framework for hypothesis testing.

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A Targeted and Untargeted Bridge Loans

At the liquidity stage before defaults, firms receive a bridge loan $\bar{A}^{brP}\sum_j w_t^j l_t^j$ from banks, where $P \in \{T, U\}$ denotes the type of program, such that their profit is

$$\pi_t = \omega_t Z_t k_t^{1-\alpha} l_t^{\alpha} - (1 - \bar{A}^{brP}) \sum_j w_t^j l_t^j - a_t^P - \varsigma k_t. \tag{5}$$

This equation reflects that firms use the bridge loans for payroll expenses. Producers with $\pi_t < 0$ are in default and shut down. This implies a default threshold in the presence of bridge loans $\omega_t^{*,brP}$, given in equation (3) in the main text.

Non-defaulting firms immediately repay the bridge loan after the liquidity stage of the problem. Their net worth is only reduced by the interest payments associated with bridge loans, relative to the baseline model without such loans. The interest expense on the bridge loans, taking into account tax deductibility of interest, is:

$$(r^{br} + r^{gov})(1 - \tau^{\Pi})\bar{A}^{brP} \sum_j w_t^j l_t^j.$$

Individual producer net worth at the beginning of next period becomes:

$$\begin{aligned}
\Pi(\omega', \tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t) = {} & (1 - \tau^{\Pi})\omega' Z_t^A \tilde{k}_t^{1-\alpha} \tilde{l}(\tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t)^{\alpha} \\
& - (1 - \tau^{\Pi}) \sum_j w_t^j \tilde{l}^j(\tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t) \\
& + \left((1 - (1 - \tau^{\Pi})\delta_K)p_t - (1 - \tau^{\Pi})\varsigma\right) \tilde{k}_t \\
& - \left(1 - \tau^{\Pi} + \delta q_t^m\right) \tilde{a}_t^P \\
& - (r^{br} + r^{gov})(1 - \tau^{\Pi})\bar{A}^{brP} \sum_j w_t^j \tilde{l}(\tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t). \qquad (6)
\end{aligned}$$

This implies that bridge loans without interest and debt forgiveness, $r^{br} = r^{gov} = 0$, leave the net worth of surviving firms and their dividends unchanged. Aggregate firm net worth needs to be reduced by the collective interest expense on the bridge loans by integrating across producers. We denote the ω of the highest-productivity firm that receives a bridge loan as $\bar{\omega}_t^P$. For untargeted loans we have $\bar{\omega}_t^U = \infty$,

implying that all firms receive loans, and for the targeted program $\bar{\omega}_t^T = \omega_t^*$, implying that only firms that would default without a bridge loan receive a loan. Thus aggregate interest is

$$r^{br}(1-\tau^{\Pi})\bar{A}^{brP}W_t \int_{\omega_t^{*,brP}}^{\bar{\omega}_t^P} dF_t(\omega) = \left(F_t(\bar{\omega}_t^P) - F_t(\omega_t^{*,br})\right)(r^{br}+r^{gov})(1-\tau^{\Pi})\bar{A}^{brP}W_t,$$

where we denote the aggregate wagebill of all firms as $W_t = \sum_j w_t^j \bar{L}^j$.

Banks

Bridge loans are junior to regular loans/bonds. Thus, defaulting firms do not pay back bridge loans. Lenders (banks and savers) apply bridge loan cash of defaulting firms towards the recovery value of regular loans/bonds. They can recover a fraction $1-\zeta_t^{br}$ of each dollar of bridge loan. The total recovery per outstanding face value is:

$$\begin{aligned} M_t = & \frac{F_{\omega,t}(\omega_t^{*,br})}{A_t^P}\left[(1-\zeta^P)\left(\omega_t^{-,brP}Y_t + \left((1-\delta_K)p_t - \varsigma\right)K_t\right)\right. \\ & \left. -(1-(1-\zeta^{br})\bar{A}^{brP})W_t\right], \end{aligned} \tag{7}$$

where we have defined

$$\omega_t^{-,brP} = \mathrm{E}_{\omega,t}\left[\omega \,|\, \omega < \omega_t^{*,brP}\right].$$

How bank wealth is affected by bridge loans depends on whether the government takes on losses incurred on these loans, i.e. whether it guarantees those loans. Aggregate bridge loan losses are:

$$\int_0^{\omega_t^{*,brP}} dF_t(\omega)\,\bar{A}^{brP}W_t = F_{\omega,t}(\omega_t^{*,brP})\bar{A}^{brP}W_t.$$

The variable I_{br} measures the fraction of losses that the government absorbs; it is between 0 (no guarantees) and 1 (full guarantee). We assume that banks receive the interest income from bridge loans, regardless of the government guarantees that are in place, as long as the interest rate on these loans is positive. Then bank net worth is:

$$N_t^{I,brP} = N_t^I + \bar{A}^{brP}W_t\left[(F_{\omega,t}(\bar{\omega}_t^P) - F_{\omega,t}(\omega_t^{*,brP}))r^{br} - (1-I_{br})F_{\omega,t}(\omega_t^{*,brP})\right],$$

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where N_t^I is bank net worth in the baseline model without bridge loans.

Government

Government expenditure is

$$G_t^{br} = G_t + \bar{A}^{brP} W_t \left[I_{br} F_{\omega,t}(\omega_t^{*,br}) - (F_{\omega,t}(\bar{\omega}_t^P) - F_{\omega,t}(\omega_t^{*,brP})) r^{gov} \right],$$

where G_t is government expenditure in the baseline model without bridge loans. For the baseline case of full government guarantees $I_{br} = 1$ and debt forgiveness $r^{gov} = -1$, government spending goes up by $F_{\omega,t}(\bar{\omega}_t^P)\bar{A}^{brP}W_t$, i.e. the wage bill multiple $\bar{A}^{brP}$ for all firms that participate.

Taxes are

$$T_t^{br} = T_t - \tau^{\Pi}(F_{\omega,t}(\bar{\omega}_t^P) - F_{\omega,t}(\omega_t^{*,brP}))(r^{br} + r^{gov})\bar{A}^{brP}W_t.$$

Tax revenue is lower by the tax benefit to firms on bridge loan interest.

Deadweight Losses

DWL from bridge loans are

$$\zeta^{br}\eta^P F_{\omega,t}(\omega_t^{*,brP})\bar{A}^{brP}W_t.$$

These need to be added to aggregate deadweight losses from the baseline model. Similarly,

$$\zeta^{br}(1-\eta^P)F_{\omega,t}(\omega_t^{*,brP})\bar{A}^{brP}W_t$$

needs to refunded to households as a transfer.

B Conditional Bridge Loans

Firms

At the liquidity stage before defaults, firms with productivity below $\bar{\omega}_t^C$ receive a bridge loan $\bar{A}^{brC}(1-\omega_t)a_t^P$ from banks such that their

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profit is

$$\pi_t = \omega_t Z_t k_t^{1-\alpha} l_t^{\alpha} - \sum_j w_t^j l_t^j - (1 - \bar{A}^{brC} + \bar{A}^{brC}\omega_t) a_t^P - \varsigma k_t. \tag{8}$$

Firms now need to repay $\omega_t a_t^P$ in total, where a_t^P are the principal and interest payments due this period. Producers with $\pi_t < 0$ are in default and shut down. This implies a default threshold in the presence of bridge loans $\omega_t^{*,brC}$ given in equation (4) in the main text.

Non-defaulting firms immediately repay the bridge loan after the liquidity stage of the problem. Their net worth is only reduced by the interest payments associated with bridge loans, relative to the baseline model without such loans. The interest expense on the bridge loans, taking into account tax deductibility of interest, is:

$$(r^{br} + r^{gov})(1 - \tau^{\Pi})\bar{A}^{brC}(1 - \omega_t) a_t^P.$$

Individual producer net worth at the beginning of next period becomes:

$$\begin{aligned} \Pi(\omega', \tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t) = &(1 - \tau^{\Pi})\omega' Z_t^A \tilde{k}_t^{1-\alpha} \tilde{l}(\tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t)^{\alpha} \\ &- (1 - \tau^{\Pi}) \sum_j w_t^j \tilde{l}^j(\tilde{k}_t, \tilde{a}_t^P, \mathcal{S}_t) \\ &+ \left((1 - (1 - \tau^{\Pi})\delta_K) p_t - (1 - \tau^{\Pi})\varsigma\right) \tilde{k}_t \\ &- \left(1 - \tau^{\Pi} + \delta q_t^m\right) \tilde{a}_t^P \\ &- (r^{br} + r^{gov})(1 - \tau^{\Pi})\bar{A}^{brC}(1 - \omega') a_t^P. \end{aligned} \tag{9}$$

This implies that bridge loans without interest, $r^{br} = r^{gov} = 0$, leave the net worth of surviving firms and their dividends unchanged. Aggregate firm net worth needs to be reduced by the collective interest expense on the bridge loans by integrating across producers. To do this, we denote the aggregate bridge loan amount going to no-defaulting producers as

$$A_t^{brC} = \left((1 - F_t(\omega_t^{*,br}))(1 - \omega^{+,brC}) - (1 - F_t(\bar{\omega}_t^C))(1 - \omega^{+,C})\right) \bar{A}^{brC} A_t^P, \tag{10}$$

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where we have defined

$$\omega_t^{+,brC} = \mathrm{E}_{\omega,t}\left[\omega \,|\, \omega \geq \omega_t^{*,br}\right]$$

and

$$\omega_t^{+,C} = \mathrm{E}_{\omega,t}\left[\omega \,|\, \omega \geq \bar{\omega}_t^{C}\right].$$

Total interest expenses for producers are

$$(1-\tau^{\Pi})(r^{br}+r^{gov})A_t^{brC}.$$

Banks

Bridge loans are junior to regular loans/bonds. Thus, defaulting firms do not pay back bridge loans. Lenders (banks and savers) apply bridge loan cash of defaulting firms towards the recovery value of regular loans/bonds. They can recover a fraction $1-\zeta_t^{br}$ of each dollar of bridge loan. The total recovery per outstanding face value is:

$$\begin{aligned} M_t =& \frac{F_{\omega,t}(\omega_t^{*,brC})}{A_t^P}\left[(1-\zeta^P)\left(\omega_t^{-,br}Y_t + ((1-\delta_K)p_t - \varsigma)\,K_t\right)\right.\\ &\left.-\sum_j w_t^j \bar{L}^j + \bar{A}^{brC}(1-\zeta^{br})(1-\omega_t^{-,brC})\right], \end{aligned} \tag{11}$$

where we have defined

$$\omega_t^{-,brC} = \mathrm{E}_{\omega,t}\left[\omega \,|\, \omega < \omega_t^{*,brC}\right].$$

How bank wealth is affected by bridge loans depends on whether the government takes on losses incurred on these loans, i.e. whether it guarantees those loans. Aggregate bridge loan losses are:

$$O_t^{brC} = \int_0^{\omega_t^{*,br}} (1-\omega)\,dF_t(\omega)\,\bar{A}^{brC}A_t^P = F_{\omega,t}(\omega_t^{*,br})(1-\omega_t^{-,br})\bar{A}^{brC}A_t^P.$$

The variable I_{br} measures the fraction of losses that the government absorbs; it is between 0 (no guarantees) and 1 (full guarantee). We assume that banks receive the interest income from bridge loans, regardless of the government guarantees that are in place. Then bank

net worth is:

$$N_t^{I,br} = N_t^I + r^{br} A_t^{brC} - (1 - I_{br}) O_t^{brC},$$

where N_t^I is bank net worth in the baseline model without bridge loans.

Government

Government expenditure is

$$G_t^{br} = G_t + I_{br} O_t^{brC} - r^{gov} A_t^{brC},$$

where G_t is government expenditure in the baseline model without bridge loans. As for the unconditional loans, the baseline case of full government guarantees with $I_{br} = 1$ and $r^{gov} = -1$ implies that government spending rises by the full amount of the loan program

$$F_t(\bar{\omega}_t^C))(1 - \omega^{-,C}) \bar{A}^{brC} A_t^P,$$

with $\omega^{-,C} = \mathrm{E}_{\omega,t}\left[\omega \,|\, \omega < \bar{\omega}_t^C\right]$.

Taxes are

$$T_t^{br} = T_t - \tau^{\Pi}(r^{br} + r^{gov}) A_t^{brC}.$$

Tax revenue is lower by the tax benefit to firms on bridge loan interest.

Deadweight Losses

DWL from bridge loans are

$$\zeta^{br} \eta^P O_t^{brC}.$$

These need to be added to aggregate deadweight losses from the baseline model. Similarly,

$$\zeta^{br}(1 - \eta^P) O_t^{brC}$$

needs to refunded to households as a transfer.

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The (structural) gravity of epidemics[1]

Alejandro Cuñat[2] and Robert Zymek[3]

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Epidemiological models assume gravity-like interactions of individuals across space without microfoundations. We combine a simple epidemiological framework with a dynamic model of individual location choice. The model predicts that flows of people across space obey a structural gravity equation. By means of an application to data from Great Britain we show that our structural-gravity framework: provides a rationale for quarantines; offers a clear mapping from observed geography to the spread of a disease; and makes it possible to evaluate the welfare impact of (expected and unexpected) mobility restrictions in the face of a deadly epidemic.

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1 This work contains statistical data from the 2011 UK Census which is Crown Copyright. We are grateful to webinar participants at the University of Edinburgh for helpful comments and suggestions. Zymek gratefully acknowledges financial support from the UK Economic and Social Research Council (ESRC) under award ES/L009633/1.

2 Professor of Economics, University of Vienna.

3 Assistant Professor of Economics, University of Edinburgh.

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1 Introduction

The Covid-19 epidemic has thrust epidemiological models into the limelight. The "Imperial College study" (Ferguson et al., 2020) received widespread public attention, and is credited with having changed the UK Government's stance on slowing the spread of the disease. Economists have started to integrate macroeconomic and epidemiological models in order to analyse jointly the economic and public-health impacts of different government interventions.[1]

Disease transmission models such as the one used in Ferguson et al. (2020) assume that people interact across space in inverse proportion to (relative) distance.[2] The epidemiological literature explicitly refers to this as a "gravity" assumption.[3] However, the functional forms assumed do not have a choice-theoretic microfoundation and are calibrated from available mobility data in an *ad hoc* manner. This precludes a formal welfare analysis of prominent interventions, such as mobility restrictions, on the basis of these models. Meanwhile, the first economic models of the epidemic have combined fully microfounded models of the macroeconomy with epidemiological frameworks by introducing somewhat arbitrary assumptions about how the disease transmission is affected by economic activity.[4] This introduces new macro parameters that are difficult to calibrate with any degree of confidence.

In the present paper, we show that economists already possess a toolkit for improving on both approaches: structural-gravity modelling. Structural gravity models are now common in international trade, where they are used to study the observed pattern of economic interactions across space and to assess the impact of trade-policy changes. They have provided simple microfoundations to explain why certain types of data – such as trade, migration or commuting flows – exhibit "gravity" patterns. There exist well-understood empirical approaches for estimating the impact of geography on interactions consistently with these models. Moreover, such models share convenient properties that make it easy to analyse the welfare impact of barriers that restrict interactions across space.

By way of illustration, we combine a simple epidemiological framework – the SIR model (Kermack and McKendrick, 1927) – with a basic dynamic model of individual location choice. The model makes assumptions that ensure that flows of people across space obey a structural gravity equation. To demonstrate the uses of our structural-gravity SIR framework, we calibrate it to match regional mobility patterns from

[1] See Atkeson (2020), Beenstock and Dai (2020), Eichenbaum et al. (2020), González-Eiras and Niepelt (2020).

[2] See the supplementary information of Ferguson et al. (2005) for a full description of the model, and Ferguson et al. (2006) for a discussion of its calibration to UK data.

[3] A detailed discussion can be found in Xia et al. (2004).

[4] For example, both Eichenbaum et al. (2020) and González-Eiras and Niepelt (2020) simply introduce the macro-level assumption that the infection rate of the disease is a positive function of economic activity.

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British census data. We then use it to simulate the course of an epidemic, inspired by the properties of Covid-19, under different regional quarantine scenarios.

In the model, temporary mobility restrictions reduce welfare but also slow the spread of a disease. As a result, the model captures the welfare trade-off inherent in the imposition of quarantines in a microfounded fashion. Moreover, it highlights key parameters that govern this trade-off and could be estimated from micro data. A suggestive welfare analysis shows that quarantines are welfare-enhancing for reasonable parameter values. It also indicates that such quarantines may be more effective if imposed early, and if they are not anticipated by the public.

Our work borrows a number of insights from the international-trade literature. Anderson (1979) and Anderson and van Wincoop (2003) pioneered the use of structural-gravity models in international trade. We estimate our model using the Poisson Pseudo-Maximum Likelihood (PPML) estimator which was introduced by Santos-Silva and Tenreyro (2006) and ensures a straightforward, theory-consistent estimation of structural gravity models (Fally, 2015). Our structural mobility gravity equation is microfounded using the same choice-theoretic assumptions that underpin the trade gravity equation derived by Eaton and Kortum (2002). As a result, it shares the common welfare properties of this class of models, first pointed out by Arkolakis et al. (2012).

We are not the first to apply structural-gravity modelling in the context of regional mobility. McFadden's (1974) classic study of urban travel demand exploits assumptions that are closely related to the microfoundation of gravity by Eaton and Kortum (2002). Anderson (2011) shows that structural-gravity models can be used in the context of migration flows. Most recently, Monte et al. (2018) use a structural-gravity model to analyse US commuting patterns. However, to the best of our knowledge, ours is the first dynamic structural-gravity model that can be used to simulate regional mobility patterns at high frequencies.

2 Model

2.1 Pre-infection Economy

We begin with a description of the model economy before the arrival of an epidemic.

2.1.1 Assumptions

There are $n = 1, ..., N$ locations. Let L_{nt} denote the mass of people who spend t in location n. For simplicity, we will refer to it as the population of n in t. The total population $L = \sum_n L_{nt}$ is fixed, and there is no aggregate uncertainty. We will think of a period t as representing one day.

The decision problem of person in location n at the start of day t can be represented by the Bellman equation

$$V_t(n) = \max_{n' \in N} \left\{ \ln \left[\frac{u_{n'}}{\delta_{nn't}} z_{n't}(n) \right] + \beta E_t \left[V_{t+1}(n') \right] \right\}, \tag{1}$$

where $\beta \in (0,1)$ denotes the discount factor; $u_{n'} > 0$ is a location-specific, constant flow of utility; $\delta_{nn't} \geq 1$ represents the cost of moving from location n to location n', with $\delta_{nnt} = 1$ for all n; and $z_{n't}(n)$ is a preference shock realised prior to an individual's location choice each t.

The location parameter u_n is a shortcut to the inherent characteristics that make a place attractive, such as its local labour market or the quality of local amenities.[5] In our analysis, the moving cost $\delta_{nn't}$ will reflect bilateral travel costs that vary across places as a result of geography, but are normally constant across time. However, we will consider scenarios in which this moving cost becomes temporarily prohibitive as a result of expected or unexpected government interventions ("quarantines").

The preference shock $z_{n't}(n)$ captures idiosyncratic reasons why an individual may want to move from n to n' on any given day. It is drawn from the Fréchet distribution

$$F_{nn'}(z) = e^{-\omega_{nn'} z^{-\theta}}, \tag{2}$$

where $\omega_{nn'} > 0$, $\omega_{nn} = 1$ for all n, and $\theta > 0$.

2.1.2 Bilateral Flows

The share of people in location n at the start of t who will find it optimal to move to n' is

$$m_{nn't} = \frac{\left(\tau_{nn't}/v_{n't}\right)^{-\theta}}{\sum_{n'=1}^{N} \left(\tau_{nn't}/v_{n't}\right)^{-\theta}}, \tag{3}$$

where $\tau_{nn't} \equiv \omega_{nn'}^{-\frac{1}{\theta}} \delta_{nn't}$ aggregates preferences and travel costs into an overall bilateral mobility barrier, with $\tau_{nnt} = 1$ for all n;

$$v_{nt} \equiv u_n \left[e^{\gamma} \sum_{n'=1}^{N} \left(\tau_{nn't+1}/v_{n't+1}\right)^{-\theta} \right]^{\frac{\beta}{\theta}}, \tag{4}$$

and γ is the Euler-Mascheroni constant. A proof is provided in the online Appendix Section A.1.1.

The share $m_{nn't}$ depends negatively on the mobility barrier between n and n' (relative to all bilateral barriers), and positively on the "place value" of n', $v_{n't}$ (relative to all place values). In turn, the place value of any n comprises the fundamental flow

[5] For simplicity, we assume throughout that u_n is constant at short time horizons.

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utility offered by n, u_n, as well as an index of connectivity, $\left[\sum_{n'} \left(\tau_{nn't+1}/v_{n't+1}\right)^{-\theta}\right]^{1/\theta}$, reflecting the attractiveness of the locations to which n offers access going forward.

The functional form of $m_{nn't}$ implies that we can write the flow of people between locations n and n' on day t as

$$m_{nn't}L_{nt-1} = \left(\frac{\tau_{nn't}}{P_{n't}O_{nt}}\right)^{-\theta} L_{n't}L_{nt-1}, \tag{5}$$

where

$$P_{n't} \equiv \left[\sum_{n=1}^{N}\left(\frac{\tau_{nn't}}{O_{nt}}\right)^{-\theta} L_{nt-1}\right]^{-\frac{1}{\theta}}, \quad O_{nt} \equiv \left[\sum_{n'=1}^{N}\left(\frac{\tau_{nn't}}{P_{n't}}\right)^{-\theta} L_{n't}\right]^{-\frac{1}{\theta}}, \tag{6}$$

and P_{nt} and O_{nt} are the so-called inward and outward multilateral resistance terms (MRTs) of a location n, respectively.[6]

Equation (5) highlights that the flow of people between n and n' can be expressed as proportional to the product of the origin and destination populations, and inversely proportional to bilateral mobility barriers relative to the MRTs. The shape parameter of the Fréchet distribution emerges as the elasticity of bilateral flows with respect to mobility barriers.

2.1.3 Welfare

We assume that mobility barriers pre-infection are (expected to be) constant: $\tau_{nn't} = \tau_{nn'}$ for all t. In this case, $v_{nt} = v_n$ and $m_{nn't} = m_{nn'}$ for all t.

Equation (4) can be re-written as

$$v_n = u_n^{\frac{1}{1-\beta}} \left[\left(e^{-\gamma} m_{nn}\right)^{-\frac{1}{\theta}}\right]^{\frac{\beta}{1-\beta}}. \tag{7}$$

Hence, variations in the connectivity index across locations in the pre-infection economy can be captured empirically by variations in the share of people who stay in their origin locations each period: places that provide easy access to many attractive locations will be characterised by a smaller share of "stayers".

Let V_t/L denote average welfare. In the online Appendix Section A.1.2 we show that

$$\frac{V_t}{L} = \frac{1}{1-\beta}\sum_n \frac{L_{nt-1}}{L}\left(-\frac{1}{\theta}\ln m_{nn} + \ln u_n + \frac{\gamma}{\theta}\right). \tag{8}$$

Suppose a government were to announce a permanent quarantine unexpectedly on day t, setting $\tau_{nnt'} \to \infty$ for all $t' \geq t$. This would imply $m_{nnt'} = 1$ for all $t' \geq t$. Based on equation (8), the welfare impact of such a scenario could be evaluated using

[6] See Head and Mayer (2014) for a proof.

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only information on the distribution of the population across locations $\{L_{nt-1}/L\}_n$, the share of "stayers" in each location, $\{m_{nn}\}_n$, and the mobility elasticity, θ. This mirrors well-established results from the trade literature.[7]

2.2 An Epidemic Outbreak

We now model the course of an epidemic that arrives as an "MIT shock" in the form of some initial infections across locations. We let $\tilde{I}_{n0}$ denote the mass of newly infected individuals on the initial day 0, with $\tilde{I}_{n0} \geq 0$ and $\tilde{I}_{n0} > 0$ for at least one n. Infections carry no inherent disutility, but for the duration of an infection, individuals face a probability π_d of death. For parsimony, the only private and social cost of death is the forgone utility of life.[8]

The dynamics of the epidemic follow a discrete-time version of the SIR model of Kermack and McKendrick (1927): individuals in location n during day t that have not yet contracted the disease are susceptible (S_{nt}); individuals in n that are currently infected (I_{nt}) create new infections among the susceptible in their location; and some infected probabilistically join the recovered (R_{nt}), whereupon they can no longer contract the disease.[9]

2.2.1 New Assumptions

As a result of the probability of death arising from the epidemic, the aggregate population is no longer constant. The population of each location is now made up of the susceptible, infected and recovered, such that

$$L_t = \sum_n L_{nt} = \sum_n \left(S_{nt} + I_{nt} + R_{nt}\right). \tag{9}$$

Each day, the new sequence of events is as follows:

1. All survivors in t find themselves in their location n.
2. Preference shocks $\{z_{n't}(n)\}$ are realised.
3. Agents choose in which n' to spend t.
4. A mass $\tilde{I}_{n't} = \pi_s S_{n't} I_{n't}/L_{n't}$ of the susceptible in n' become newly infected.
5. The non-newly infected recover with probability π_r and die with probability π_d.

[7] See Arkolakis et al. (2012), Costinot and Rodríguez-Clare (2014), and Ossa (2015).
[8] This assumption is discussed more thoroughly in Hall and Jones (2007).
[9] See Allen (1994) for an in-depth treatment of a one-location, discrete-time SIR model.

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2.2.2 Bilateral Flows Revisited

Let $m_{nn't}(S)$, $m_{nn't}(I)$ and $m_{nn't}(R)$ denote the bilateral movement propensities of the susceptible, infected and recovered in the post-outbreak economy. In the online Appendix Section A.2.2, we show that if $\pi_d \to 0$,

$$m_{nn't}(S) \to m_{nn't}(I) \to m_{nn't}(R) = m_{nn't}. \tag{10}$$

Therefore, for small π_d, the susceptible, infected and recovered in location n post-outbreak behave (approximately) like the average person in location n of the pre-infection economy. From now on, we will restrict our attention to epidemic outbreaks characterised by $\pi_d \approx 0$. This allows us to make inferences about the (approximate) behaviour of agents in the wake of an epidemic outbreak from pre-infection mobility data in a straightforward way.

2.2.3 The Geographic Spread of the Epidemic

Assuming $\pi_d \approx 0$, we obtain

$$S_{n't+1} = \sum_n m_{nn't}\left(S_{nt} - \tilde{I}_{nt}\right), \tag{11}$$

$$I_{n't+1} = \sum_n m_{nn't}\left[(1-\pi_r) I_{nt} + \tilde{I}_{nt}\right], \quad \tilde{I}_{nt} = \pi_s \frac{I_{nt} S_{nt}}{L_n}, \tag{12}$$

$$R_{n't+1} = \sum_{n'} m_{nn't}\left(R_{nt} + \pi_r I_{nt}\right), \tag{13}$$

$$I_{n0} = R_{n0} = 0, \quad S_{n0} = L_{n0}, \quad \tilde{I}_{n0} \geq 0. \tag{14}$$

We consider two types of scenarios. In the first, people continue to expect that $\tau_{nn't} = \tau_{nn'}$ for all $t \geq 0$, as in the pre-infection economy. As long as they do, $m_{nn't} = m_{nn'}$. In the second scenario, people expect $\{\tau_{nn't}\}_{n' \neq n, t>0}$ to vary as a result of government action. Given values for $\{u_n\}_n$ and $\{\tau_{n'n}\}_{n' \neq n}$ consistent with the observed pre-infection mobility patterns, $\{m_{n'nt}\}_{n,n',t \geq 0}$ in the post-infection economy can then be derived conditional on mobility-barrier expectations using equations (3) and (4).

2.3 Mobility Barriers and Disease Spread: Two Special Cases

We briefly explore two special cases of the model, characterising the spread of the disease under extreme assumptions about bilateral mobility barriers. These special cases offer some intuition about the impact of mobility barriers – due to geography

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or government policy – on the course of an epidemic. We impose $\pi_d = 0$ for the remainder of this section.

2.3.1 Perfect Mobility

Suppose there are no mobility barriers: $\tau_{nn't} = 1$ for all n, n', t. It is easy to show that in this case $m_{nn'} = L_{n'}/L$ for all n, n'.

It follows immediately from (12) that, irrespective of the distribution of initial infections across n on day 0, infections will be proportional to local populations from day 1 onwards. As a result, the behaviour of $S_t \equiv \sum_n S_{nt}$, $I_t \equiv \sum_n I_{nt}$ and $R_t \equiv \sum_n R_{nt}$ can be characterised completely independently of $\{\tilde{I}_{n0}\}_n$.[10]

2.3.2 No Mobility

Suppose now there are prohibitive mobility barriers: $\tau_{nn't} \to \infty$ for all $n \neq n', t$. In this case, the behaviour of S_t, I_t and R_t will reflect the weighted sum of S_{nt}, I_{nt} and R_{nt} across N autarkic "islands". The spatial distribution of initial infections is now essential.

For different values of t, Figure 1 plots $(I_{nt} + R_{nt})/L_n$ – the share of the population in n that has contracted the disease by day t – against the share of initial infections in the population, $\tilde{I}_{n0}/L_n$. As can be seen from the figure, that relationship is concave for all t. Therefore, unless $\tilde{I}_{n0}/L_n = \sum_n \tilde{I}_{n0}/L$ for all n, the share of infections in the total population, I_t/L_t, will be smaller or equal than it would have been under perfect mobility. In the case in which $\tilde{I}_{n0}/L_n = 0$ for some n it will be strictly smaller forever. This illustrates the case for quarantines: mobility restrictions generally slow the overall spread of a disease in an economy, and they may even prevent some infections all together.[11]

3 Data and Calibration

3.1 Data

3.1.1 Population, Migration and Commuting Flows from 2011 UK Census

To illustrate how our structural-gravity SIR framework can be put into action, we use it to analyse the spread of a disease across local authorities in Great Britain (England, Scotland and Wales). The properties of the disease are inspired by the Covid-19

[10] More details on this special case can be found in the online Appendix Section A.3.2.

[11] The concavity on display in Figure 1 is crucial to this argument. While the graph in the figure is drawn for particular disease parameters, we show in the online Appendix Section A.3.3 that the concave relationship is generic.

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pandemic. Crucially, they include a relatively small average daily probability of death for the infected (see Section 3.2.2).

We rely on information on population, migration and commuting from the latest UK Census, conducted in 2011.[12] The data can be aggregated to the local-authority level using concordances provided by the UK's Office for National Statistics (ONS). The boundaries of local authorities circumscribe areas administered by a single local government, typically a local council. After aggregation, we obtain data for 378 local authorities covering all of Great Britain. The median local-authority district had a population of 130,000 in 2018, with 90% of local-authority populations in the range of 60,000 to 360,000.

The 2011 Census reports information on all regular residents of an area in 2011 who lived at a different address one year prior. It also reports the location of an individual's usual place of residence and place of work in 2011. After aggregation this allows us to compute, for any two local authorities A and B, what share of residents of A moved to B permanently in 2010-11 and what share of residents of A commuted for work to B in 2011. As we show in online Appendix Section B.1.1, the corresponding bilateral flows of migrants and commuters exhibit strong gravity features: both "naive" and structural gravity regressions capture a large share of the variation in bilateral flows observed in the data.

3.1.2 Daily Bilateral Flows of People Between Local Authorities

We combine the Census migration and commuting data to calculate a daily flow of people between any two local authorities. For migrants, we divide the 2010-11 figures by 365 to obtain the daily flow. For commuters, we first "balance" flows to reflect that commuting represents gross flows that do not cause a net change in local populations. For example, if 60 people report commuting from A to B in 2011, and 40 people report commuting from B to A, we put the potential number of people from each place who could spend the day in the other at $(60+40)/2=50$. We then adjust for the fact that commuters will travel between A and B only for half of the average workday. In our example, this implies that on the average day $(5/7-34/365)\times 50/2$ people go for work from A to B, and from B to A, where we assume that the average work week is 5 days and the average annual number of holidays is 34.

Adding average daily migrant and commuter flows thus constructed, we obtain our final measure of the daily bilateral flow of people − including the shares of resident populations that tend to stay within their respective local authorities on the average day. This data is described in more detail in Section B.1.2 of the online Appendix. Unsurprisingly, the bilateral daily flows inherit the gravity features of the underlying variables used to construct it. This can be seen in Table 1.

[12] See Office for National Statistics (2015).

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[Insert Table 1 here]

Column (1) of Table 1 reports the results of a "naive" gravity regression of bilateral flows on only size variables, distance measures and a constant term. Column (2) reports the results of a structural gravity regression of the form

$$m_{nn'}L_n = e^{\Pi_{n'}+\Omega_n+\phi_1 \ln dist_{nn'}+\phi_2 contig_{nn'}}\varepsilon_{nn'}, \tag{15}$$

where $\Pi_{n'}$ is a place-n'-as-destination fixed effect, Ω_n is a place-n-as origin fixed effect; $dist_{nn'}$ and $contig_{nn'}$ are measures of geographic distance; and $\varepsilon_{nn'}$ is an error term. Note that the sets of origin and destination fixed effects are not of full rank, so we impose the restriction $\Pi_N = 0$ for an arbitrary benchmark local authority N. Both the "naive" and structural gravity regressions are estimated in levels using Poisson Pseudo-Maximum Likelihood (PPML). This makes it possible to accommodate the fact that approximately 12% of daily bilateral flows between local authorities are zero. It also allows us to leverage some convenient properties of the PPML estimator in the context of structural gravity models, as discussed in subsection 3.2.1.

Columns (1) and (2) in Table 1 show that gravity-style regressions can account for a large share of the observed variation in bilateral flows of people between local authorities: both columns report very high values of R^2. Moreover, column (2) reveals a distance elasticity of -1.9 and shows that daily bilateral flows between contiguous places are approximately ($e^{.971} =$) 2.6 times as large as between non-contiguous places.

3.2 Calibration

3.2.1 Bilateral Mobility Barriers and Relative Place Values

As shown in Fally (2015), the estimated fixed effects in a PPML specification of equation (15) are consistent with the definition of the inward and outward MRTs in equation (5) and the equilibrium constraints that these need to satisfy.[13] In turn, this implies that our structural gravity regression supplies us with two sets of parameter restrictions of the form

$$\frac{v_n^{-\theta}}{v_N^{-\theta}} = e^{-\hat{\Pi}_n}, \tag{16}$$

$$\tau_{nn'}^{-\theta} = (dist_{nn'})^{\hat{\phi}_1} \left(e^{contig_{nn'}}\right)^{\hat{\phi}_2}. \tag{17}$$

[13] Crucially, in our setting the estimation of (15) by PPML with place-destination and place-origin fixed effects implies:

$$\sum_{n=1}^{N} \hat{m}_{nn'}L_{nt-1} = L_{n't}, \text{ and } \sum_{n'=1}^{N} \hat{m}_{nn'}L_{nt-1} = L_{nt-1}.$$

Equation (16) pins down the place value of any local authority n relative to the benchmark local authority N, as a function of the destination fixed effects and the benchmark's population, and up to the value of θ. Equation (17) yields the level of bilateral mobility barriers as a function of distance, the contiguity indicator, and the coefficient estimates $\hat{\phi}_1$, $\hat{\phi}_2$, up to the value of θ.

These parameter restrictions imply daily bilateral movement propensities

$$\hat{m}_{nn'} = \frac{(dist_{nn'})^{\hat{\phi}_1} \left(e^{contig_{nn'}}\right)^{\hat{\phi}_2} e^{-\hat{\Pi}_{n'}}}{\sum_{n'=1}^{N} (dist_{nn'})^{\hat{\phi}_1} \left(e^{contig_{nn'}}\right)^{\hat{\phi}_2} e^{-\hat{\Pi}_{n'}}}. \tag{18}$$

Note that $\hat{m}_{nn'}$ combines model-consistent estimates of the impact of geography on bilateral mobility with model-consistent estimates of the relative attractiveness of different destinations. This constitutes one of the key advantages of our structural-gravity SIR framework: it provides a clear mapping from geographic observables and regional mobility data into bilateral movement propensities that have choice-theoretic microfoundations and ultimately shape the spread of a disease across space. Using (7), (16) and (18), we can also back out the relative flow utilities associated with different places for a given values of β and θ.

Descriptive statistics for the relative place values, mobility barriers and relative flow utilities derived from our structural gravity regression can be found in the online Appendix Section B.2.1.

3.2.2 Disease Parameters, Initial Infections and Initial Populations

We base our calibration of the disease parameters on the "Imperial College Study" (Ferguson et al., 2020) that assessed the likely spread of the Covid-19 pandemic in the UK and the US in the absence of public intervention as of 16 March 2020. Ferguson et al. (2020) assume that the disease is characterised by a 6.5 day generation period, with an average probability of death of 0.9% among the infected. In line with this, we impose $\pi_d = .009/6.5$ and $\pi_r = .991/6.5$. In our model π_s/π_r represents the so-called "r zero" of the disease. Based on initial evidence from the spread of the pandemic in Wuhan, Ferguson et al. (2020) examine values of the "r zero" between 2.0 and 2.6. We choose a value close to the middle of this range, setting $\pi_s = 2.2\pi_r$.

Official statistics on Covid-19 cases in the UK have been released since 9 March 2020. For our simulations, we seed initial infections at the local-authority level consistent with the pattern of Covid-19 cases reported by the UK, Scottish and Welsh Governments on 10 March 2020. The sources of this data, and distribution of cases, are detailed in the online Appendix Section B.2.2. Ferguson et al. (2020) cite evidence from China and repatriation flights suggesting that 40-50% of infections are not identified as cases. To reflect this, and the relative initial scarcity of Covid-19 testing

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in the UK, we assume that the number of cases reported at the local-authority level on 10 March reflected 30% of actual infections, and set initial infection levels $\{\tilde{I}_{n0}\}_n$ accordingly.

For expositional convenience, we set initial local-authority populations $\{L_{n0}\}_n$ to equal the steady-state populations implied by $\{\hat{m}_{nn'}\}_{n,n'}$. However, these steady-state populations are almost perfectly correlated with 2018 mid-year population estimates for local authorities published by ONS.

3.2.3 Discount Factor, Mobility Elasticity and Value of Life

We set the discount factor to $\beta = .96^{1/365}$, implying an approximately 4% annual discount rate as in Eichenbaum et al. (2020). Since θ is a crucial parameter in our welfare analysis, we experiment with different values. However, in our baseline calibration, we impose $\theta = 3.3$ to reflect evidence on heterogeneity in location preferences from US commuting data (see Monte et al., 2018).

Finally, equations (7) and (16) only pin down place values and flow utilities in *relative* terms. We are thus free to select u_N to determine the absolute values of $\{v_n, u_n\}_n$. This "level" choice has no impact on individuals' location decisions in the model, but it translates into the average daily utility received by agents. By assumption, the only utility consequence of an infection is the risk of death, and the only cost of death is the forgone utility of life. Therefore, u_N emerges as another crucial parameter for the welfare trade-off between mobility restrictions and disease control.

We perform our welfare analysis under two different calibrations of u_N. In the first, we make the conservative assumption that $u_{n'} z_{n't}(n) / \delta_{nn'}$ reflects only the real consumption of an agent from n who spends period t in n.[14] We then set u_N such that average daily consumption is equal to \$126, which corresponds to 2018 UK daily GDP per capita in purchasing-power-adjusted US dollars. In the second calibration, we assume that $u_{n'} z_{n't}(n) / \delta_{nn'}$ reflects a broader notion of value of life, and set its average daily value across the pre-infection population to \$1040. Under the assumption of a 4% annual interest rate, the latter calibration translates into an average value of life of \$9.3m − the economic value of life used by US public authorities, such as the Environmental Protection Agency.

[14]This would be true under the following narrow interpretation of our model assumptions: all agents produce a homogenous, perfectly tradable good and choose locations to maximise their productivity in in t, given by $u_{n'} z_{n't}(n) / \delta_{nn'}$.

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4 Simulations

4.1 Baseline: "Do Nothing"

We first simulate the course of the epidemic in the absence of any public intervention: a "do nothing" scenario. The resulting evolution of the shares of the susceptible, infected and recovered in the total population of Great Britain, as well as the number of deaths per day, are shown in Figure 2 (black lines). The share of the infected peaks at 18,500 per 100,000 population on day 67. The number of deaths per day peaks at 26 per 100,000 population on day 68. Over the entire course of the epidemic 494,000 people die, equivalent to 0.77% of the total population. 85% of the population ultimately contract the disease.

While our model is considerably simpler than the model used in Ferguson et al. (2020), it replicates the aggregate evolution of the Covid-19 epidemic envisaged in their baseline scenario fairly closely. In Ferguson et al. (2020), British infections and deaths in a "do nothing" scenario peak in late-May 2020, around day 70 in our model. The number of deaths per day peaks at 22 per 100,000 population, with a total number of deaths of 510,000 overall. In the long run, 81% of the British population contract the disease.[15]

There is also a short time window during which the model can be evaluated against actual data. After adopting a fairly light-touch approach to the containment of Covid-19 initially, the UK Government imposed a lockdown on 23 March 2020. In the online Appendix Section C.1, we compare the growth of infections reported across the 9 main administrative areas of the British National Healthcare System (NHS) during the 10-23 March period with the model-predicted growth of infections in this regions during days 0-13. We find that model-predicted and observed growth rates are strongly but by no means perfectly correlated.

4.2 Quarantine Scenarios

We now consider 3 regional-quarantine scenarios. In each scenario, the UK Government requires the public not to leave their local-authority districts for 120 days.[16] We choose 120 days because this period is sufficiently long for new infections to have dropped to (almost) zero by its end in each simulation. In all cases, the government commits publicly and credibly to the length of the quarantine. The scenarios only differ as to the date in which the quarantine is introduced, and whether the introduction is expected by the public or not.

[15] See Ferguson et al. (2020), pp. 6-8 and Figures 1 and 2.

[16] However, people may continue to move freely within local authorities. This is much less restrictive than the lockdown actually imposed by the UK Government on 23 March 2020.

4.2.1 120-Day Regional Quarantine from $t = 0$

We first assume the quarantine is introduced as an "MIT shock" along with the original outbreak on day 0. The resulting dynamics of the epidemic are shown in Figure 2 (blue line). It is clear that the course of the epidemic is considerably milder. Infections and deaths peak around the same time as in the baseline scenario, but at much lower levels. In the long run, only 60% of the population contract the disease, and a quarter of the baseline-scenario deaths are avoided.

The relative effectiveness of the day-0 quarantine stems from the fact that a considerable number of local authorities are virus-free on day 0. With an instant quarantine, residents of these local authorities never contract the virus. This can be seen in Figure 3 which compares the regional spread of the disease on day 30 of our simulations across different scenarios. A comparison between panels A and B reveals the local authorities which are "spared" infection as a result of the quarantine. The long-run effect is a smaller share of the recovered and of deaths in the population.

4.2.2 Unexpected 120-Day Regional Quarantine from $t = 13$

We then assume that the quarantine is introduced as an "MIT shock" on day 13, roughly corresponding to the timing of the UK Government's lockdown. Figure 2 (maroon line) illustrates that this delayed quarantine is considerably less effective than the day-0 quarantine: the long-run number of infections and deaths is the same as in the baseline scenario. However, even the delayed quarantine achieves some "flattening of the curve": the peak of deaths and infections occurs later than in the baseline, and the peak number of infections and deaths are somewhat lower.

Unlike on day 0, by day 13 the virus has reached all local authority districts. However, the share of infections in local populations still varies considerably. As shown in Section 2.3.2 mobility restrictions can still slow the spread of a disease in such a setting. This gives rise to the "flattened" maroon curves in Figure 2. It is also evident from a comparison of panels A and C of Figure 3: by day 30, the epidemic has spread more evenly across local authorities if the government does nothing than if a quarantine is unexpectedly introduced on day 13.

4.2.3 Expected 120-Day Regional Quarantine from $t = 13$

Finally, we assume that a quarantine is introduced on day 13, but that the public expects its introduction from day 0. The green line in Figure 2 traces the resulting course of the epidemic. However, it is obscured by the black line, since the course of the disease is virtually the same as in the "do nothing" baseline.

The anticipation of a 120-day regional quarantine on day 13 undoes all "flattening" benefits that would arise if the quarantine were introduced unexpectedly. The reason

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is that individuals re-optimise their locations during days 0-13. For the duration of the quarantine, in which all movements across local-authority boundaries are ruled out, locations with a low connectivity index in normal times gain in utility value relative to locations with a high index. Therefore, there is some reshuffling of populations from the latter to the former before day 13. With the initial conditions we impose in Section 3.2.2, the incidence of infections in period 0 is relatively high in high-connectivity places. Agents' responses in anticipation of the quarantine thus spread the epidemic around the country more quickly.

Panel D of Figure 3 gives some sense of the impact: 30 days into the simulation, and 17 days after the imposition of a regional quarantine, the disease is spread more evenly around the country than in *any* of the other three scenarios.

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4.3 Welfare Comparison

In the wake of an epidemic outbreak, the introduction of a quarantine presents a clear welfare trade-off: while mobility restrictions reduce social welfare in the short run, they may delay – or even prevent – infections and deaths. An advantage of our structural-gravity SIR framework is that it provides a tool to explore this trade off in a parsimonious manner, conditional on the values of a well-specified set of parameters.

Here we proceed with a suggestive welfare assessment of the three quarantine scenarios from Section 4.2 against the "do nothing" baseline. Needless to say, these scenarios do not span the full set of conceivable policy interventions. Moreover, the model we have outlined captures the fundamental trade-off between mobility and disease control in a bare-bones fashion. For these reasons, our welfare analysis should not be taken as the definitive assessment of plausible (or even likely) interventions in the face of a Covid-19-style epidemic. Instead, they only serve to illustrate that structural-gravity SIR can serve as a useful building block upon which to base such assessments.

Table 2 reports log changes in welfare relative to baseline from introducing the three quarantines described in Section 4.2. We report results for two different average values of life (values of u_N): \$126 and \$1040 per day, as discussed in Section 3.2.3. We also vary the value the mobility elasticity, θ, between 2 and 10 with a baseline value of 3.3. All other parameters are held constant.

Across different parametrisation, the table presents a consistent ranking of the alternative scenarios: the instant quarantine significantly improves welfare relative to "doing nothing", while the delayed quarantine constitutes a marginal welfare improvement. The expected delayed quarantine *reduces* welfare, as it introduces temporary mobility restrictions without controlling the spread of the disease. If agents value mobility less (higher values of θ), the welfare improvements from the instant and delayed quarantines are larger. The same is true if the value of life is higher.

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5 Conclusion

We set out to show that insights from structural-gravity modelling may prove useful in the emerging economics of epidemics. To this end, we build a bare-bones model in which flows of people across space are governed by a structural gravity equation, and contribute to the spread of a deadly disease. We demonstrate that the model can be readily applied to real-world data, and captures the fundamental welfare trade-off between mobility restrictions and disease control in a fully microfounded fashion.

Our simple framework could be generalised in a variety of ways to explore this welfare trade-off more thoroughly. Such generalisations may include the incorporation of a formally modelled production side (as in Eichenbaum et al. 2020), heterogeneous agents (as in Acemoglu et al., 2020), or broader welfare costs of infections and hospital-capacity constraints (as in Ferguson et al, 2020). With suitable modifications and the right data, it may also form the basis of an analysis of mobility restrictions and disease spread at the level of neighbourhoods and households, or at the level of countries.

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Dep. variable: # persons from origin going to destination on the average day	(1)	(2)
Ln distance (km)	-1.925***	-1.907***
	(0.015)	(0.013)
= 1 if contiguous	0.977***	0.971***
	(0.057)	(0.053)
Ln population in origin	0.502***	
	(0.029)	
Ln population in destination	0.502***	
	(0.029)	
Observations	142,884	142,884
Places	378	378
Adjusted R^2	.997	.996
Fixed effects:		
- Constant term	Yes	No
- Place-origin	No	Yes
- Place-destination	No	Yes

* $p < .10$; ** $p < .05$; ***$p < .01$;

Table 1: Gravity regressions on daily bilateral flows of people between GB local authorities

Regressions estimated with Poisson Pseudo-Maximum Likelihood (PPML). Robust standard errors in parentheses. The dependent variable is the daily bilateral flow of people from the origin local authority to the destination local authority. This flow is calculated on the basis of UK 2011 Census data (see text for details). "Ln distance (km)" is the natural logarithm of the kilometre distance between the geographic mid-points of the origin and destination local authorities; "= 1 if contiguous" represents a dummy which takes value 1 if two local authorities share a common border, 0 otherwise; "Ln population in origin/destination" is the natural logarithm of the resident population in the origin/destination local authority.

Avg. value of life = \$126 per day			
	Quarantine in		
θ	$t = 0$	$t = 13$ (unexp.)	$t = 13$ (exp.)
2	1.028	.021	-.017
3.3	1.039	.032	-.013
10	1.050	.043	-.008

Avg. value of life = \$1040 per day			
	Quarantine in		
θ	$t = 0$	$t = 13$ (unexp.)	$t = 13$ (exp.)
2	1.489	.042	-.020
3.3	1.500	.056	-.015
10	1.51	.064	-.010

Table 2: Welfare assessments of different quarantine scenarios

The table shows the permanent log change in daily consumption the average agent would require from day 0 to be compensated for the "do nothing" baseline being adopted over a particular quarantine scenario. The required compensations are shown for different values of the mobility elasticity, θ, and different values of the reference local authority's utility flow, u_N (resulting in different average values of life). For details on the calibration, see Section 3.2. For details on the different scenarios, see Sections 4.1-4.3.

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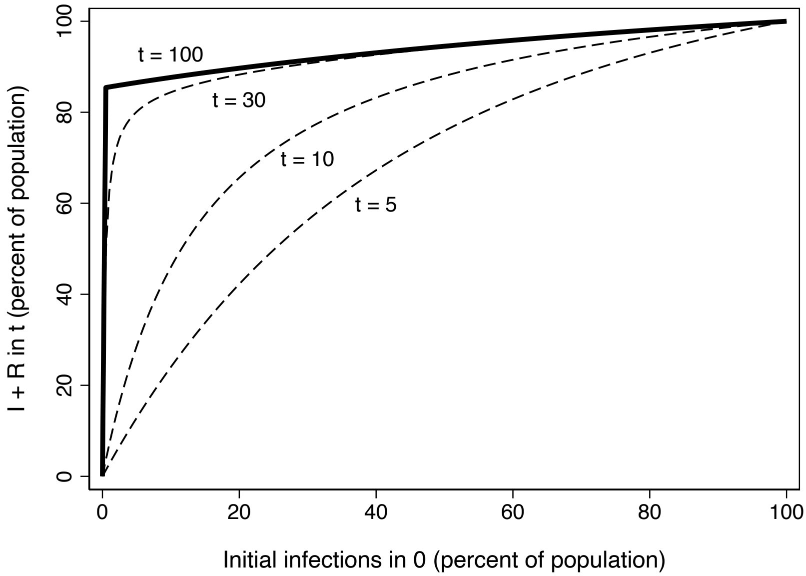

Figure 1: Share of population that has contracted disease in t against share of initial infections

The horizontal axis measures the infections seeded in a(n autarkic) location on day 0, as a percentage of the location's population. The vertical axis measures the number of people who have contracted the disease by day t in that location, $I_{nt} + R_{nt}$, as a percentage of the location's population. Graph drawn using equations (11)-(14) for $t = 5, 10, 30, 100$, imposing $\pi_d = 0$, $\pi_r = 1/6.5$, $\pi_s = 2.2\pi_r$.

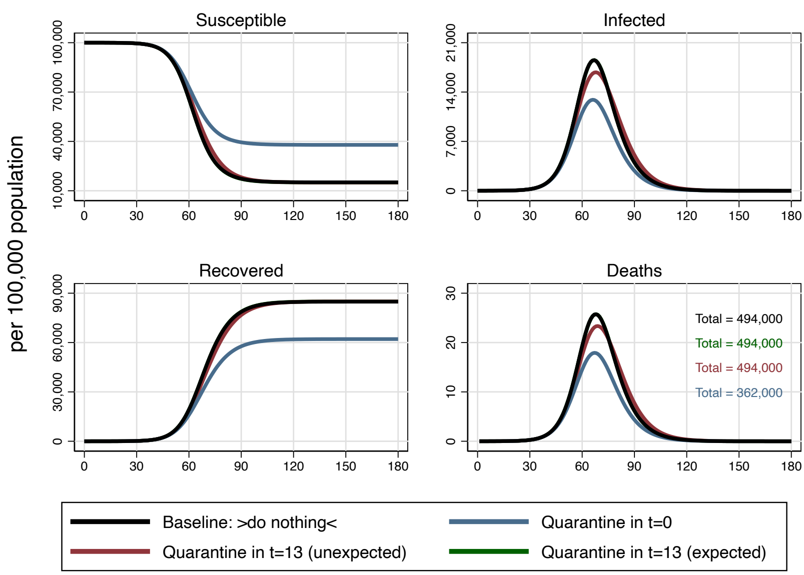

Figure 2: Susceptible, infected, recovered and deaths per day under different scenarios

The top-left panel plots the susceptible per 100,000 population against time in days. The top-right panel plots the infected per 100,000 population against time in days. The bottom-left panel plots the recovered per 100,000 population against time in days. The bottom-right panel plots deaths per day against time in days. All reported output represents Great Britain totals. Black line: baseline "do nothing" scenario (see Section 4.1). Blue line: quarantine in $t = 0$ (see Section 4.2.1). Maroon line: unexpected quarantine in $t = 13$ (see Section 4.2.2). Green line: expected quarantine in $t = 13$ (see Section 4.2.3).

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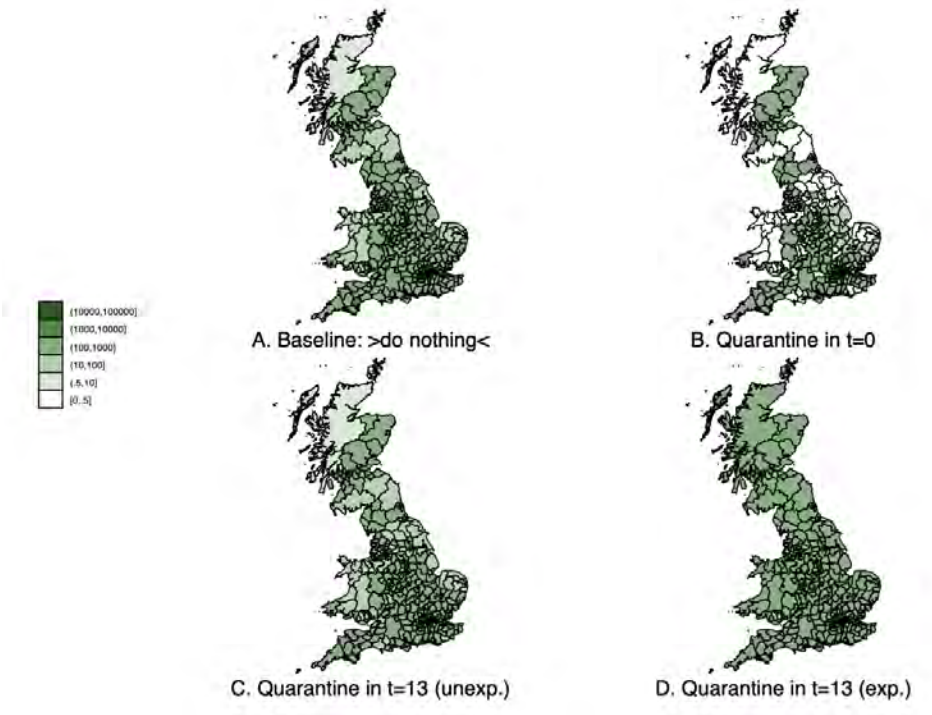

Figure 3: Infections per 100,000 population in $t = 30$ under different scenarios

Total number of infections at the local authority-level (I_{nt}) per 100,000 population in $t = 30$ for four different scenarios. Panel A: baseline "do nothing" scenario (see Section 4.1). Panel B: quarantine in $t = 0$ (see Section 4.2.1). Panel C: unexpected quarantine in $t = 13$ (see Section 4.2.2). Panel D: expected quarantine in $t = 13$ (see Section 4.2.3). Note: Shetland Islands excluded.

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Mitigation of risks of Covid-19 contagion and robotisation: Evidence from Italy[1]

Mauro Caselli,[2] Andrea Fracasso[3] and Silvio Traverso[4]

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The rapid and dramatic diffusion of the Covid-19 epidemic in Italy was tackled by the Italian government with social distancing measures and with the suspension of all economic activities, except "essential" sectors. A lively policy debate on more refined criteria to choose what activities to allow and to suspend in the future led INAIL (National Institute for Insurance against Accidents at Work) to develop a measure of the risk of contagion in the workplace. In this paper we exploit this novel source of information about the risk of contagion in the workplace to study, for the first time, the cross-industry relationship between the estimated risk of contagion at work and the adoption of robots, in order to test the hypothesis that robotisation may facilitate social distancing and lower the risk of contagion. The analysis, which includes various controls of possible automation-related confounding factors and addresses possible issues of endogeneity, provides evidence that industries employing more robots per worker in production tend to exhibit a lower risk of contagion due to Covid-19. Results and policy implications for the selection of suspension criteria are discussed.

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2 Assistant Professor, School of International Studies and Department of Economics and Management, University of Trento.

3 Full Professor, School of International Studies and Department of Economics and Management, University of Trento.

4 Postdoctoral Fellow, School of International Studies, University of Trento.

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1 Introduction

The rapid and dramatic diffusion of the Covid-19 epidemic in Italy in the first quarter of 2020 forced the national authorities to implement measures to curb the transmission of the infection, preserve public health and protect people at work. Preventing physical proximity and limiting the exposure to the disease were the guiding principles that informed the permission to adopt flexible workplace practices whenever possible, the implementation of serious limitations on individual mobility and social interactions, and the decision to discontinue most economic activities on the basis of the alleged risk of contracting and spreading the disease in the workplace.[1]

More precisely, on March 22, 2020, the Italian government provided strong recommendations and established demanding protocols for individual behaviour, and it also decided the temporary suspension (also referred to as lockdown) of almost all economic sectors. Starting from March 25 until May 3, industries were suspended with the exception of those considered as "essential activities", that is necessary to either the survival of the population or to the full operation of the healthcare sector.[2] The identification of the activities not to suspend was based on the existing taxonomy of economic sectors (i.e., the Ateco classification, which is equivalent to the NACE classification). This approach differed from what was done in other countries where the continuation of the activities was decided on the basis of the actual ability of individuals and firms to comply with safety protocols.

This observation has opened a lively policy debate in Italy on what criteria to choose for the immediate future (during the so-called recovery period) and in case of a comeback of the epidemic. Some observers suggested to focus on preserving the functioning of the most intertwined sectors of the economy with a view to reducing bottlenecks along the structure of the production network (as pointed out by Barba Navaretti et al., 2020, and Barrot et al., 2020, while others stressed the primacy of shedding from the risk of being infected (for instance by working at home) those occupations that are most exposed to social and physical proximity (Boeri et al., 2020).[3] The Italian government, in turn, has continuously made reference to the necessity to keep essential activities going: even though the government did not clarify what the term "essential" exactly meant, the

[1]At the time of writing, the debate is still lively on whether the transmission of the virus is higher in the workplace, within households, at school, in nursing homes, and the like. This paper does not take a stance on this and it rather focuses on the decisions made by the authorities regarding the suspension of economic activities. As a matter of fact, the restrictions imposed by the Italian government on social and economic behaviour covered all the categories mentioned above.

[2]On April 10, 2020, another decree extended the number of "essential activities" and allowed entrepreneurs and individual workers to carry out minor activities not related to production.

[3]By integrating O*Net and INAPP data, Boeri et al. (2020) identified which jobs can be performed keeping the risk of infection reasonably low. Their classification is based not only on the possibility of performing the job from remote, but also on the type and the frequency of face-to-face contacts. Using Italian data at the occupation level from INAPP (ICP, equivalent to O*Net), Barbieri et al. (2020) offer a descriptive characterisation of the sectors that were suspended by the Italian governmental decrees and of the workers who are in close physical proximity and more exposed to diseases and infections. A similar exercise has been done by Dingel and Neiman (2020), who use O*Net data on work context and generalised work activities to assess the feasibility of remote working. They conclude that the share of jobs that can be done at home grows with the countries' income level. These results are in line with the conclusions by Saltiel (2020), who adopts STEP, a survey on skills, productivity, and labour market outcomes, designed by the World Bank for developing economies.

common understanding of it is that the adjective applies to pharmaceutical and medical products and services, as well as the production and delivery of food. Contributing to this debate, in late April 2020, INAIL (National Institute for Insurance against Accidents at Work) developed a measure of the risk of contagion in the workplace on the basis of the exposure, the proximity and the aggregation of individual occupations and tasks, and it calculated the average risk of contagion in the workplace for the list of industries used by the Italian government to indicate what sectors not to suspend (INAIL, 2020). As revealed by one of the task forces appointed by the Italian government, the document produced by INAIL was meant to inform the selective lifting of the restrictive measures for the upcoming recovery period.

The taxonomy carried out by INAIL makes it possible for us to document and assess the cross-industry relationship between the estimated risk of contagion at work and an important industry-specific characteristic that has gained relevance in the current policy debate, that is the adoption of robots. As a particular form of automation, robots could help to limit workers' exposure to the virus and to reduce the likelihood that companies might be suspended again in the future. The editorial of volume 40, issue 5 of *Science Robotics*, for instance, maintains that new robot-related solutions are needed to carry out remote operations for applications requiring manipulation in clinical care and disease management (Yang et al., 2020). On April 19, the BBC referred to the possibility that robots may replace human workers to reduce risks and made the example of warehouses where robots are already used to improve efficiency and may now be used for sorting, shipping and packing.[4] Similar stories were reported by the Wall Street Journal in several occasions.[5] On the contrary, the well-known magazine Wired published an article titled "If Robots Steal So Many Jobs, Why Aren't They Saving Us Now?", which was more sceptical about the replacement of human workers.[6]

While the extent of robotisation in the future cannot be addressed statistically yet, the available data allow us to see whether the extent to which robotisation has been adopted across sectors has already had an impact on sectors' risk of contagion. This can lead to an empirical hypothesis, with strong grounds in the economic literature, to test: does the risk of contagion vary across industries according to the intensity of robot adoption? If so, what is the sign of the relation? If negative, it would strengthen the intuition that one way to adapt production to the post-Covid-19 environment is a more intense use of robots in the workplace.

This, in turn, could have valuable implications in designing the incentives and the state aid measures to support the recovery because it raises a potential trade-off between safety and employment at the workplace. Indeed, some observers, such as Dalia Marin on *Project Syndicate*,[7] have already expressed their concerns that the Covid-19 pandemic and the associated recession might eventually create the incentives to introduce labour-replacing automation. Even trade unions would be in a difficult position as the decision would be motivated by the goal of reducing the tasks requiring physical proximity among workers.

Testing the hypothesis and discussing these issues is indeed the object of this paper,

[4]The article can be found at this url.

[5]The related articles can be found at this first url, this second url, and this third url

[6]The article can be found at this url.

[7]The comment can be accessed at this url.

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which, borrowing from the recent work by INAIL, studies for the first time the relationship between the risk of contagion and the adoption of robots across industrial sectors in Italy.[8]

It is worth noticing that this empirical study is made possible by a number of circumstances making Italy an interesting case to study. As Italy was hit first and hardest among the industrialised countries, the government quickly decided to implement a prolonged and generalised suspension of economic activities and to postpone the definition of refined methods to select the activities to suspend or not. This, in turn, has led INAIL to produce a task-based taxonomy of industrial sectors in terms of their differentiated exposure to the risk of contagion in the workplace. The importance, and therefore the degree of accuracy, of such study can be fully appreciated by considering that the suspension of economic activities in Italy was and will be imposed, monitored and sanctioned, rather than simply recommended as instead done in other countries.

As a preview of the main results, the analysis finds that industries that employ more robots per worker in production tend to have a lower risk of contagion due to Covid-19 epidemic. As a by-product, the analysis confirms that the choice of sectors that the Italian government decided not to suspend was not driven by their relative riskiness, in line with the government's claim to preserve "essential" sectors (whatever their riskiness). Our findings confirm that the adoption of robots may contribute to reduce risky interactions. Given the low level of interest rates at the moment, the need to reduce risks of contagion at work may stimulate investment in robotics in the future, in line with anecdotal accounts that a similar trend has already started in China after the suspension of the lockdown. This scenario opens up a number of relevant trade-offs for policymakers.

The remaining of the article develops as follows. Section 2 will be dedicated to present the data used in the empirical analysis, whereas the model to estimate will be described in Section 3. The results of the estimations and their discussion will be included in Section 4. Section 5 will provide some concluding remarks.

2 Data

The analysis in this paper makes use of several data sources. First of all, it takes advantage of the work done by INAIL (2020), which estimates the integrated risk of SARS-CoV-2 contagion in the workplace by two-digit NACE revision 2 industries (divisions). As anticipated, the risk of contagion in the workplace is classified on the basis of three components: i) exposure, defined as the probability of coming in contact with the virus on a scale from 0 to 4; ii) proximity, related to the intrinsic job characteristics that may not permit sufficient social distancing, also defined on a scale from 0 to 4; iii) the product of the first two components is then multiplied by aggregation, a factor ranging from 1 to 1.5 that describes whether some forms of contact with other people other than work colleagues is required by a specific job. The resulting values at the job level are

[8]It is important to notice that the classification of occupations used by INAIL differs from the O*Net Classification developed in the US. While sharing the same logic, the Italian classification adheres more closely to the specific features of the Italian labour market and industrial characteristics. This is particularly important given that the risk of contagion at the level of occupations are consistently grouped at the sectoral level by leveraging on the exact sectoral composition of the labour force. Boeri et al. (2020) have explored a different approach for they had to integrate the US-based O*Net classification and INAPP data.

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Table 1: Descriptive statistics

	Mean	St. Dev.	25th pct	Median	75th pct
Risk of Covid-19 contagion	1.324	0.679	1	1	1
Robots per 1000 workers	5.029	12.584	0.003	0.133	4.515

Notes: The table shows the mean, standard deviation, 25th percentile, median and 75th percentile for the risk of Covid-19 contagion in the workplace in Italy, and the number of robots per 1000 workers in 2017. The number of observations is 259.

then aggregated at the level of two-digit industries and mapped into four integrated risk categories: low (which we assign value 1), medium-low (value 2), medium-high (value 3) and high (value 4).[9]

Data on robots were purchased from the International Federation of Robotics (IFR), which defines an industrial robot as "an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". The IFR dataset contains the stocks of industrial robots purchased in Italy and other countries (for our purposes, Japan and South Korea) by industry (up to three digits for specific industries) and by year for the period from 1993 to 2017, which is the year used in our analysis. The IFR data are based on the ISIC revision 4 classification and it is possible to easily match such data with employment data at the three-digit NACE industry level from the 2011 census of industries and services (CIS) to construct robot use per 1000 workers and with the INAIL data above.[10]

Finally, our analysis includes a set of confounding variables that make it possible to control for other industry characteristics. In particular, we are interested in controlling for other factors related to the automation of the production process so as to make sure that we capture how robotisation, rather than other related factors, affect the risk of contagion. Accordingly, we make use of data from ISTAT (Italy's National Institute of Statistics) based on the survey on information and communication technology (ICT) in enterprises. This survey covers the universe of enterprises with 10 or more persons employed active and different variables related to the use and purchases of ICT by firms are made freely available for different years and at aggregate (either one- or two-digit) industry levels.

Table 1 shows some summary statistics for the two main variables used in our analysis, that is, the risk of Covid-19 contagion in Italy, and the number of robots per 1000 workers. Just over 75% of three-digit industries are categorised as having a low risk of virus contagion for their workers. Table 1 also shows that there are about 5 robots per 1000 workers in Italy, even though this variable shows considerable variability across

[9]Interestingly, INAIL (2020) provides also information on the decree of March 25, 2020, regarding the suspension of narrowly-defined activities (up to six digits) done by the Italian government to contain the spread of the virus. In this paper, we use information at the level of three-digit industries (groups) and define a whole industry as suspended if the majority of its six-digit activities were suspended.

[10]For Italy, we use the 2011 CIS data for employment because they are the only data that include all industries and sectors. The latest available year for private non-agricultural sectors from ISTAT is 2017 based on the database ASIA UL. We check the robustness of our results by constructing robots per 1000 workers using ASIA UL and all the results do not change qualitatively. For Japan and Korea, we collect employment data at the industry level from World KLEMS. For these countries, the latest employment data available are 2009 and 2012 respectively.

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industries.

3 Empirical Model

We conduct our analysis by estimating the following model, which is suitable to test the null hypothesis that the number of robots per worker across economic sectors is correlated with their risk of contagion in the workplace:

$$risk_i = \alpha + \beta \ln robpw_i + \gamma x_i + \epsilon_i, \tag{1}$$

where $risk_i$ is the risk of Covid-19 contagion in three-digit industry i in Italy as estimated by INAIL, $\ln robpw_i$ is the log of the number of robots per 1000 workers in industry i in Italy in 2017, x_i is a vector of additional controls at the industry level and ϵ_i is a random error.

The vector x includes several variables useful to control for other ways through which firms can try to increase the automation of the production process. This is important as we would like to reduce the possibility of technology-related omitted factors that, by correlating with the adoption of robots and with the risk of contagion, may confound the estimates of coefficient β. More specifically, the vector of additional controls includes: the percentage of firms buying cloud computing services in 2018; the percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; the percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; the percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; the percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; and the percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. This last variable was also used by Barrot et al. (2020) as a proxy for home workers. We posit that this set of controls is effective to capturing those technology-related features of companies operating in different economic sectors that may also be associated with robotisation. In so doing, we believe that the empirical analysis captures specifically the role of robots, rather than other forms of automation and investment in ICT.

Our measure of robotisation of an industry is taken from 2017 as this is the latest robotisation data available to us at the time of the analysis. However, the fact that the robotisation variable predates the risk of Covid-19 contagion (calculated using 2019 data on the labour force) does not fully exclude the possibility of endogeneity. In particular, in this case, there could be omitted variables that affect at the same time the degree of robotisation of an industry and its level of risk of Covid-19 contagion. Such factors could be related either to the specific technologies used in that industry in Italy, such as other modes of automation not included in the additional controls, or to other industry-specific features, such as the strength of trade unions, which might be related with decisions to adopt robots and with worker density in the workplace.

In order to tackle this potential issue of endogeneity, we run additional regressions based on the 2-Stage-Least-Square (2SLS) estimator. In particular, we instrument the log of the number of robots per 1000 workers in Italy with the same variable for Japan and for South Korea. The idea behind the use of these instruments is that we want to

capture the exogenous technological differences that exist across industries and that lead to different use of robots in the production process. We choose Japan and South Korea because they show among the highest robot adoption rates, they provide reliable and readily available data on employment by industry, and they are not part of the European Union and so are less likely to be influenced by robot adoption in Italy. We will not only show that these instruments are informative, but given that we have more instruments that endogenous variables we can also provide some evidence that the instruments are valid.

4 Results

4.1 Risk and robotisation

This section presents the results of the analysis of the cross-industry relationship between robotisation and the risk of Covid-19 contagion. The first two columns of Table 2 report the estimation results of equation (1) based on the OLS estimator (without and with additional controls, respectively), while the last two columns show the estimates based on the 2SLS estimator (again without and with additional controls, respectively). It can be noticed that the R-squared ranges from 0.15 to 0.27, which we consider as satisfactory given the lack of any fixed effects. More importantly, the instruments used in the 2SLS specifications are not only informative as the Kleibergen-Paap F statistics are rather high (and higher than the corresponding Stock-Yogo critical values), but they also seem to be valid as the Hansen J statistics are low enough that we cannot reject the null hypothesis of exogeneity of the instruments.[11]

The estimates in Table 2 indicate that, in all cases, industries that employ more robots per worker in production tend to have a lower risk of contagion due to Covid-19. The coefficient is relatively stable across the four specifications, ranging from -0.069 to -0.119. This implies that other controls do not seem to drive the results and that our robotisation measure is robust to potential endogeneity. If one considers that the risk of contagion is a discrete variable with a fairly left-skewed distribution, this finding is worth noticing. Based on the specification in which we use the 2SLS estimator with additional controls, the size of the estimated coefficient implies that an increase in the use of robots equal to the difference in robot usage between the industry at 25th percentile and that at the 75th percentile is associated with a lower risk of contagion by approximately one standard deviation.[12]

These findings provide evidence in favour of the hypothesis that the more intense and diffuse is the adoption of robots, the lower the need for workers to operate in physical proximity and the lower the risk of contagion. However, our findings should be interpreted with care if one would like to draw policy recommendations from this. To start, it is not clear to what extent it is possible to increase further the adoption of robots in all sectors. It is possible that robotisation has already reached its limits in certain industries, or that

[11]Appendix A shows the results of the first stage regressions.

[12]The results are robust to the exclusion of industries strictly related to the provision of health services and social assistance (industries 86-88 according to NACE revision 2), in which risk is obviously relatively higher but robot adoption is limited at best. In addition, as our measure of risk is at the two-digit level, we re-run all the above regressions at this more aggregated level and we show that the results are robust to the level of aggregation. These additional results are provided in Appendix B.

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Table 2: Effects of robotisation on risk of Covid-19 contagion, Italy

	Baseline OLS (1)	Add controls OLS (2)	Baseline 2SLS (3)	Add controls 2SLS (4)
Robots per 1000 workers, ln	-0.073***	-0.119***	-0.069***	-0.098***
	(0.004)	(0.023)	(0.005)	(0.031)
Additional controls	no	yes	no	yes
Observations	259	257	259	257
R-squared	0.152	0.272	0.151	0.267
Kleibergen-Paap F			61.31	21.32
Hansen J			1.357	1.975

Notes: The dependent variable is the risk of Covid-19 contagion by industry in Italy as estimated by INAIL. The additional controls in columns (2) and (4) are: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. The 2SLS specifications instrument the log of the number of robots per 1000 workers in Italy in 2017 using the same variables for Japan and South Korea. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. *** indicate coefficients significantly different from zero at the 1% level.

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most small enterprises have neither the means nor the scale to purchase robots. Even assuming that there is indeed further room to boost the adoption of robots, thereby reducing risk, it is worth recalling that this would have, in the short term, an impact on employment levels. As shown by previous studies (such as Acemoglu and Restrepo, 2019; Chiacchio et al., 2018; Dauth et al., 2017; Graetz and Michaels, 2018), robotisation may be overall beneficial to workers for its positive impact on average productivity in the country, but this can hardly be the case in a period characterised by subdued demand and by the termination of short-term contracts after the lockdown.

There is rich evidence that automation and robots mainly substitute routine and manual occupations, thereby reducing (ceteris paribus) the number of "human hands" (i.e., people) at work on conveyor belts along the production process (see literature on skill-biased technological change, as discussed in Acemoglu and Autor, 2011). Moreover, as pointed out by Mongey et al. (2020), the jobs characterised by the highest level of physical proximity and by the lowest level of working place flexibility are those associated with poor socioeconomic backgrounds of the workers.[13] In the short and medium term, the adoption of robots to reduce risk at the firm level could indeed hinder the absorption of the labour force expelled by the system. On April 10, the New York Times argued that "broad unease about losing jobs to machines could dissipate as people focus on the benefits of minimising close human contact", even though it also acknowledged that robots may augment workers at first but eventually facilitate reassignment and layoffs. We beg to differ on such positive acceptance of more robotisation in society. Such a situation, for instance, may put trade unions in a difficult position as they will have to face a trade-off

[13]Lekfuangfu et al. (2020) offer similar findings and notice that low-income households face a disproportionately larger risk of income loss from the suspension of economic activities.

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between safety and employment levels.[14] Ultimately, this discussion bears on the policy response that the Italian government may design: for instance, state aid measures and other incentives to upgrade the production process and to adjust it to the presence of social distancing restrictions could be associated with conditions on labour shedding and hoarding. Moreover, this discussion can contribute to the debate initiated by Boeri et al. (2020) and Barba Navaretti et al. (2020), among others, regarding the work-safety trade-off and what criterion should be used to decrease the spread of contagion and, thus, what should be suspended.

4.2 What to suspend: risk vs essentiality

As explained in the introduction, about half of the economic sectors were suspended by the government to contain the spread of the virus. The list includes also many industries that, according to the INAIL document, can be considered at low risk. Indeed, we find a negative raw correlation (-0.237) between industries' risk of contagion and their suspension status. This finding is only seemingly counter-intuitive as the average risk of contagion of an industry may hide the presence of a few (even just one) high-risk tasks that required the entire industry to be suspended.[15] More likely, however, the negative correlation between industries' risk of contagion and their suspension status may be due to the fact that relatively medium- and high-risk industries remained active because they were considered as essential, regardless of their risk. Indeed, the Italian government never claimed to follow an approach related to risk and rather the approach was to shut down each and every activity, but for those considered as essential, such as those connected with pharmaceutical and medical products and services and those related to the production and delivery of food (Boeri et al., 2020; Barbieri et al., 2020).

To substantiate this reading of the decisions made by the government, Table 3 shows the results of the regression for a dummy representing the suspension of three-digit industries after the decree of March 25, 2020, on the risk of contagion. The first column shows that there is a negative and statistically significant correlation between the suspension of an industry and its risk level. In the following two columns, to account for essential sectors, we include dummy variables for the food and healthcare sectors and then further for the utilities and public sectors. In these additional regressions, there is still a negative correlation between suspension and risk of contagion, but this correlation is no longer statistically significant. Thus, the risk of contagion in the workplace played an insignificant role in the Italian government's decision regarding what to suspend.

[14] Interestingly, in a recent comment for *Project Syndicate*, Dalia Marin tackled the issue from a different perspective by noticing that robot adoption will concentrate in large companies and in the sectors that are most exposed to global value chains, thereby accelerating a process of reshoring that will hurt developing countries' growth models, based on the exports of intermediate low-cost manufacturing products. The comment can be accessed at this url.

[15] We recall that the average risk of contagion assigned by INAIL to each of the 259 industries is based on a task-based classification of risks for about 800 occupations heterogeneously distributed across sectors.

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Table 3: Suspension of activities on March 25 and risk of Covid-19 contagion, Italy

	Baseline OLS (1)	Food & Health OLS (2)	Utilities & Public OLS (3)
Risk of contagion	-0.175***	-0.152*	-0.067
	(0.059)	(0.081)	(0.085)
Food & Health	no	yes	yes
Utilities & Public	no	no	yes
Observations	259	259	259
R-squared	0.056	0.126	0.204

Notes: The dependent variable is a dummy equal to one if the industry was suspended by decree of March 25, 2020, in Italy. Food & Health stands for the inclusion of dummy variables for the food sector (industries 1-3 and 10-11 according to NACE revision 2) and the health sector (industries 21 and 86-88 according to NACE revision 2). Utilities & Public stands for the inclusion of dummy variables for the utilities sector (industries 35-39 according to NACE revision 2) and the public sector, including defence and education (industries 84-85 according to NACE revision 2). Standard errors clustered at the two-digit industry level are shown in parentheses. * and *** indicate coefficients significantly different from zero at the 10% and 1% level respectively.

5 Conclusion

Following the rapid and dramatic diffusion of the Covid-19 epidemic in Italy and the measures taken by the Italian government, a lively discussion started regarding different ways to decrease the risk of contagion at work while preserving employment levels. This paper starts off from this debate and studies the cross-industry relationship between a novel measure of the risk of Covid-19 contagion at work computed by INAIL and the adoption of robots. We find evidence that industries employing more robots per worker in production tend to exhibit a lower risk of contagion. Our results are robust to the inclusion of several controls for other forms of automation in production and to potential issues of endogeneity.

This result may tempt readers to see this as an endorsement for a fully automated society or, at the very least, for massive investment in robotisation in order to preserve production and economic activity. However, it is important to consider the trade-off that may exist between safety at work and employment levels.

In this context, we show that the Italian government's decision regarding which activities to suspend (and, thus, which workers to let idle) has not been based on their relative level of risk of contagion at work, but rather on whether an activity could be deemed "essential" or not, that is belonging primarily to the food or healthcare sectors. However, even though risk at work did not necessarily play a role in the Italian government's decision back in March 2020, at the height of the epidemic in Italy, it does not mean that it cannot play a role in the future, especially with regards not only to which activities to re-open first, but also to which activities to suspend in case the epidemic were to come back again in full swing.

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Appendix

A First-Stage Results

Table A1: First-stage results of robotisation

	Baseline (1)	Add controls (2)
Robots per 1000 workers, ln, Japan	1.311***	1.240***
	(0.383)	(0.351)
Robots per 1000 workers, ln, South Korea	-0.240	-0.250
	(0.348)	(0.285)
Additional controls	no	yes
Observations	259	257
Kleibergen-Paap F	61.31	21.32

Notes: The dependent variable is the log of the number of robots per 1000 workers in Italy in 2017. The additional controls in columns (2) and (4) are: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. *** indicate coefficients significantly different from zero at the 1% level.

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B Robustness Checks

Table B1: Effects of robotisation on risk of Covid-19 contagion, Italy, excluding health services

	Baseline OLS (1)	Add controls OLS (2)	Baseline 2SLS (3)	Add controls 2SLS (4)
Robots per 1000 workers, ln	-0.053***	-0.080***	-0.049***	-0.059***
	(0.003)	(0.016)	(0.004)	(0.023)
Additional controls	no	yes	no	yes
Observations	250	248	250	248
R-squared	0.133	0.260	0.132	0.252
Kleibergen-Paap F			57.59	20.06
Hansen J			0.764	1.953

Notes: The dependent variable is the risk of Covid-19 contagion by industry in Italy as estimated by INAIL. The additional controls in columns (2) and (4) are: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. The 2SLS specifications instrument the log of the number of robots per 1000 workers in Italy in 2017 using the same variables for Japan and South Korea. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. *** indicate coefficients significantly different from zero at the 1% level.

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Table B2: Effects of robotisation on risk of Covid-19 contagion, Italy, two-digit level

	Baseline OLS (1)	Add controls OLS (2)	Baseline 2SLS (3)	Add controls 2SLS (4)
Robots per 1000 workers, ln	-0.070***	-0.129***	-0.063***	-0.105***
	(0.006)	(0.023)	(0.009)	(0.034)
Additional controls	no	yes	no	yes
Observations	82	81	82	81
R-squared	0.104	0.238	0.103	0.252
Kleibergen-Paap F			72.24	19.69
Hansen J			0.318	1.628

Notes: The dependent variable is the risk of Covid-19 contagion by two-digit industry in Italy as estimated by INAIL. The additional controls in columns (2) and (4) are: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. The 2SLS specifications instrument the log of the number of robots per 1000 workers in Italy in 2017 using the same variables for Japan and South Korea. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. *** indicate coefficients significantly different from zero at the 1% level.

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In and out lockdowns: Identifying the centrality of economic activities

Giorgio Barba Navaretti,[1] Giacomo Calzolari,[2] Andrea Dossena,[3] Alessandra Lanza[4] and Alberto Franco Pozzolo[5]

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The effects of the Covid lockdown have been very severe in Italy, with a reduction in the value of potential output produced peaking at 69% for the construction and real estate and 63% for Mechanics. As a result, GDP is expected to drop by around 10% in 2020, according to most forecasts. Most activities were reopened on May 4th, although within strict social distancing and health safety guidelines. In this paper we argue that a targeted exit from the lockdown could have been implemented instead. Priority could have been given to those activities with the greatest impact on the national economy. This targeted strategy, combined with an assessment of the inherent health risks of each activity, would have reduced the risks of a second wave of contagion, still reactivating gross output and jobs to a similar extent of the general reopening actually implemented. In this study we propose a methodology to identify production activities for which total or partial closures or reopening would have the greatest impact on the country's GDP, output and employment, using input output tables and network centrality measures in production chains. The administrative lockdown implemented up to May 4th, if kept for one year, would wipe out 52% of GDP. The targeted reopening proposed

1 Professor of Economics, University of Milan; Scientific Director, Centro Studi Luca d'Agliano and CEPR.
2 Professor of Economics, European University Institute and CEPR.
3 Specialist, Prometeia.
4 Senior Partner, Prometeia.
5 Professor, Università Roma Tre.

here would reduce this negative impact by 70%. Our methodology could be applied also in the in the unfortunate event of a new wave of contagion and a new targeted lockdown.

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1. INTRODUCTION

The projections of the International Monetary Fund and of the main research institutes foresee a substantial reduction in world GDP in 2020 of more than 3%, driven by two main factors. On one hand, a supply shock due to the containment policies imposed by governments or by the self-restraint measures adopted by many firms. On the other hand, a demand shock triggered by uncertainty about the future and a decline in incomes and revenues hampering both consumption and investment.

The effects of the containment policies have been especially severe in Italy, with an overall reduction of 44% in the value of potential output produced, peaking at 69% for the construction and real estate and 63% for Mechanics. As a result, GDP in expected to drop close to 10% in 2020.

Closing economic activities, and reopening them when viable, requires a careful and measured action, aimed at minimizing health risks for those returning to work and for the country at large. Yet, at the same time, priority should be given to those activities with the greatest impact on the national economy. How to identify such activities? A similar question would emerge in case a country needs to control the risk of diffusion and thus has to introduce restriction on activities.

In this study, we propose a methodology to identify production activities for which total or partial closures have the greatest negative impact on the country's GDP, output and employment, and therefore have the greatest impact when reopened. Our approach aims at providing a tool for guiding the discussion on how to find a balance between operating safely and allowing the economy work as much as possible.

Understanding how to minimize the impact of the lockdown on the economy is of course important to design the re-opening strategy, but it is even more crucial to be ready to face a possible resurgence of the Covid-19 pandemic in the coming months, or the spread of a new pandemic in the next years. While we all wish that these events will never happen, we cannot risk being again unprepared to face them.

Identifying core sectors of the economy is not easy, because dimension is not the only issue. Given the tangled nature of value-chains, there are activities that weigh little from a quantitative point of view, but are fundamental links in several production chains, and therefore have a significant indirect impact on the production capacity of the country. Unfolding the impact of the interconnections among different sectors of activity has a long tradition in the economic literature, starting at least from the seminal contribution of Vassily Leontief (1936) on Input-Output (IO) relations. A parallel strand of analysis, closer to the business and management literature, has developed from the concept of value chain, building on the seminal contribution of Porter (1985). We merge these two strands of literature, integrating information from the IO matrices of the Italian economy (produced by Istat), with those from the structure of the value chains of the Italian economy, built by Prometeia.[1] To this purpose, we exploit and combine two sets of analytical tools that have been developed in the recent years: the methodology to extract some economics sectors from IO matrices proposed by Dietzenbacher et al. (2013), and the techniques used by social network analysis to identify key players within a system (Jackson, 2008).

We apply our analysis to the case of Italy, where prior to May 4th, 2020 only essential activities were exempted from the lockdown. Our results clearly show how a targeted action on a limited number of

[1] Value chains refers primarily to the value added in each step of production; since we are interested on the relevance of each step for the production and sale of the final goods, in the following we will interchangeably identify these networks as production chains.

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industries, experiencing major lockdowns, can have a very significant impact on aggregate output. The activation of 20 central sectors in the national production system identified with this approach would have increased the value of production of Italian companies from 56% to 76% of the pre-Covid-19 national levels, with a particularly strong impact in some production chains. For instance, output of Mechanics would increase from 37% to 84% and of Constructions from 31% to 77% with respect to their pre-Covid-19 level. The prevailing level of lockdown, if kept for a year long, would have implied a drop in GDP of 52%. The reopening of the sectors identified above would have reduced this fall to 16%.

With our approach we identify three types of activities. First, we identify cross-cutting sectors, generally located upstream in the production processes. These are sizeable suppliers of many production chains at the same time, such as e.g. wholesale of industrial goods; machines for wrapping and packaging. Second, we identify activities with impact contained within a single production chain, but which are sizeable and central in some very large value chains like Automobile or Textile and Clothing. Finally, activities that are quantitatively less significant, but the activation of which is necessary for the functioning of an entire chain, for example chemistry for the Food industry.

This work faces some caveats.

First, we refrain from any epidemiological evaluation or the relative degree of safety of the various activities and how they can be reorganized to reduce the risk of contagion among workers. This is outside our areas of expertise. Yet, it is clear that security concerns are the key factor in the reopening decisions. However, operationally, such concerns will also have to be combined with an assessment of the economic impact of specific activities, as discussed in the present work. Many of the papers that have been written in these last months mainly focus on the epidemiology of the now famous SIR model and its variants, but they often treat the economy as a monolithic single sector. The present paper thus offers a complement to these works.

Second, the economic impact of industries also has a fundamental local dimension at a regional/provincial level in a country, given the heterogeneous spread of economic activities and, from the point of view of safety, the heterogeneous distribution of the outbreaks. It is our intention to extend this work later to include these considerations.

Finally, there is an international dimension to consider, given the global nature of the value chains. There is an issue of locked markets, both for the supply of components and semi-finished products and for the sale of exported products. And there is also an issue of strategic competition. In many cases, foreign competitors were open in certain countries but not in others. For instance, in France and Germany, most of the production activities were not affected by administrative. Seen from the perspective of an individual market, like Italy there is of course a risk of production chains relocating towards other competing countries. In this work, we will take stock of the international openness of industries, but we do not consider potential and actual constraints faced in international markets and we just focus on the national dimension of value chains.

The rest of the paper is organized as follows. Section 2 presents the data uses in the analysis. Section 3 describes the methodology and the intermediate results of each step of the analysis. Section 4 discusses the overall picture and proposes some possible extensions of the analysis.

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2. THE DATA: INPUT-OUTPUT TABLES AND PRODUICTION CHAINS

Ideally, to describe accurately the network of relationships among suppliers and users along a value chain we could use invoice data at the firm level, which are in principle available in some countries like Italy. To evaluate the total impact of the closure of one or more production activities, we would also need to assess the degree of substitutability between suppliers producing similar products, and between similar factors of production. Some suppliers can in fact be easily replaced, others less so. At the same time, some factors of production are essential, energy is a good example, while others may not be necessary for the continuation of production activities, especially if the shortage is limited to a tolerable period of time.

Unfortunately, this detailed information on the relationships between individual firms is rarely available for economic analysis. It is therefore necessary to make the best use of the information available, by integrating different sources, as we do in this paper. Our analysis is based on two main complementary sources: Istat's Input-Output (IO) tables and Prometeia's analysis of the structure of production chains.

Built following a standardized methodology (see, for example, Miller and Blait, 2009), Istat's IO tables report the value of intermediate flows of goods among the 63 sectors of the Italian economy, according to the classification of NACE revision 2 (the Statistical Classification of Economic Activities in the European Community).[2] For each sector, IO tables report along a column the value of the goods purchased from another sector, and value added (capital and labour). Symmetrically, along a row, they report the value of the goods sold to another sector or used to satisfy final demand. Total values are consistent with the aggregates of national accounts.

Both the direct contribution of individual industries to GDP and their ability to activate other branches can be measured by using IO matrices. As it is well known, if production in each sector can be described by fixed-coefficients, such as with a "Leontief technology", IO tables fully capture the upstream impact of changes in downstream sectors. A 10% increase in the final demand of goods produced by a given sector, for example, will cause a proportional increase in the usage of each factor necessary for the production of this good. In turn, this will cause a proportional increase in the usage of all factors necessary for the production of these inputs, and so on recursively according to the process at the basis of Leontief's intuition. While in the long-run a fixed-coefficient technology would be a strong assumption, it is acceptable to describe the short-term impact of an unexpected shock such that caused by the Covid-19 pandemic.

What IO tables are not good at capturing is the impact of changes in upstream sectors on the activities of downstream sectors. Even following the methodology first introduced by Ghosh (1958), when it comes to downstream relationships, the implicit assumption of IO tables is that a 10% contraction in the supply of a given input causes a proportional drop in the production in the downstream sectors, which is the same as assuming that the production technology is linear, implying an infinite elasticity of substitution among inputs. Indeed, this is a strong assumption, that would certainly lead to an underestimation of the impact of shocks in upstream sectors.

To partly overcome the limits of IO tables in studying the impact of shocks in upstream sectors, we have used the information collected by Prometeia on Italy's production chains. It is well known that the Italian economy is characterized by a large number of medium and small firms, intertwined in a web of usually

[2] ATECO, the classification commonly used in Italy, used the national version of NACE revision 2.

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informal connections at the geographical level and at different phases of the production process (Camagni and Silone, 1993). Although a proper and unique definition of production chains is not available, production chains are in fact practical and effective tools of analysis that practitioners use in applied research.[3]

To account for the characteristics of this industrial structure, Prometeia has classified the entire Italian economy into 12 production chains ("filiere produttive"): Agrifood, Automotive, Home: furniture and design, Shipbuilding and aerospace, Construction and real estate, Energy and utility, Mechanics and Engineering, Fashion & beauty, Health, Media and TLC, Land transport and logistic, Tourism and travel. With respect to Italy's GDP, this mapping leaves aside only part of the activities provided by the public sector, such as defense and education. The objective of this classification is to describe "the full range of activities that firms and workers perform to bring a product from its conception to its end use and beyond" (Gereffi and Fernandez-Stark, 2011). Its rationale follows from the analysis of value chains in the business literature (Porter, 1985), and shares many points with the recent literature on global value chains, that are characterized by fragmentation of production processes, specialization in tasks and business functions rather than in the production of specific products.[4]

Within each production chain, identified by the main product or service sold in the final markets, Prometeia has identified all sectors producing goods and services used as inputs, including distribution and support services. The unit of this classification is at the level of 192 micro-sectors, obtained aggregating the Ateco (NACE revision e) classification at 5 digits into cluster of activities characterized by common inputs, working processes and final markets. Each chain is therefore fully characterized by the set of micro-sectors that contribute to the production of the a good or service. In addition, the production chain is split into four major sequential phases in the pace of production: sourcing and raw materials processing, intermediate output and part and component processing, final production of goods or services, distribution (wholesale and retail) and support services.

This provides a complete assessment of the links involved in production chains, including those crucial upstream services for the functioning of most production chains (design, marketing, logistics, etc.), the provision of capital goods for production (e.g., machines for the food industry in agri-food production chain) and the wholesale and retail distributive channels necessary for such products to reach their respective markets. Table 1 describes the agri-food production chain in detail, showing that: 1) agriculture and wholesalers of agricultural products belong to the first stage; 2) firms providing the transformation of agricultural products, producers of food packaging, food processing and manufacturers of packaging machines, producers of food and beverage additives belong to the second stage; 3) producers of final food products ready for consumption (e.g., beer, pasta, pet food) are in the third stage; and 4) distribution (wholesale and retail), logistics and transportation of food products and support to food businesses (certifications, marketing) belong to the fourth stage.

[3] For a discussion see Bidet-Mayer and Toubal (2013).

[4] Starting from the seminal contribution of Antras (2003), the literature on global value chains is burgeoning; for some recent developments, see Antras and Chor (2013), Alfaro et al. (2019), and Cipollina et al. (2020).

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Table 1 – The agri-food production chain

Sourcing and raw materials processing	Intermediate output and part and component processing	Final output products and/or services	Distribution and support services
Agriculture and Fishery	Butchery, meat and other animal products processing	Processed food (pasta, bakery, frozen foods, cheese, ...)	Wholesale trade of food and beverages
Wholesale trade of agricultural products	Milling industry	Non-alcoholic beverages	Retail trade of food and beverages
Chemicals products for agriculture	Chemical products for food processing	Wine, beer and spirits	Maketing, certification and other services for the food industry
	Food and beverage packaging materials	Coffee and tea	Cold chain and other food trasnsportation and logistic
	Machinery for food processing and packaging	Confectionery and chocolate	
		Pet food	

3. <u>EMPIRICAL METHODOLOGY AND INTEMEDIATE RESULTS</u>

Our empirical strategy is based on threes steps. First, among all sectors present in the IO tables, we identify those sectors whose closure causes a larger drop of GDP. Second, we identify the production chains that characterize these sectors and use social network analysis to study the links among each micro-sector. In this way we can identify what are the most central micro-sectors within each production chain. Third, assuming that these micro-sectors contribute to the activity of the entire sector to which they belong in proportion to their output value, we use IO tables to estimate back the impact on GDP of their re-opening. In the following, we will describe each step in detail. The steps are assessed with specific reference to the Italian experience but the approach can be generalized to other countries.

3.1. Input-Output tables

To identify those sectors whose closure causes a larger drop of GDP, we use the methodology proposed by Dietzenbacher and Lahr (2013), simulating the effect of the total or partial lockdown of a sector. In practice, we single out each row of the table referring to one of the 63 sectors of the Italian IO tables and multiply its values (excluding those along the main diagonal, but including those of the final demand) by zero if the sector is fully closed and by its share of activity if only part of the sector is closed. To this purpose, we assume that only essential activities – that are defined by the two decrees promulgated by Italy's Prime Minister on March 22 and April 10, 2020 at a finer disaggregation level than the 63 sectors of the IO tables – are open, and that they contribute to the overall activity of each sector in proportion to their share in its total production.

Proceeding in turn for each sector (i.e., excluding interaction effects), we calculate the impact of a yearly lockdown on GDP. Table 2 below lists those sectors with an impact greater than 3% on GDP.

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Table 2 – Impact of the lockdown on GDP

The table reports the estimates of the drop in GDP caused by the lockdown of a sector's economic activities, excluding essential activities as defined by the decrees promulgated by Italy's Prime Minister on March 22 and April 10, 2020. Only sectors with an estimated drop larger than 3% of GDP are listed.

NACE Code	Description	Impact on GDP (in %)
V28	Manufacture of machinery and equipment n.e.c..	-11,1
VF	Construction	-10,7
V46	Wholesale trade, except of motor vehicles and motorcycles	-9,2
VI	Accommodation and food service activities	-8,7
V29	Manufacture of motor vehicles, trailers and semi-trailers	-8,3
V13_15	Manufacture of textiles wearing apparel, leather and related products	-7,6
V25	Manufacture of fabricated metal products, except machinery and equipment	-7,5
V24	Manufacture of basic metals	-6,4
V31_32	Manufacture of furniture and other manufacturing	-3,4
V22	Manufacture of rubber and plastic products	-3,2
V27	Manufacture of electrical equipment	-3,2
V47	Retail trade, except of motor vehicles and motorcycles	-3,1

The size of the decline in GDP can be decomposed into three factors. First, the size of the sector; second, the degree of interconnection between the sector and others upstream and downstream; third, the degree of closure of the sector imposed by the Ministerial Decrees (i.e., the impact will be larger, the larger the extent of the lockdown).

The impact of the closure of production activities on GDP is consequently not uniform across industries. For example, the decline in GDP of over 10% related to the manufacture of machinery and equipment is because the industry is large, highly interconnected and 70% of its output is foregone because of the administrative restrictions. The lockdown of the construction industry, operating at 30%, is estimated to have a similar impact.

The sectors identified at NACE 2 digits are large and made of heterogeneous activities. At the same time, activities which are relatively small and have small weights in Input Output tables, may provide crucial inputs or crucial outlets to more than one production chain. Hence their closure may endanger a large share of national output anyway. This effect would not be detected by input-output table. For this reason, we must revert to finer industry statistics, and also to the analysis of specific production chains.

3.2. Production chains

In the analysis of the production chains, our unit of analysis is what we call "micro-sector", i.e. the smallest unit of observation available in the chains. Using the terminology of social network analysis, each production chain naturally maps into a weighted and possibly directional graph, in which the node is the micro-sector, the link corresponds to a business relationship, the orientation corresponds to the supplier-

customer direction, and the weight can be measured by the relevance of the links, such as the value or the number of upstream and downstream connections.[5]

In our analysis, we posit the existence of a link between two micro-sectors if they belong to at least one common production chain. Moreover, we weight the link with the number of production chains that each couple of micro-sectors have in common. In practice, if micro-sector A belongs to production chains 1, 2, 3 and 4 and micro-sector B belongs to the production chains 2, 3, 4, 5, 6 and 7, A and B are linked with a weight of 3 (since they are linked in production chains 2, 3 and 4). Using this methodology, and assuming no directionality, we build a 192x192 symmetric adjacency matrix, in which each cell *i,j* represents the weight of the link between micro-sector *i* and micro-sector *j* (with a value of zero if there is no link).

In principles, we could have focused on all the links among the 192 micro-sectors uncovered by our 12 production chains. However, such a network would have been excessively dense and the results difficult to interpret. For this reason, we have focused only on the links among micro-sectors which belong to the 12 sectors listed in Table 2, those whose closure has a stronger negative impact on GDP. We therefore obtain an adjacency matrix with 12,838 potential links, 9,392 of which within a single production chain.[6] Figure 1 reports the degree distribution, depicting on the y-axis the number of micro-sectors that have the number of connections reported on the x-axis (excluding those unconnected).

Having characterized the network of productive relationships, the next step is to identify the most relevant nodes.

[5] See Jackson (2008) and Newman (2010) for a thorough introduction to social network analysis and the methodologies used in this paper.
[6] Restricting to this smaller adjacency matrix is also consistent with the subsequent identification of the most central micro-sector of the basis of the ranking based on eigen values, which is specific to the network considered.

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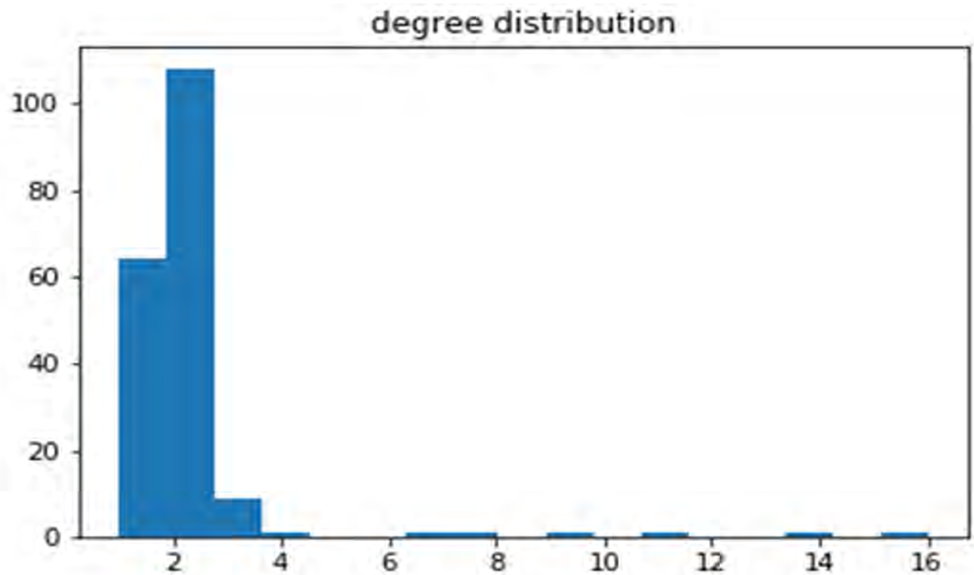
Figure 1 – Network degree distribution

The y-axis reports the number of micro-sectors that have the number of links reported on the x-axis (unconnected micro-sectors are excluded)

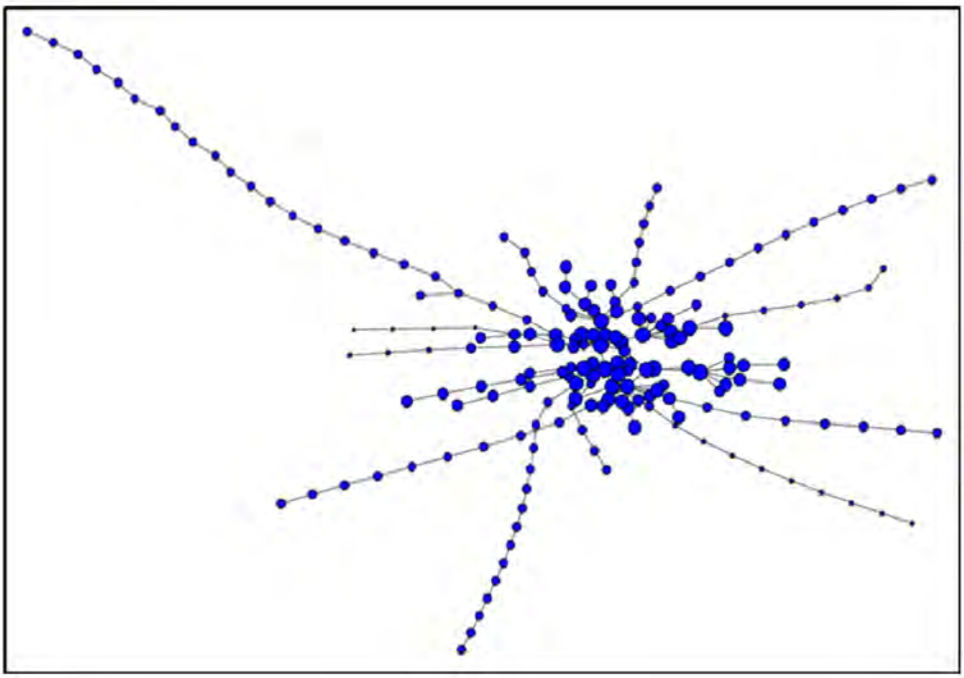


Clearly, the micro-sector with 15 links is more likely to have a prominent role in production than those with just one link. The literature on social networks has proposed several measures to characterize the relevance of each unit (or node) in addition to the number of connections. We choose the eigenvector centrality, that is a measure frequently used to estimate the relative relevance of a node within a network which increases with the number of connections (production chain links) and with the centrality of the nodes with which each node is connected to. Micro-sectors with a higher eigenvector centrality, therefore, are more relevant within each production chain and across a larger number of production chains.

Figure 2 provides a representation of our network, obtained with the Python library *igraph* using the Kamada-Kawai display algorithm. To allow a neater presentation, the graph is first reduced through a maximum spanning tree algorithm (which retains only the strongest links between micro-sectors) and then plotted according to a force directed layout (to spread the sectors dependently on their proximity). Each dot represents a micro-sector, with a size proportional to its eigenvector centrality. The 'tails' in the picture represent production chains and their dots correspond to micro-sectors which only belong to a single production chain, therefore having lower centrality values. Dots in the center represent micro-sectors with higher centrality values, because they interact with a larger number of micro-sectors across different production chains (e.g., wholesalers of intermediate industrial goods).

Figure 2 – Micro-sector's network

Representation of the relationships among micro-sectors within the network of the 12 production chains; each node represents a micro-sectors, with size proportional to its eigenvector centrality.



Having represented the web of production relationships as a network, we have then ranked the micro-sectors according to their eigenvector centrality. In this way we have identified a first group of 20 micro-sectors with a total value of production when fully open of over 820 billion (23% of the total production of the Italian economy). Allowing only for essential activities, as included in the list defined by the two decrees promulgated by Italy's Prime Minister on March 22 and April 10, 2020, these micro-sectors operate at 13% of their potential output (Table 2). Similar figures are reported for employment: of the approximately 4 million people employed before the crisis (22% of the entire economy), just over half a million are at work. When, in addition to those deemed essential, these additional 20 micro-sectors are allowed to produce, the total value of output to rise from 56% of its potential to 76% (similar values also for the number of employees).

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Table 3 – impact of lockdown in central micro-sectors

	% share on Total Economy		Lockdown, in %	
	Value of output	Employees	Value of output	Employees
20 most central	22.8	21.5	86.9	86.1
additional 20	9.4	8.5	91.8	87.3
additional 10	3.9	2.2	74.4	78.2

Nonetheless, in some production chains (e.g., fashion) many core activities, such as clothing and footwear, would still remain closed, making the opening up of the identified micro-sectors within the production chain ineffective. We have therefore considered a second set of 20 additional micro-sectors, which are less central than the initial 20, but still relevant to ensure that the output capacity of some production chains reaches sizeable levels. The total value of output of these additional 20 micro-sectors is 304 billion euros, accounting for 9% of the entire economy. Allowing only essential activities, in lockdown they operate at 8% of their potential output. If, in addition to those deemed essential and the first 20 micro-sectors considered above, also these addition 20 micro-sectors were open, the value of production would rise to 84% of the potential output, with all the chains, with the exception of Construction and Real Estate and Tourism, operating at more than 90% of potential.[7]

Finally, by combining information on the centrality of the network with qualitative assessments regarding the articulation of the individual production chains, one can identify 10 additional micro-sectors. Since they are fairly small, accounting for only 3.9% of total production, they are not identified using our procedure, despite the fact that they are crucial to enable the activity of entire production chains. A prototype example is packaging paper for the food industry or textile finishing in fashion.

Tables 4 and 5 report the values total production and employment in each production chain under the hypotheses that: only essential activities are allowed as contemplated in lockdown (panel 1); the first 20 micro-sectors identified using our procedure are allowed to operate at full capacity (panel 2); the additional 20 micro-sectors are also allowed (panel 3); the additional 10 micro-sectors are also allowed (panel 4).

With just 50 micro-sectors operating at full capacity in addition to those deemed essential, out of a total number of 192, production chains such as Agrifood, Media and TLC, Transport and logistics, Energy and utilities, Health and Mechanics would be almost entirely active (reaching a capacity between 93% and 100%). Furthermore, some important industrial stages would be completely reactivated for the Home and Fashion production chains, such as furniture, home textiles and clothing.

[7] We have considered the centrality of micro-sectors of the original network, unaffected by lockdown. We have also checked ex-post that the central micro-sectors that we identify are also very central in the network that would emerge if they were reactivated. An alternative, and more comprehensive approach that we haven't explored yet (for its computational complexity) is that of identifying the combination of the top 20 micro-sectors by the increase in centrality they bring to the respective network (i.e. the network that would emerge adding these sectors to the economy in lockdown), among all possible combinations of 20 micro-sectors.

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Table 5 – central micro-sectors and total production

The table reports the percentage of total output activated in four different scenarios: Lockdown (Italy), activation of the 20, 40 and 50 most central micro-sectors.

	Lockdown: essential activities Panel 1	Including 20 micro-sectors Panel 2	Including 40 micro-sectors Panel 3	Including 50 micro-sectors Panel 4
Agrifood	81.4	94.2	94.2	95.8
Automotive	46.2	82.3	91.0	91.9
Home: furniture and design	45.3	86.1	90.3	91.7
Shipbuilding and aerospace	40.6	86.9	92.7	93.9
Construction and real estate	31.0	76.8	80.5	81.6
Energy and utility	85.5	94.1	97.8	99.2
Mechanics and Engineering	36.8	83.9	90.4	92.2
Fashion & beauty	48.5	75.2	88.9	90.8
Health	56.9	87.0	89.8	91.6
Media and TLC	96.6	96.6	96.6	100.0
Land transport and logistic	100.0	100.0	100.0	100.0
Tourism and travel	53.4	79.9	81.8	81.8

Table 6 – central micro-sectors and total employment

The table reports the percentage of total employment represented by the 20, 40 and 50 most central micro-sectors.

	Essential activities Panel 1	Including 20 micro-sectors Panel 2	Including 40 micro-sectors Panel 3	Including 50 micro-sectors Panel 4
Automotive	58.9	88.4	93.6	94.4
Home: furniture and design	55.1	85.5	89.5	90.6
Shipbuilding and aerospace	56.9	89.9	94.8	95.7
Construction and real estate	42.3	69.5	72.8	73.4
Energy and utility	86.2	94.5	97.3	98.7
Mechanics and Engineering	58.5	86.3	92.0	93.7
Fashion & beauty	59.6	73.4	87.7	89.5
Health	54.9	80.4	82.5	83.4
Media and TLC	97.4	97.4	97.4	100.0
Land transport and logistic	100.0	100.0	100.0	100.0
Tourism and travel	47.8	73.6	75.8	75.8

To verify the robustness of our results, we have performed two additional checks. First, we have verified that the 40 micro-sectors that we have identified as central would not be operating at a level of production above 75% of full capacity if only the activities defined as essential according to the Ministerial decree were allowed. This confirms that we are identifying micro-sectors whose operations are significantly hindered by the lockdown. Second, we have verified that if we add the 20+20+10 micro-sectors which we have identified as central to a network built considering only those micro-sectors which have more than

75% of their activities defined as essential by the Ministerial decree, all these newly added micro-sectors enter the network with higher levels of centrality than those defined as essential. This confirms that we are identifying micro-sectors whose operations are more central than those defined as essential.

3.3. Impact on GDP

The final step of our methodology is to estimate the impact on GDP of the core micro-sectors identified above. To this aim, we carry out an exercise similar to the one performed to identify the sectors whose closure has a stronger impact on GDP, listed in Table 2. The difference is that now we only focus on the impact of the micro-sectors identified by their centrality in the production network, which represent a subset of all micro-sectors included in each one of the sectors defined according to NACE revision 2 of the IO tables. In practice, we have singled out each row of the table referring to one of the 63 sectors of the Italian IO tables and multiplied its values (excluding those along the main diagonal, but including those of the final demand) by one minus the share of total production represented by essential activities and those of the micro-sectors identified above, therefore assuming that all other micro-sectors included in the given sector are inactive.

Table 7 reports the loss in GDP due to the closure of all but essential activities as in the Italian lockdown, and the losses that would occur under two scenarios: if the first 20 micro-sectors identified by our analysis were opened and then if also the subsequent 20 were reopened. Remarkably, allowing production in the first 20 micro-sectors identified above would reduce the negative impact on GDP of a lockdown of the construction industry by more than 10%. Equally sizeable would be the impact on wholesale trade, excluding that of cars and motorcycles (from 9.2% to 1.7%) and accommodation and restaurant services (from 8.7% to 1.4%). Opening of the second group of 20 micro-sectors would in turn have a sizeable impact for the manufacture of vehicles, trailers and semi-trailers, narrowing the reduction in GDP from 8.3% to 1.4% and also for the manufacture of metal products and textiles.

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Table 7 – Central micro-sectors and GDP

The table reports the estimates of the drop in GDP caused by the lockdown of a sector's economic activities, excluding essential activities as defined by the decrees promulgated by Italy's Prime Minister on March 22 and April 10, 2020 and the 20 or 40 most central micro-sectors.

NACE Code	Description	impact on GDP		
		Essential activities	+20 micro-sectors	+ 40 micro-sectors
V28	Manufacture of machinery and equipment n.e.c..	-11,1	-5,7	-4,4
VF	Construction	-10,7	-0,0	-0,0
V46	Wholesale trade, except of motor vehicles and motorcycles	-9,2	-1,7	-0,3
VI	Accommodation and food service activities	-8,7	-1,4	-0,0
V29	Manufacture of motor vehicles, trailers and semi-trailers	-8,3	-8,3	-1,4
V13_15	Manufacture of textiles wearing apparel, leather and related products	-7,6	-7,2	-5,2
V25	Manufacture of fabricated metal products, except machinery and equipment	-7,5	-2,7	-0,4
V24	Manufacture of basic metals	-6,4	-2,4	-0,0
V31_32	Manufacture of furniture and other manufacturing	-3,4	-3,4	-2,3
V22	Manufacture of rubber and plastic products	-3,2	-1,1	-0,6
V27	Manufacture of electrical equipment	-3,2	-2,2	-1,1
V47	Retail trade, except of motor vehicles and motorcycles	-3,1	-2,6	-1,6

CONCLUSIONS

The Covid-19 pandemic has forced lockdowns in several countries worldwide. Governments were then urged to plan re-openings of economic activities, according to both health and economic criteria. In our view, in defining the trade-off between the reactivation of the activities subject to the lockdown and the health risks that this poses, the economic impact of specific activities should be carefully taken into account, so as to maximize the impact on GDP, minimizing the risk of new epidemic outbreaks.

The methodology described in this paper allows to identify priority activities and sectors by combining information from IO tables with those on the structure of production chains. This approach has the advantage of combining information on the economic relevance of sectors, with a more granular information on the interconnections between the various production stages typical in value chains.

While our exercise is preliminary, the methodology can be widened to consider a number of additional factors, from the geographical dimension of the links in production using regional IO tables, to the international dimension of global production chains. This analytical framework can also be extended to consider the impact of the different probabilities of contagion of each production process.

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Six-country survey on Covid-19[1]

Michèle Belot,[2] Eline van den Broek-Altenburg,[3] Syngjoo Choi,[4] Julian C. Jamison,[5] Nicholas W. Papageorge,[6] and Egon Tripodi[7]

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This paper presents a new data set collected on representative samples across 6 countries: China, South Korea, Japan, Italy, the UK and the four largest states in the US. The information collected relates to work and living situations, income, behavior (such as social-distancing, hand-washing and wearing a face mask), beliefs about the Covid 19 pandemic and exposure to the virus, socio-demographic characteristics and pre-pandemic health characteristics. In each country, the samples are nationally representative along three dimensions: age, gender, and household income, and in the US, it is also representative for race. The data were collected in the third week of April 2020. The data set could be used for multiple purposes, including calibrating certain parameters used in economic and epidemiological models, or for documenting the impact of the crisis on individuals, both in financial and psychological terms, and for understanding the scope for policy intervention by documenting how people have adjusted their behavior as a result of the Covid-19 pandemic and their perceptions regarding the measures implemented in their countries. The data is publicly available.

1 Survey and data col-lection protocol were approved by the ethics board at the University of Exeter (application id eUEBS003014v2.0). The survey was conducted following a suggestion by David Levine and as part of the Covid Research Conduit initiative (http://covid-19-research-conduit.org/). Research funding from the Creative-Pioneering Researchers Program at Seoul National University, and from the European University Institute are gratefully acknowledged. Individual level data collected in anonymous form is being made publicly available at https://osf.io/aubkc/. At this page readers can also find the Online Appendix to this paper.

2 Professor of Economics, European University Institute.
3 Assistant Professor, Larner College of Medicine, University of Vermont.
4 Professor of Economics, Seoul National University.
5 Professor of Economics, University of Exeter.
6 Broadus Mitchell Associate Professor of Economics, Johns Hopkins University.
7 PhD Candidate, Department of Economics, European University Institute.

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1 Introduction

In the context of the current pandemic, a big challenge has been the lack of adequate information on important elements that should guide policy-making. Not only have there been difficulties measuring the prevalence of the disease and its spread in the population, but governments have also had to make decisions with limited information on associated costs and benefits. Levels of population support for different measures have been difficult to gauge, and the scarcity of data has also hampered research efforts. Epidemiologists and economists have had to make predictions and policy recommendations using very limited information about key parameters.

Large data collection initiatives have now been started across the world (e.g. Jones, 2020; Fetzer et al., 2020; Adams-Prassl et al., 2020). We contribute to this effort by presenting a new data set on representative samples across 6 countries: China, South Korea, Japan, Italy, the UK and the four largest states in the US. The information collected relates to work and living situations, income, behavior (such as social-distancing, hand-washing and wearing a face mask), beliefs about the pandemic and exposure to the virus, socio-demographic characteristics and pre-pandemic health characteristics. In each country, the samples are nationally representative along three dimensions: age, gender, and household income. In the United States, where we ask respondents to identify their race, the sample is also nationally representative for race.

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Our aim in this paper is to introduce the data set, which we will make available for public use. The sample consists of roughly 1,000 individuals in each of the six countries where we collected data. We picked these countries because at the time of data collection there were at different stages of the epidemic. These countries also differ in the measures implemented in response to the epidemic and in the course of the epidemic. South Korea, in particular, has been pointed to as an example of success in managing the spread of the disease through early interventions with comparably small economic disruption.

While the data are unique, they do not offer anything close to a final word on a complex set of issues. They should be combined with other resources coming available to generate a more accurate picture. For example, virus or antibody tests collected alongside the type of survey data we collect here would allow researchers to directly link individual characteristics to behavior and infection rates.

Below, we will highlight some key features of the data, including a description of variables, selected summary statistics along with research projects currently underway that use the data. However, the survey was put together hastily, which was necessary to provide real-time information on a rapidly evolving situation, but also has its downsides. Given the seriousness of the topic, we believe thus it is important to discuss some caveats in an effort to prevent researchers from using our data to draw

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unduly strong or unwarranted conclusions.

First, while a core strength of the data set is that we collected information from respondents across several countries, we strongly advise caution in how to interpret cross-country differences. Cross-country variation could arise from nation-specific differences (e.g., culture, institutions or government), the stage of the epidemic at which the data were collected, or country-specific differences in policies. We discuss this issue in more detail below when comparing some variables across countries.

Second, we believe our survey represents a marked improvement in terms of representativeness over surveys using convenience samples or relying on self-selection into this particular type of survey. However, despite balancing the sample on several key socio-demographic characteristics, selection bias remains a concern, meaning it would be problematic to interpret estimated associations as *causal*. For example, income differences in social-distancing behaviors could represent a causal impact of additional income on behavior, but could also represent unobserved factors driving selection into the sample, which vary by income.

Third, we collected data at one point in time, once the pandemic was already underway. Existing surveys that are ongoing (with data collection occurring before and during the pandemic) allow the researcher to observe changes in behavior from before to during (and presumably also after) the pandemic. Our survey collects retrospective information and asks specifically about changes in behavior, which is a useful but problematic substitute (e.g., due to inaccurate recall). The upside is that we were able to ask questions directly pertinent to the current pandemic, such as those on social distancing and beliefs about Covid-19.

Fourth, because the survey was put together quickly, questions were added and dropped midstream. This resulted in some regrettable omissions. For example, we failed to include questions on risk attitudes and highest degree or years of completed education. These kinds of oversights might have been avoided had we had more time and will be corrected in future versions of the survey and data collection efforts.

Despite these limitations, we hope these data help to shed light on some timely and important issues, and we are making them publicly available to accelerate research.

2 Data Collection and Sampling

Our sample consists of approximately 1000 from each of the six countries, for a total of 6082 respondents. The sample is nationally representative along age, gender, and household income. In the United States we sample respondents from the 4 most populous states: California, Florida, New York and Texas. American respondents self-identify their race, and the sample is also nationally representative along this dimension.

Data were collected between April 15 and April 23 with the support of market research companies Lucid for Western countries (Italy, UK and US) and dataSpring for Asian countries (China, Japan and Korea). Potential participants were drawn from several different samples to which the surveying firm has access. Individuals were initially contacted via email to participate in the online survey (programmed in Qualtrics). New invitations were sent up to the point where representativeness

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was achieved on age, gender and household income (along with race in the US).[1] Before participating in the survey respondents review a consent form that specifies that individual-level data will be made publicly available in anonymized form (excluding a short list of health related variables clearly marked in the survey). Prior to starting data collection, we obtained approval for this study from the ethics board at the University of Exeter.

Participation was remunerated according to general compensation schemes defined by the companies for their survey panelists. The median time to complete the survey was about 14 minutes. Respondents were prevented from taking the survey multiple times, and they were excluded for completing the survey too quickly (in under 50% of the median response time). Full contents of the survey for the US are presented in Appendix C.

3 Descriptive Statistics

The information we collected is organized around the following themes:

1. Basic demographic characteristics
2. Health-related variables (including variables relevant to Covid-19 vulnerability)
3. Exposure to the disease
4. Behavioral responses to the epidemic and to the governmental recommendations and restrictions
5. Economic impact (such as impact on labor supply, income and expenditure) and non financial impact of the disease
6. Measures of beliefs about the disease and attitudes towards the policy approach taken by the national governments

In the rest of this section we highlight some interesting facts coming out of this survey.

3.1 Socio-demographics

By construction, because our samples are nationally representative along some key socio-demographics, we obtain that each sample is well balanced for gender and household income quintiles. With adequate representation (see Table 1), our data can also be useful for understanding how most at risk groups (like the elderly) and marginalized groups are affected by the pandemic. For the US, where we collect data on race, we also have adequate representation of racial minorities, with e.g. 11% of respondents identifying as African American/Black.

[1]Further information on samples, including quality control measures, is available at www.luc.id and www.d8aspring.com).

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Table 1: Socio-demographic characteristics

	China	Japan	Korea	Italy	UK	US
			Age distribution			
Age above 65	0.117	0.197	0.134	0.172	0.158	0.229
			Gross household income distribution			
Bottom quintile	$\leq$ ¥25.000	$\leq$ ¥1.900.000	$\leq$ ₩15.000.000	$\leq$ €14.000	$\leq$ £15.000	$\leq$ \$23.000
	0.201	0.204	0.208	0.163	0.177	0.172
Top quintile	$\geq$ ¥86.001	$\geq$ ¥7.320.001	$\geq$ ₩61.000.001	$\geq$ €50.001	$\geq$ £56.001	$\geq$ \$106.001
	0.198	0.162	0.165	0.158	0.214	0.189

Notes: For the income question, respondents choose one of five income brackets, which are obtained by calculating quintiles of the gross household income distribution from the last available wave of nationally representative household surveys (or census data), as available at the Luxembourg Income Study.

3.2 Health

Health data include important variables such as pre-existing conditions of respondents that have been associated with greater risks of experiencing severe complications from the virus, and Covid-19 related symptoms. As Table 2 shows, the share of respondents reporting at least one relevant pre-existing condition is rather high, with Japan (21.2%) and the US (43.8%) recording the minumum and maximum shares respectively. We observe much less variation, though very high levels, in the share of respondents reporting at least one symptom.

Table 2: Pre-existing conditions and symptoms

	China	Japan	Korea	Italy	UK	US
At least 1 relevant pre-existing condition	0.255	0.212	0.269	0.349	0.333	0.438
At least 1 symptom	0.419	0.347	0.498	0.482	0.444	0.429

Notes: Relevant pre-existing conditions include: diabetes, high blood pressure/hypertension, asthma or other chronic respiratory issue, allergies. Relevant symptoms include: dry cough, fever, tiredness, runny nose, sore throat, nasal congestion, aches and pains, diarrhea, loss of smell or taste.

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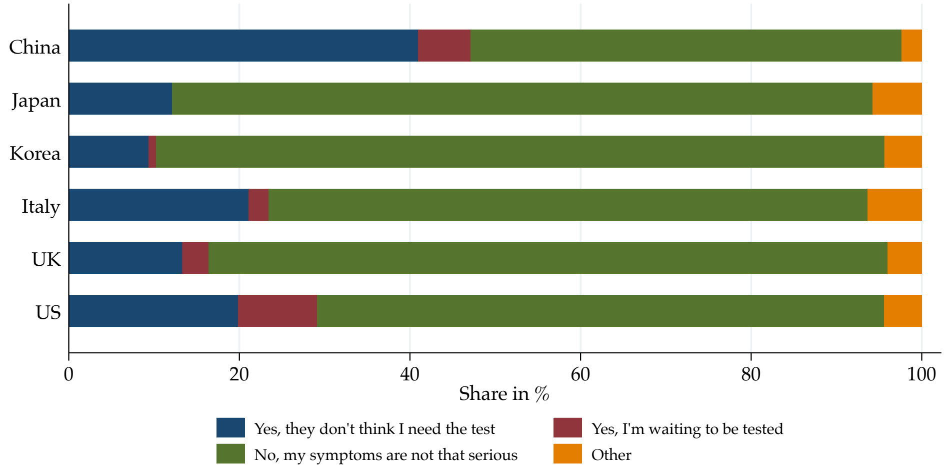

Figure 1: Contacted doctor, conditional on showing any symptom

Figure 1 shows some heterogeneity in how citizens and medical authorities have responded to patients experiencing Covid-19 related symptoms. First, we notice that a much larger share of respondents from China, compared to any other country, have reached out to a doctor after experiencing symptoms. Second, we find that a larger share of people are waiting to be tested in the US and China, suggesting that these countries are facing especially strong mismatch between the demand and supply of testing.

3.3 Exposure

Our data set includes a rich set of variables characterizing exposure, including information on the number of close daily interactions at work and use of public transport during normal times, the number of close daily interactions in the past two weeks, as well as information on household composition and living arrangements. We also elicit information on the job of respondents using a comprehensive list of professions from the US department of labor (O·Net database), which maps professions into risks of exposure to disease and infections.

Living arrangements are potentially an important element in determining the further spread of the disease once measures are relaxed. If the young are allowed back at work, but share their home with older people, it may be difficult to shield the old from the disease. Figure 2 shows the fraction of those age 65 and older who share their home with a younger person (0-18 years old or 18-65). Multi-generation arrangements are common in South Korea, Italy and China, but much less so in the UK, the US and Japan.

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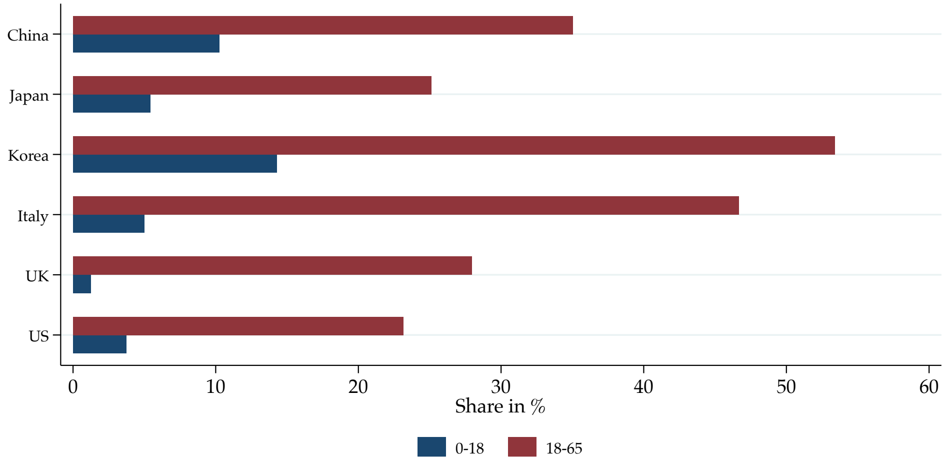

Figure 2: Fraction of 65+ living with children and middle age adults

In Figure 3, we use box plots to report the risks of exposure faced by survey respondents. Risks are measured in two ways. In the left panel, we examine exposure variation by respondent profession. In the right panel, we look at the reported number of daily close contacts at work during normal times. As expected, jobs in groups of industries like health and education appear to put individuals at substantially greater risk of infection according to the professional risk measure from the O·Net database. At the same time, it is interesting to notice that these risks do not closely map to the number of close interactions that respondents report having. Such a disconnect poses a challenge for the calibration of models that treat the spread of infections primarily as a function of the number of contacts and ignore e.g. individual choices that people with different backgrounds might be able to make to mitigate their risks.

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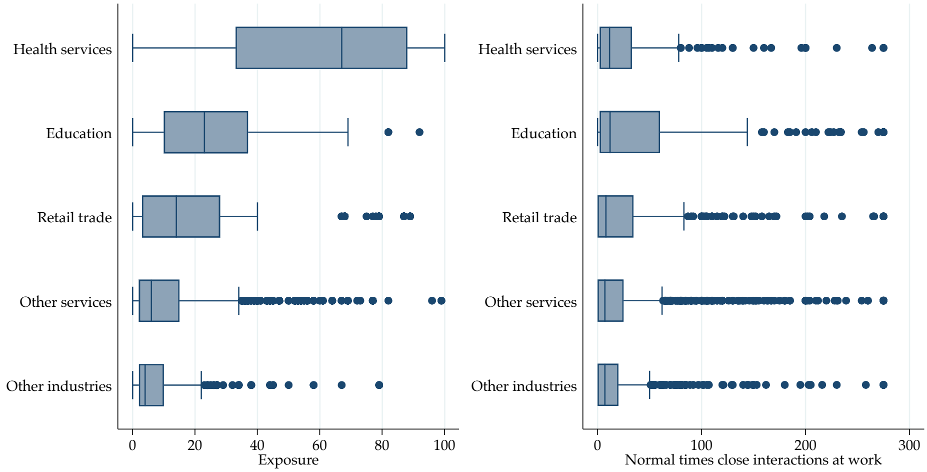

Note: Both panels represents all respondents in employment, by industry. Risk of exposure in the left panel is based on the assessment by profession made by O·Net attributes of the risks of exposure to disease and infections. Other services include: (i) accommodation and food, (ii) administrative and support, (iii) arts, entertainment, and recreation, (iv) finance and insurance, (v) government, (vi) information, (vii) management of companies and enterprises, (viii) other (except public administration), (ix) professional, scientific and technical, (x) real estate, rental and leasing, (xi) transportation and warehousing, (xii) utilities, (xiii) wholesale trade. Other industries include: (i) agriculture, forestry, fishing and hunting, (ii) construction, (iii) manufacturing, (iv) mining, quarrying, and oil and gas extraction. The number of close daily interactions at work in normal times is censored at the 99th percentile to constrain the influence of outliers.

Figure 3: Risks of exposure and close in person interactions at work in normal times

3.4 Behavioral response

A distinctive feature of our retrospective data set is that for a large number of individual behaviors, relevant both for the spread of infection and for coping with social isolation due to the pandemic, we collect information on how people typically behave (i) in normal times, (ii) shortly after the beginning of the outbreak of the Covid-19 pandemic, and (iii) at the time of data collection.

We show how these behaviors evolve over time in Figure 4. By and large people have responded to the recommendations to practice social distancing. Interestingly, except for China, there is little response in terms of increasing healthy behavioral habits. On the other hand, there is also substantial variation in response to wearing face masks, with Asian countries being acquainted to and willing to increase the use of such a device, the US and (to a greater degree) Italy fast increasing adoption, and the UK hesitating to adopt face masks.

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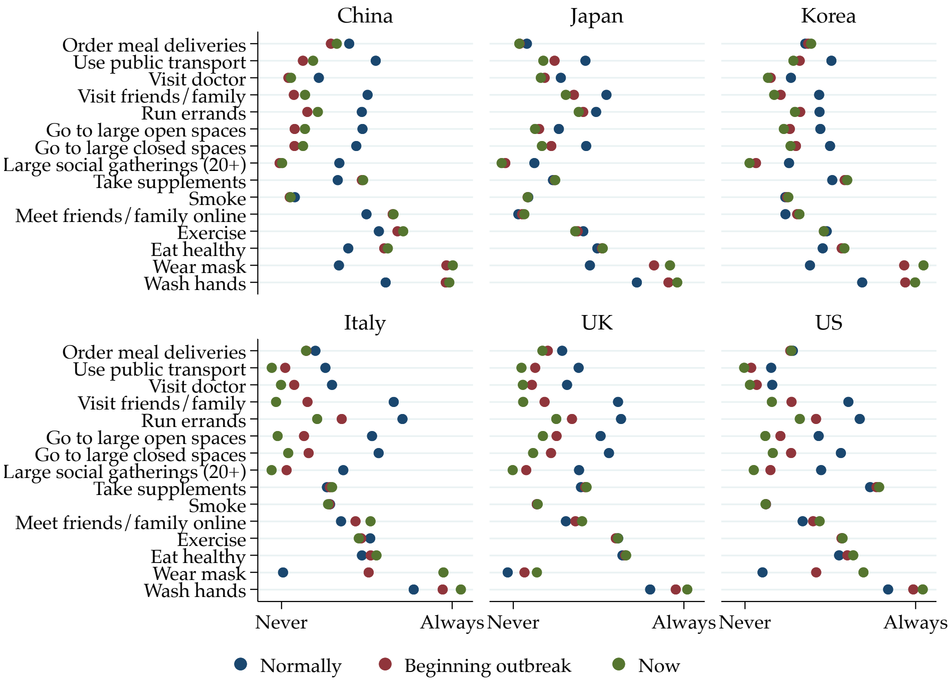

Figure 4: Changes in behavior over time

Another set of variables in the dataset illustrates how, during the pandemic, people have been able to volunteer to support people in need and continue attending religious services. Especially on the latter we observe substantial heterogeneity with a striking 20% of respondents reporting to have attended religious services at least once a week since the outbreak of the pandemic in their country (see Figure A3).

Through the pandemic people are less likely to visit a doctor, and as some of the variables in our data could illustrate, they are also quite concerned about the needed healthcare they had to defer (see Figure A4).

It will be interesting for future research to better understand what are the drivers of behavioral change. Some might have to do with household composition and living arrangements. Some might be driven by economic circumstances, which we discuss in turn.

3.5 Work related behavior and economic effects

In this section of the survey we capture the effects of the pandemic on the economy of the household both qualitatively and quantitatively. For example, we ask respondents to quantify how much of their gross household income was lost in the first quar-

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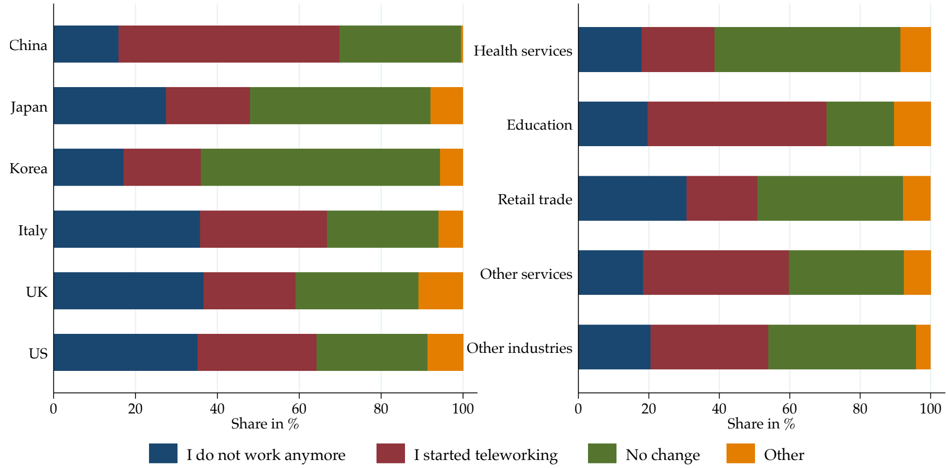
ter of 2020, what are their expected income losses for the second and third quarters, changes in weekly savings and expenses. Qualitatively, we measure e.g. individual ability to reduce in person interactions at work and changes in work arrangements. We also measure both positive and negative non-financial effects of the pandemic on the households.



Note: The left panel represents all respondents, by country. The right panel represents all respondents in employment, by industry. Other services include: (i) accommodation and food, (ii) administrative and support, (iii) arts, entertainment, and recreation, (iv) finance and insurance, (v) government, (vi) information, (vii) management of companies and enterprises, (viii) other (except public administration), (ix) professional, scientific and technical, (x) real estate, rental and leasing, (xi) transportation and warehousing, (xii) utilities, (xiii) wholesale trade. Other industries include: (i) agriculture, forestry, fishing and hunting, (ii) construction, (iii) manufacturing, (iv) mining, quarrying, and oil and gas extraction.

Figure 5: Changes in the work situation

Here we focus on how the work situation of people who report being employed was affected by the pandemic. In Figure 5, we see vast variation across countries in the share of workers who are currently unable to work, who were able to continue to work remotely and who did not experience any change in work arrangement. In Korea, where contact tracing has been particularly effective, we observe that a large share of workers could continue to work as normal. China has been particularly effective in moving its workers to teleworking arrangements. Western countries in particular have instead struggled the most to maintain their work force productive, as indicated by the high shares of employed respondents that are currently not at work. The right panel of the chart illustrates differences across sectors. As expected, we see pronounced resilience due to the ability to telework in the education sector, where 51% of respondents with a job were able to start teleworking, and high vulnerability of the retail trade sector, in which 31% of employed respondents had to cease working.

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3.6 Beliefs

Finally, in this section we capture quantitative beliefs that people have about the severity of the pandemic in their local area, the risks of several kinds of complications that may arise once a person becomes infected, and qualitative beliefs on the effectiveness of different policies that different governments have been implementing to counteract the spread of the virus.

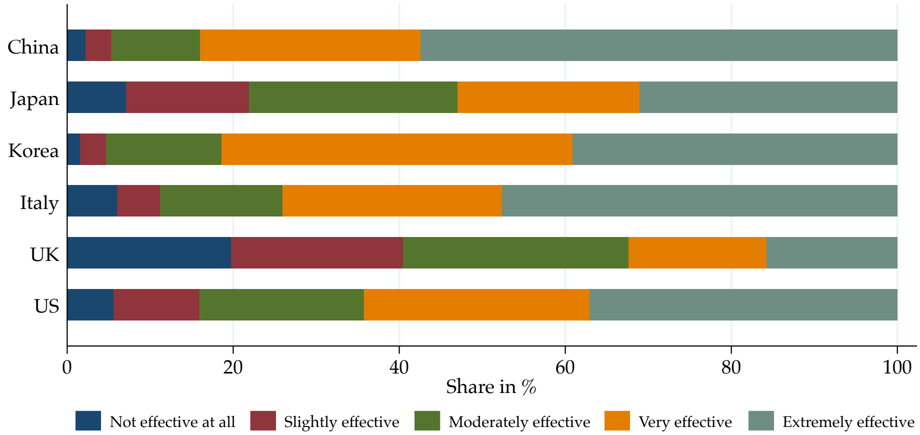
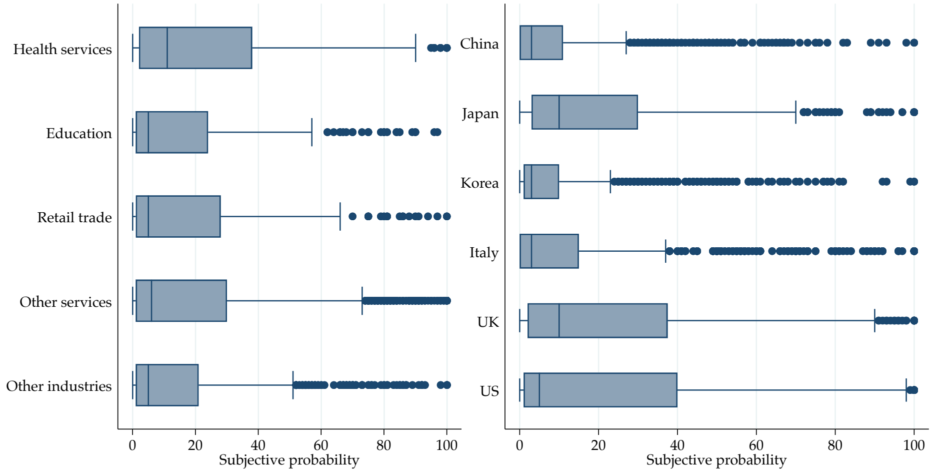


Figure 6: Beliefs on effectiveness of public safety measures: Requiring to wear masks outside

Having beliefs data to combine with behavioral change patterns can greatly help in understanding how to best coordinate the response of the public to tame the pandemic. As an illustration, we come back to the policy of requiring face masks to be worn outside, for which we also have information on how effective the policy is (see Figure 6). As previously pointed out, UK respondents stand out for not wearing face masks as much as people in other countries. As a demand-side explanation for that evidence, we find that people from the UK are especially skeptical of the effectiveness of such policy.



Note: The left panel represents all respondents in employment, by industry. The right panel represents all respondents, by country. Other services include: (i) accommodation and food, (ii) administrative and support, (iii) arts, entertainment, and recreation, (iv) finance and insurance, (v) government, (vi) information, (vii) management of companies and enterprises, (viii) other (except public administration), (ix) professional, scientific and technical, (x) real estate, rental and leasing, (xi) transportation and warehousing, (xii) utilities, (xiii) wholesale trade. Other industries include: (i) agriculture, forestry, fishing and hunting, (ii) construction, (iii) manufacturing, (iv) mining, quarrying, and oil and gas extraction.

Figure 7: Belief on having been infected with Covid-19

Figure 7 shows how likely people think it is that they have been infected, by industry (left panel) and by country (right panel). Variation across industries is interesting because it again underscores the suggestion from Figure 3 of a weak mapping between sector and (perceived) risk of exposure. Country differences seem largely consistent with official statistics on infections (keeping in mind that for the US we have sampled respondents from the 4 most populous states, which include New York).

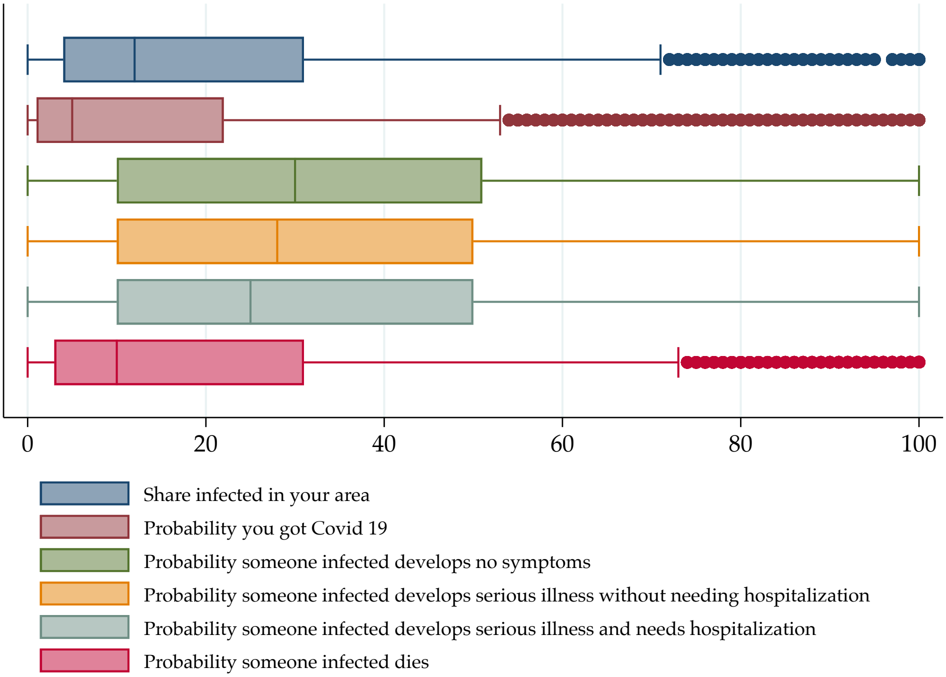


Figure 8: Beliefs related to Covid-19

Figure 8 illustrates the distribution of beliefs on a broad range of Covid-19-relevant events. We caution readers against interpreting levels of reported beliefs literally, as we see that these tend to be inflated.[2] That said, beliefs over complementary events appear largely consistent, in the sense of satisfying *additivity* for the majority of respondents. For example, the median respondent reports believing that about 30% of infected people will be asymptomatic and 10% of infected people die.

4 Ongoing research and additional questions these data can address

There are several projects that we have begun.

[2]The challenges of eliciting subjective beliefs using surveys without incentives for correct responses are well documented (see e.g. Hurd, 2009, for a review). Common techniques to improve accuracy of reported beliefs (such as interactive forms and incentivized procedures) were either not feasible or not practical without fatiguing subjects in an already long survey.

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4.1 Beliefs about the pandemic

A burgeoning literature in economics studies subjective beliefs and expectations about key economic phenomena. A subset of this literature focuses on how beliefs, including biases in beliefs, are formed. The Covid-19 pandemic is an interesting context in which to study what drives variation in beliefs as it represents a large and unexpected shock, individuals are tasked with forming beliefs about possibly severe consequences of their behavior, and information about the pandemic is overwhelming and often conflicting and confusing. Using the data set presented in this paper, we aim to examine which factors help to explain variation in beliefs across individuals about pandemic-related phenomena. We pay particular attention to what appear to be biases, such as a reported belief that the Coronavirus has a 100% fatality rate.

4.2 Factors Associated with Social Distancing

Another research question asks what factors are associated with decisions to social-distance or take other measures that are protective and could also slow the spread of infection. In many cases, there are likely to be strong positive externalities to self-protective behaviors, such as social-distancing, along with differences in the economic burden they imply, arising from work arrangements, income, household characteristics, etc. It is therefore crucial to understand who social distances and under what circumstances. This information could be used to shape policy that could slow the spread of illness, which takes account of heterogeneity in household willingness to engage in protective measures.

4.3 Individual Behavior and the Spread of Illness during a Pandemic

An ongoing project is to build a structural model that examines individually optimal self-protecting behavior during an infectious disease pandemic. The framework incorporates features from epidemiology literature to link individual choices to the spread of the disease. The model will be used to assess how potential, counterfactual policies affect the spread of illness through endogenous behavior change. The model will be used to examine behavior during the Covid-19 pandemic. Empirical moments used to estimate the model will come from a variety of sources, including from the data set presented here. This project complements numerous ongoing efforts to incorporate behavior change into epidemiological models of disease spread. To our knowledge, however, no such model has incorporated socio-demographics (other than age), work arrangements, household structure, all of which could affect individual behavior.

5 Conclusion

Despite the limitations and caveats discussed in the Introduction, we believe the data set introduced in this paper can be used to address a number of timely and policy-

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relevant questions about behavior during the Covid-19 pandemic. We offer the data set as a public resource and hope it is useful for other researchers. We have endeavored to collect and describe the data with adequate caution and care.

While many of the questions we can address with the data set focus on the here-and-now, the Covid-19 pandemic will eventually run its course. However, it would be short-sighted and naive to think that another virus, perhaps an even more damaging one, will not come about in the future. Indeed, many specialists believe that this virus be cyclical, returning annually. If so, the questions we are addressing now will be important not only as we move through the current crisis, but also as we begin to prepare for the next one. Medical doctors, public health experts, epidemiologists, virologists and so forth have an obvious role to play in such preparations. However, the spread of the virus is not just a biological phenomenon, but is also driven by human behavior, which is the purview of social science. Thus, as we develop policy for future pandemics, social scientists who study behavior—and the policies that affect it—must also play a critical role. One way is through the collection and analysis of the type of data we present here, which shed light on what behavior can be expected of different segments of the population during a pandemic given heterogeneity in the incentives, constraints and circumstances people face.

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