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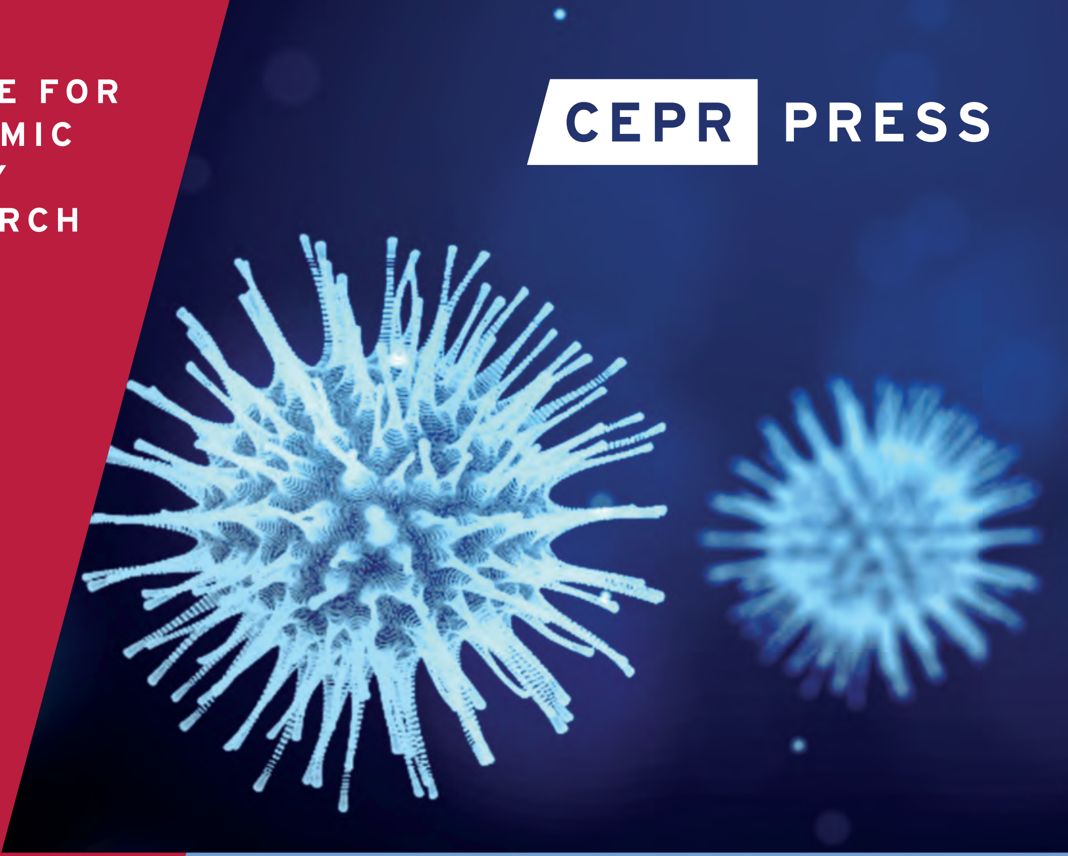

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

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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.

Founder: Beatrice Weder di Mauro, President of CEPR
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Ethics

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

Submission to professional journals

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

American Economic Review
American Economic Review, Applied Economics
American Economic Review, Insights
American Economic Review, Economic Policy
American Economic Review, Macroeconomics
American Economic Review, Microeconomics
American Journal of Health Economics
Canadian Journal of Economics
*Econometrica**
Economic Journal
Economics of Disasters and Climate Change
International Economic Review
Journal of Development Economics
*Journal of Econometrics**
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Journal of Monetary Economics
Journal of Public Economics
Journal of Public Finance and Public Choice
Journal of Political Economy
Journal of Population Economics
*Quarterly Journal of Economics**
*Review of Corporate Finance Studies**
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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Contents

Economic epidemiology in the wake of Covid-19[1]

David McAdams[2]

Date submitted: 4 September 2020; Date accepted: 9 September 2020

Infectious diseases, ideas, new products, and other "infectants" spread in epidemic fashion through social contact. The Covid-19 pandemic, the proliferation of "fake news," and the rise of antibiotic resistance have thrust economic epidemiology into the forefront of public-policy debate and re-invigorated the field. Focusing for concreteness on disease-causing pathogens, this paper provides a taxonomy of economic-epidemic models, emphasizing both the biology / immunology of the disease and the economics of the social context. An economic epidemic is one whose diffusion through the agent population is generated by agents' endogenous behavior. I highlight properties of the Nash-equilibrium epidemic trajectory and discuss ways in which public-health authorities can change the game for the better, (i) by imposing restrictions on agent activity to reduce the harm done during a viral outbreak and (ii) by enabling diagnostic-informed interventions to slow or even reverse the rise of antibiotic resistance.

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1 I thank David Argente, Chris Avery, Troy Day, Mike Hoy, Gregor Jarosch, Philipp Kircher, Anton Korinek, Ramanan Laxminarayan, Tomas Philipson, Elena Quercioli, Steve Redding, Tim Reluga, Bob Rowthorn, Yangbo Song, Arjun Srinivasan, and Flavio Toxvaerd for helpful comments and encouragement. This paper will be published as: McAdams D. 2021. Economic epidemiology in the wake of Covid-19. *Annual Review of Economics* 13.

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The spring of 2020 will long be remembered for the loss of life and widespread economic disruption due to Covid-19, the disease caused by the novel coronavirus SARS-CoV-2. Yet something constructive came out of those awful months: many economists discovered infectious-disease epidemiology. The volume of new work was so great that *Covid Economics*, an online journal of the Centre for Economic Policy Research launched in April 2020, published twelve issues in May alone. Avinash Dixit, a renowned economic theorist, wittily remarked: "If any pandemic spread faster than Covid-19, it is that of research about Covid-19" (Dixit 2020).[1]

In fact, this was the second wave of infectious interest among economists in infectious disease. The first came in the 1990s, motivated by the global HIV/AIDS pandemic and adding an economic dimension to the classic epidemiological models used to chart the course of a viral outbreak. Because HIV spreads primarily through sexual intercourse, people's decisions around sex clearly impact HIV's spread. Geoffard and Philipson (1996, 1997), Kremer (1996), and others therefore argued that the transmission rate of the virus needed to be treated as a time-varying endogenous variable, derived as a Nash-equilibrium outcome of a dynamic game.

The new generation of economists studying SARS-CoV-2 fits the same basic mold but, much like a superbug returning with new genetic machinery, today's economic epidemiologists come with new tools and perspectives drawn from other subfields of economics. The intellectual connectedness between economic epidemiology and other subfields was readily apparent in the various online workshops that sprung up in the virus' wake. For instance, the *Covid-19 Search and Matching Workshop* series (hosted by the labor economist Simon Mongey) had "an emphasis on understanding how the economics of search and matching models can be useful for understanding economic and virological aspects of the coronavirus epidemic."

Of course, viruses aren't the only things that spread infectiously, and SARS-CoV-2 isn't the only parasite currently burdening our society. False information and hateful beliefs are colonizing our minds, spreading much like viruses but accelerated by social-media platforms and amplified by partisan outlets and foreign adversaries. Interestingly, the 1990s also saw the first substantial wave of interest in this other form of infection. Social-learning models emerged in which *infectious behavior* played a central

[1] After the National Bureau of Economic Research (NBER) released more than a dozen pandemic-related working papers on April 13th, the MIT economist Jonathan Parker quipped, "Do we need to flatten the curve so we don't exceed NBER WP capacity?" (https://twitter.com/ProfJAParker/status/1249739129962876928).

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role, most notably Bikhchandani et al. (1992) and Banerjee (1992) on "information cascades / herding" and Banerjee (1993) on "rumors." New work has evolved these foundational early models in directions that draw even closer parallels with infectious-disease epidemiology, for instance, by re-framing social learning in an epidemic context (McAdams and Song 2020a) and highlighting the possibility of mutation and selection during an information outbreak (Jackson et al. 2018).

The general topic of economic infection intersects with enormous literatures in several fields, from parasitology and public health (global pandemics, antibiotic resistance, evolution of virulence) to finance and information systems (information diffusion, media). Rather than attempting to provide a comprehensive review, I have decided to focus on two central thematic questions: *how an economic epidemic unfolds over time* and *whether economic infectants can "survive" in the long run.* Moreover, I restrict attention here to epidemics of biological pathogens—leaving information epidemics as fertile ground for a future review.

I focus here on recent developments, but credit is due to the handful of economists who pushed economic epidemiology forward during the 2000s and 2010s,[2] a time when most economists showed little interest in the field. A steady trickle of notable empirical contributions appeared in leading economics outlets (e.g., Lakdawalla et al. (2006), Adda (2016), Chan et al. (2016), Greenwood et al. (2019)) but, with a few exceptions (e.g., Auld (2003)), the best new theoretical work by economists found its home in biology journals (e.g., Chen (2004, 2006, 2012), Chen and Toxvaerd (2014)) or remained unpublished for years (e.g., Rowthorn and Toxvaerd (2012)). Fortunately, theoretical biology was a welcoming space for economic theorists, as mathematical epidemiologists and evolutionary ecologists had already embraced game-theoretic methods; see e.g., Bauch et al. (2003), Bauch and Earn (2004), Cressman et al. (2004), and Reluga (2010, 2013). What they did in those years, economists and biologists together, laid the groundwork for the blossoming of economic epidemiology that we see today.

The rest of the paper is organized as follows. Section 1 provides a taxonomy of economic-epidemic models, based on the immunology of infection, manner of transmission, agent decision-making, and economic impacts of agent behavior. Section 2 discusses key features of the equilibrium epidemic trajectory, accounting for agents' behavioral response. Section 3 then examines "lockdown policies" that restrict agents' ability to remain socially active. Section 4 concludes by exploring the possibility of

[2]Useful surveys include Philipson (2000), Gersovitz (2011), and Manfredi and D'Onofrio (2013).

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eradicating a disease-causing pathogen through treatment (Section 4.1) and of eradicating the antibiotic-resistant strains of a pathogen—thereby restoring the effectiveness of existing antibiotics—through diagnostic-informed interventions (Section 4.2).

1 A taxonomy of economic-epidemic models

This section provides a taxonomy of economic-epidemiological models of a viral epidemic, categorizing these models along four main dimensions: immunology; transmission; agent decision-making; and economic impacts. Along the way, I introduce notation and preliminary analysis used throughout the rest of the paper.

1.1 Immunology

The epidemiological dynamics of infection hinge on how the virus interacts with the host immune system. Is it possible to recover from infection? If so, does recovery confer subsequent immunity from re-infection? Does transmission begin immediately after infection? How about harmful symptoms? Is it possible to spread the virus without showing any symptoms? Is infection deadly? Are some hosts more prone to be infected, experience symptoms, transmit the virus, or die? Because there are so many possibilities, there is no single benchmark model of a viral epidemic. There is rather an array of benchmark models, what I will refer to as the "SI-X models."[3] See Hethcote et al. (2002) for an epidemiological review and Avery et al. (2020) for a useful critical survey of early models of the SARS-CoV-2 epidemic from an economic perspective.

SI model. The simplest variation is the "Susceptible-Infected (SI) model." A pathogen circulates among a unit-mass population of hosts, each of whom is either uninfected (i.e., "susceptible," state S) or infected (state I) at each point in time t. Let $S(t)$ and $I(t)$ be the mass of susceptible and infected agents at time t. Each susceptible host becomes infected upon meeting an infected host, with such meetings occurring at rate

[3]These models build on an intellectual foundation laid over a century ago by Ronald Ross and Hilda Hudson (Ross 1916, Ross and Hudson 1917) and further systematized by Kermack and McKendrick (1927). For more on the history of the theory of epidemics, see Serfling (1952) and the citation tree on Tim Reluga's website (http://personal.psu.edu/tcr2/post20150624.html).

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$\beta I(t)$, where $\beta > 0$ is the "transmission rate."[4]

In the SI model, hosts never recover from infection but may[5] be born into the susceptible state and may die due to infection and/or for other reasons. In the simplest case when the host population is fixed, epidemic dynamics are characterized by the differential equation

$$I'(t) = \beta I(t)S(t) \tag{1}$$

and the adding-up condition $S(t) + I(t) = 1$. In this case, everyone in the population will eventually be infected. More generally, suppose that there is an equal flow $z \geq 0$ of births and deaths across the population, and assume for simplicity that each host dies at constant rate z. Equation (1) then becomes $I'(t) = \beta I(t)S(t) - zI(t)$, and the steady-state mass of infection $I^\infty \equiv \lim_{t\to\infty} I(t) = 1 - \frac{z}{\beta}$.

What if, in addition, infected hosts die at some rate $x > 0$? The host population, typically denoted $N(t) = S(t) + I(t)$, is no longer fixed:

$$I'(t) = \beta I(t)S(t) - (z + x)I(t) \tag{2}$$

$$N'(t) = z - z(S(t) + I(t)) - xI(t) \tag{3}$$

For simplicity, I henceforth focus on models with a fixed host population, an assumption that is most appropriate when the epidemic is fast-moving and the disease is not deadly.

SIRS/SIR/SIS model. Suppose next that infected hosts recover at rate $\gamma > 0$ and, after recovery, are initially immune but lose their immunity at some rate $\iota \geq 0$, after which they become susceptible to re-infection. In addition to the susceptible and infected states, let R denote the "recovered with acquired immunity" state and let $R(t)$ denote the mass of hosts in this state. The special case with permanent immunity ($\iota = 0$) is called the "SIR model," while that with no immunity ($\iota = \infty$) is the "SIS model." The more general case spanning both possibilities is the "SIRS model."

Epidemic dynamics in the SIRS model (with a fixed host population) are governed

[4] If each host meets another randomly-selected host at rate β, then each susceptible host meets an infected host at rate $\beta I(t)$. Note that each such "meeting" corresponds to exposure *plus* successful infection. If a susceptible person exposed to the virus only becomes infected with probability $y \in (0, 1)$, then the rate of infection for susceptible agents is $\widehat{\beta} I(t)$, where $\widehat{\beta} = \beta y$.

[5] If transmission occurs mainly within a single age cohort (as might approximately be the case, say, for sexually-transmitted diseases), then the relevant host population consists of all those in the same age cohort, with death but no birth.

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by the following system of differential equations

$$S'(t) = -\beta I(t)S(t) + \iota R(t) \tag{4}$$
$$I'(t) = \beta I(t)S(t) - \gamma I(t) \tag{5}$$

plus the adding-up condition $S(t) + I(t) + R(t) = 1$.

Each infected person on average exposes $R_0 = \beta L$ others during the course of their infection, where $L = 1/\gamma$ is the average length of time until recovery. R_0 (pronounced R-naught) is the pathogen's "basic reproduction number." An epidemic with $R_0 \leq 1$ is self-extinguishing, the prevalence of infection falling over time toward zero. By contrast, an epidemic with $R_0 > 1$ grows explosively and, so long as $\iota > 0$, persists with long-run steady state prevalence of infection $I^\infty = \frac{1-\gamma/\beta}{1+\iota/\gamma}$.[6]

In the SIR model, equation (4) simplifies to $S'(t) = -\beta I(t)S(t)$. When $R_0 > 1$, the prevalence of infection increases until the number of previously infected hosts $1 - S(t)$ reaches $1 - \gamma/\beta$, the level required for "herd immunity." More hosts become infected after that point, but at a decreasing rate, and some escape infection entirely. The fraction of hosts who are eventually infected is known as the "attack rate" and is always less than one; see Brauer et al. (2012) and Katriel and Stone (2012).

In the SIS model, equation (4) simplifies to $S'(t) = -\beta I(t)S(t)+\gamma I(t)$. When $R_0 >$ 1, the prevalence of infection increases monotonically from approximately zero (when the pathogen first enters the host population) to a steady-state level $I^\infty \equiv 1 - \gamma_0/\beta$.

SCIRS/SCIR/SCIS model. Many bacterial pathogens colonize hosts for an extended period of time, an asymptomatic infection phase referred to as "carriage" (C) during which they may also be transmitted to new hosts.[7] For instance, enteric pathogens are transmitted through feces, whether or not they are currently causing harmful symptoms. Some viruses, including SARS-CoV-2 and HIV, can also transmit from carriage. To avoid confusion, I refer to a pathogen as "colonizing" its host while in carriage and "infecting" the host while causing symptomatic infection.

Suppose for simplicity that the transmission rate β and recovery rate γ are the same during carriage and infection, and let $\psi > 0$ be the rate at which the pathogen

[6] In the SIRS model, the system oscillates around this steady state while converging toward it. Other more complex variations may never reach a steady state (Hethcote et al, 2002).

[7] For pathogens that are unable to transmit during an initial quiescent phase, the SIRS model is typically extended to include a non-transmitting "exposed" state (E) prior to infection.

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proceeds from carriage to infection. All other variables and parameters are the same as in the SIRS model.

Epidemic dynamics are governed by the following system:

$$S'(t) = -\beta(C(t) + I(t))S(t) + \iota R(t) \tag{6}$$

$$C'(t) = \beta(C(t) + I(t))S(t) - (\psi + \gamma)C(t) \tag{7}$$

$$I'(t) = \psi C(t) - \gamma I(t) \tag{8}$$

plus the adding-up condition $S(t) + C(t) + I(t) + R(t) = 1$.

From an economics point of view, it is useful to divide the recovered state R into two substates: R_C, for those who recovered most recently from carriage (without experiencing any symptoms); and R_I, for those who recovered from symptomatic infection. Note that $R'_C(t) = \gamma C(t) - \iota R'_C(t)$ and $R'_I(t) = \gamma I(t) - \iota R'_I(t)$.

The SCIRS model differs qualitatively from the others discussed so far, in that hosts do not immediately observe when they have been colonized. For instance, consider the special case of the "SCIR model" with permanent immunity after recovery. An agent who has not yet experienced disease by time t might currently be (a) susceptible (state S), (b) colonized (state C), or (c) recovered from carriage (substate R_C). On the other hand, agents know when they begin to experience disease (state I) and when they recover from disease (substate R_I).

Absent diagnostic testing, the epidemiological states $\{S, C, R_C\}$ constitute an *information set*, referred to as "not-yet-sick" and denoted by N, with $S(t)+C(t)+R_C(t)$ being the mass of not-yet-sick agents. For each state (or "health status") $h \in N$, let $p_h(t)$ denote agents' belief about the likelihood that their health status is h, conditional on being not-yet-sick. By Bayes' Rule, $p_h(t) = \frac{h(t)}{S(t)+C(t)+R_C(t)}$.[8]

Agent heterogeneity. Agents naturally differ in many ways that impact infection and transmission. For example: older people and those with co-morbidities may be more likely to die of infection; those with access to health care will receive supportive care (and curative treatment, if available) that reduces their subsequent transmissibility; those who have been vaccinated are less likely to become infected after exposure;

[8]The resulting belief dynamics are non-trivial. For instance, although fewer agents remain susceptible over time in the SCIR model, their likelihood $p_S(t)$ of being susceptible *conditional* on being not-yet-sick—a key consideration in the "social distanicng" game-theoretic models considered later—may rise or fall over time.

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those with wider social networks are more likely to be exposed and to expose others; and so on.

Such heterogeneity is typically captured by defining "sub-compartments" (i.e., sub-states) of each of the basic epidemiological states and modeling the epidemic as following a Markov process with respect to this enriched state space. For instance, suppose that some of the population is vaccinated and that vaccination cuts in half the likelihood of developing infection each time that an agent is exposed to the virus.[9] This can be incorporated by dividing susceptible agents into two classes—those who are vaccinated (substate S_V) and those who are not (substate S_0)—with vaccinated people becoming infected at half the rate. In particular, in the SIR model, the differential equation $S'(t) = -\beta I(t)S(t)$ would be replaced by the pair of equations $S_0'(t) = -\beta I(t)S_0(t)$ and $S_V'(t) = -\beta I(t)S_V(t)/2$, with $S_V(t) + S_0(t) = S(t)$.

From an economic-theory perspective, an especially intriguing (and understudied) source of heterogeneity is *information*, especially: information about the epidemic, which itself may spread infectiously; information about one's own health status, creating new options for targeted treatment and control; and information about others' health status, enabling people to avoid infectious contact.

1.2 Manner of transmission

How a virus circulates among the host population, and what agents know about transmission, is essential to the trajectory of an epidemic.

"Fully mixed" vs. network models of transmission. In 1999, an American psychiatric facility was struck with an outbreak of *Mycoplasma pneumonia*, a leading cause of "walking pneumonia." The bacterium spread widely through the facility, but not through random meetings. Each patient was confined to a single ward, and hence unable to transmit the bacterium directly to those in other wards. However, some caregivers worked in multiple wards and, as such, served as links in a *transmission network* over which the bacterium spread throughout the facility. Meyers et al. (2003) modeled this network as a directed graph, based on detailed data collected by the Centers for Disease Control and Prevention (CDC) (Hyde et al. (2001)), and estimated the rate of transmission along each edge of the graph—finding, for instance, that the

[9] If vaccination reduces the harm of infection and increases the degree or duration of immunity after recovery, then one would also want to divide the infection and recovery classes in an SIRS model.

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bacterium was more likely to pass from caregivers to patients than vice versa.

Models with random meetings (referred to as "fully-mixed") are especially easy to analyze, in terms of a system of differential equations tracking how many hosts are in each epidemiological state at each point in time. Due to this simplicity, many applied-theory papers in the theoretical biology literature (and most of the recent Covid-inspired literature within economics) assume that transmission occurs via random meetings, or slight variations thereof with a small number of agent types.

Richer models with transmission over a network might seem hopelessly complex but, in fact, infection that spreads over a network can also be tractably analyzed. Newman (2002) characterizes epidemic dynamics for an arbitrary directed graph in terms of an adjacency matrix capturing exposure/transmission intensities between different agents or types of agents. Jackson and López-Pintado (2013) builds on this analysis, providing conditions on the adjacency matrix under which a new infectant ("an idea, a product, a disease, a cultural fad, or a technology") will spread from a small seed of initially-infected agents to a significant fraction of the population. See also Prakash et al. (2012), who provide thresholds for epidemic spread over a network.

Network models of transmission are appealing given their generality and tractability, and I expect the literature to shift in the near future more in this direction, especially given the increasing availability of individual-level data on physical mobility; see e.g., Fang et al. (2020) and Glaeser et al. (2020). However, in this review, I will follow the bulk of the existing literature and focus on models in which the infectant, here a biological virus, is spread through random meetings.

Awareness of contagious contact. The SARS outbreak of 2003 was quickly brought under control, with only about 8,000 people infected, in large part because the SARS-CoV-1 virus is (mostly) unable to transmit itself to new hosts until after causing severe symptoms, at which point those hosts are in the hospital and out of the general population. By contrast, SARS-CoV-2 can transmit from an asymptomatic state, making containment much more challenging absent diagnostics capable of determining who is carrying the virus.

This critical difference between SARS-CoV-1 and SARS-CoV-2 highlights an important modeling distinction in the economic epidemiology literature, regarding what hosts know about their own and/or others' health status. In particular, models differ on (i) whether there is an asymptomatic phase before symptomatic infection and (ii)

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whether others can detect whether a host is infected, e.g., by measuring their temperature or performing a rapid diagnostic. It also matters whether people can credibly *disclose* their health status to others. As Paul Romer explained in a *New Yorker* article featuring his advocacy for greater testing: "I don't want to go back to the dentist's office in New York City until I know that he can show me a recent negative test, and he doesn't want me to come into his office until I can show him that I've got a recent negative test" (Chotiner 2020).

1.3 Agent decision-making process

Hosts (also called "agents") make many sorts of decisions that impact the trajectory of an epidemic, such as how frequently to wash their hands, whether to stay at home, whether to get tested, and so on. The way in which hosts are assumed to make decisions varies across the literature, falling into three main categories:

1. *mechanistic behavior*: agents' actions are determined by the current state of the epidemic
2. *rule-of-thumb behavior*: agents act to maximize an objective different (and typically simpler) than maximizing their own welfare
3. *individually-optimal behavior*: agents' actions are individually optimal given others' current and future behavior

All three approaches have their merits. Mechanistic models allow one to gain insight into the epidemiological properties of infection phenomena and lay the groundwork for future research that seeks to endogenize behavior. (Indeed, this is how the literature on infectious-disease dynamics has progressed, with about a century of work in mostly mechanistic models now growing in new directions that account for the dynamics of agent intention.) Models with individually-optimal behavior are useful as a fully-rational benchmark but, of course, may fail to predict actual outcomes if people are not the sophisticated reasoners that such models assume them to be. If so, rule-of-thumb models may come closer to capturing how people actually reason and process information and hence do a better job at predicting epidemic outcomes.

Example: social distancing. Consider a SCIR model in which not-yet-sick hosts decide at each point in time whether to reduce their likelihood of exposure to the virus

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	mechanistic	rule-of-thumb	forward-looking
SI			Geoffard Philipson (1996) Kremer (1996) Geoffard Philipson (1997) Auld (2003) Chen (2004, 2006) Chan et al. (2016)
SIR / SIS / SIRS	Del Valle et al. (2005) Bootsma Ferguson (2007) Cochrane (2020)		Rowthorn et al. (2009) Reluga (2010) Chen (2012) Rowthorn Toxvaerd (2012) Farboodi et al. (2020) Alvarez et al. (2020) Bethune Korinek (2020) Toxvaerd (2020) Brotherhood et al. (2020)
SCIR		Keppo et al. (2020) McAdams Day (2020)	McAdams (2020) McAdams Song (2020)
SCIS	McAdams et al. (2019)		

Table 1: A selection of papers with dynamic economic-epidemiological models, categorized by their assumptions about decision-making and pathogen transmission.

by staying away from others. Bootsma and Ferguson (2007) model such decisions by assuming that "individuals reduce their contacts as a function of the number of deaths occurring in the population in the previous time period."[10] However, because the risk of infection is not tied directly to the number of recent deaths, it is difficult to construct a reasonable objective function maximized by such a rule. Thus, in my phraseology, Bootsma and Ferguson (2007) assumes "mechanistic behavior."

Keppo et al. (2020) (and its predecessor Quercioli and Smith (2006)) approach behavioral adaptation during an epidemic in a different way, assuming that hosts' social distancing choices constitute a Nash equilibrium of a game in which each host acts *as if* maximizing an objective that depends only on the current epidemic state, their own distancing choice, and others' choices, i.e., agents are strategic yet also myopic. Since agents maximize an objective, but this objective does not correspond to their actual payoffs, Keppo et al. (2020) assumes "rule-of-thumb behavior." Having a simpler objective makes it easier to characterize the epidemic trajectory, relative to models that assume agents maximize the expected present value of their lifetime payoffs; see e.g., Reluga (2010), Farboodi et al. (2020), Toxvaerd (2020), McAdams

[10] The economist John Cochrane took a similar approach in a May 2020 blog post, assuming that distancing varies with current infection prevalence or current death rate (Cochrane 2020).

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(2020), and McAdams and Song (2020b), discussed in more depth later.

Table 1 categorizes several papers highlighted in this review, depending on (i) how agents make decisions (mechanistic, rule-of-thumb, or forward-looking), and (ii) the transmission model (SI, SIR/SIS/SIRS,[11] SCIR, or SCIS).

1.4 Economic impacts

Infectious disease creates economic harm directly through sickness, and indirectly as people take costly steps to avoid becoming sick.

Standard framework: Geoffard and Philipson (1996). The economic literature on infectious disease has for the most part followed Geoffard and Philipson (1996) in modeling the economic impacts of infection. In their approach, agents get instantaneous flow utility of the form $u(h_t, a_t)$, where h_t is an agent's health status and $a_t \in [0, 1]$ is their chosen level of "social activity," and seek to maximize the expected present value of their lifetime utility stream. (Equivalently, one can describe agents as choosing their "social distance" $d_t = 1 - a_t$.) A recent paper that takes this modeling approach is Farboodi et al. (2020). As they explain:

> "The assumptions that preferences u depend on social *activity* while disease transmission depends on social *interactions* are central to our view of social distancing. The former captures the idea that individuals value social activity (going to a restaurant, going for a walk, going to the office) and, absent health issues, are indifferent about whether other people are also engaging in social activity. On the other hand, if an individual goes for a walk and doesn't encounter anybody, they cannot get sick. Thus interactions are critical for disease transmission."

Under these assumptions, the "social-distancing game" at time t exhibits both positive externalities (agents benefit when others distance more, due to reduced exposure risk) and strategic substitutes (agents have less incentive to be active themselves when others are more active). These properties of the game have significant theoretical implications, such as uniqueness of the epidemic trajectory, and policy implications, such as that a social planner always finds it optimal to tax social activity; see Rowthorn et al. (2009) and Rowthorn and Toxvaerd (2012).

[11] Some of these papers consider just the SIR model or just the SIS model, while others consider both separately or the more general SIRS model that encompasses both as special cases.

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Extension: multi-dimensional actions. Agents are typically modeled as making a one-dimensional choice—*either* (i) how much to curtail their public / social activities ("self-isolation") *or* (ii) how much to protect themselves during such activities ("vigilance")—but both sorts of decisions are relevant. For instance, a person might reduce how frequently they visit with friends *and* take precautionary steps such as wearing a mask when doing so. Monotone equilibrium comparative statics can be unintuitive in games with strategic substitutes (Roy and Sabarwal (2010)), especially with multidimensional actions, and social distancing is no exception. Salanié and Treich (2020) examine this issue in a static-game context. If self-isolation protects others but vigilance does not, they show that a social planner can increase social welfare by taxing vigilance. Why? Slightly reducing each agent's vigilance from its equilibrium level has a negligible (second-order) welfare effect due to the Envelope Theorem, but induces agents to increase their self-isolation, creating a first-order indirect benefit.

Extension: Complementarities in social activity. In the standard framework, social activity creates an *infection spillover* as more active agents are more likely to infect others with the virus, but there are no *economic spillovers* associated with activity. This seems reasonable if "activity" in akin to going for a walk. But what if "activity" is going to work in an office or playing a team sport? The risk of infection due to social activity is highest when others are active, but so is the benefit of being active yourself. Consequently, the social-activity game may exhibit strategic complements—and perhaps have multiple Nash equilibria—and it might sometimes be optimal to subsidize social activity. McAdams (2020), discussed later, is to my knowledge the first paper to extend the standard framework to allow for economic complementarities associated with economic activity.

Extension: Impact on search and matching. In the standard framework, social activity has no impact on who "matches" with whom but does impact the likelihood of viral transmission due to each match. As Geoffard and Philipson (1996) explains:

> "Agents continuously meet one another over time, and upon each meeting, they must decide whether to engage in transmissive or protective behavior. If a susceptible agent chooses [transmissive behavior], he runs a risk of contracting the disease.."

This seems reasonable if "protective behavior" corresponds, say, to wearing a condom, but less so if it corresponds to abstaining from sexual activity altogether. A person looking for a sexual partner will find, not a random person, but someone else who is also looking. In a seminal contribution discussed more later, Kremer (1996) shows how such selection effects create the potential for multiple equilibrium epidemic trajectories, driven by a positive feedback between the composition of those looking for sex and the riskiness of doing so.

2 Equilibrium epidemic trajectory

This section examines how an epidemic unfolds over time, when agents decide for themselves whether to incur a cost to "distance" themselves from others. The analysis here synthesizes ideas in Toxvaerd (2020) and McAdams (2020), while also drawing on ideas in several other papers, especially Reluga (2010), Farboodi et al. (2020), and Keppo et al. (2020). A common theme in all these papers is that behavioral adaptation can have a profound impact on the epidemic trajectory.

2.1 Epidemic limbo

As the SARS-CoV-2 virus ripped through the United States in May 2020, two hair stylists in Springfield, Missouri continued working for several days despite having Covid symptoms. They saw 139 clients in total during that time but, when public-health officials scrambled to trace those contacts, they were surprised to find that none tested positive for the virus, and none developed symptoms. A subsequent field report published in the CDC's *Morbidity and Mortality Weekly Report* attributed this lack of transmission to the fact that the hair stylists and their clients wore face coverings throughout their interactions (Hendrix et al. 2020). Citing this report, CDC Director Robert Redfield said that "If we could get everybody to wear a mask right now, I really think in the next four, six, eight weeks, we could bring this epidemic under control."

Del Valle et al. (2005) examines the impact of behavioral change on the course of a viral epidemic. Within the context of a mathematical model of a biological attack resulting in a smallpox outbreak, they computed (i) how many people in a population of one million are ultimately infected and (ii) how long it takes until 99% of all infections have occurred, under various medical interventions and behavioral responses. In the baseline case with no intervention and no behavioral response, over 966,000 are infected and the outbreak lasts 307 days. By contrast, quick adoption of a behavioral response

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that reduces transmission by 90% reduces the number of cases to 306 over 208 days, while slower adoption of this response leads to 1,647 cases over 274 days.

Sustained and effective behavioral response speeds the end of the epidemic by driving down the basic reproductive number (R_0) of the virus, the average number of people exposed to the virus by each infected person. R_0 naturally changes over time, depending on public-health interventions and voluntary behavioral change. Smallpox's R_0 is estimated at being between 3 and 6; so, a behavioral change that reduces transmission by 90% will drive R_0 down to less than one and result in an exponentially decreasing number of cases. But as the number of cases falls, people's incentive to continue to "distance" themselves from others also naturally declines. Indeed, as the outbreak is squashed and almost no one in the community is infected, people have an incentive to relax, in which case the outbreak could flare up once again.

Game-theoretic models of social distancing have emerged to account for this feedback between the state of the epidemic and people's behavior. These models differ in several important respects, but a common feature emerges in many of them, what I refer to as *epidemic limbo*. People have an incentive to adopt precautionary measures once the epidemic has become sufficiently severe; so, the epidemic turns out to be not as bad as one would have predicted without accounting for behavioral response. However, as the epidemic wanes and there is less risk of being exposed, people eventually have an incentive to return to their usual behavior. Due to this self-limiting feedback, the epidemic can remain for an extended period of time in a limbo of intermediate severity: not so bad that *all* people take it seriously enough to distance themselves, but remaining enough of a threat that *some* people do so.

Fine and Clarkson (1986) was the first to provide a game-theoretic analysis of agents' incentives to take precautionary measures to avoid infection during an epidemic. More sophisticated dynamic analysis followed in the 1990s, with pioneering work by Philipson and Posner (1993), Kremer (1996), and Geoffard and Philipson (1996), among others.[12] A recurring theme of this literature is that there is a limit to what can be achieved through voluntary precautionary measures, because of the negative feedback between infection prevalence and the incentive to take precautions. For instance, diseases that spread through random meetings[13] cannot be eradicated by

[12]The economists working on the game theory of infection prevention in the 1990s and 2000s were apparently unaware that epidemiologists had beat them to the punch. Yamin and Gavious (2013) were the first to cite Fine and Clarkson (1986) in an economics journal.

[13]Perisic and Bauch (2009) show that equilibrium eradication may be possible for diseases that spread over a persistent network.

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costly vaccination alone, since the benefit of vaccination vanishes as the disease comes close to being eradicated; see e.g., Geoffard and Philipson (1997).

In the same way, there is a limit to how much voluntary social distancing can reduce the overall harm done during an epidemic. Reluga (2010) provides a game-theoretic model of a viral epidemic with forward-looking agents, in which agents decide at each point in time how intensively to distance themselves from others. Numerically solving the equilibrium epidemic trajectory for a relatively wide range of parameters, he finds that voluntary distancing reduces the overall harm done during the epidemic by at most 30%, relative to a no-distancing benchmark. That's a far cry from the 99.9% reduction in infection cases found by Del Valle et al. (2005), when assuming that agents engage in quick and sustained social distancing.

SIR model with rule-of-thumb vigilance. Consider an SIR model with transmission rate β and recovery rate γ, and hence basic reproduction number $R_0 = \frac{\beta}{\gamma}$. Suppose that agents have the option at each point in time to take an action (referred to by Keppo et al. (2020) as "vigilance") that has no effect on who they meet but reduces the likelihood of viral transmission during each given meeting. In particular, for simplicity, suppose that vigilance is a zero-one decision that reduces the instantaneous risk of transmission during a meeting (being infected or infecting others) to zero, at flow cost $c > 0$. Moreover, suppose that agents are rule-of-thumb decision-makers who act *as if* willing to pay $H > 0$ to avoid becoming infected. H is their "perceived harm" from being infected. (The actual economic harm associated with being infected varies over the course of the epidemic, as discussed later.)

Those who are infected have no individual incentive to be vigilant. Any susceptible agent who is not vigilant will therefore become infected whenever meeting an infected agent, which happens at rate $\beta I(t)$, creating expected perceived harm of $H\beta I(t)$ per unit time. So, each susceptible agent strictly prefers to be vigilant when $I(t) > \overline{I} \equiv \frac{c}{\beta H}$, strictly prefers not to be vigilant when $I(t) < \overline{I}$, and is indifferent when $I(t) = \overline{I}$.

The resulting equilibrium epidemic trajectory is uniquely determined and easily characterized, with three distinct phases, as illustrated in Figure 1 below.

Phase #1: Rising epidemic. Let t_1 be the first time at which $I(t_1) = \overline{I}$, i.e., $t_1 = \sup\{t : I(t) \leq \overline{I}\}$. If $\overline{I}$ is sufficiently high that $t_1 = \infty$, then no one is ever vigilant and the epidemic progresses as in a standard SIR model without behavioral adaptation. Otherwise, no one is vigilant and infection prevalence is strictly increasing up until

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time t_1, at which point the epidemic transitions to Phase #2.

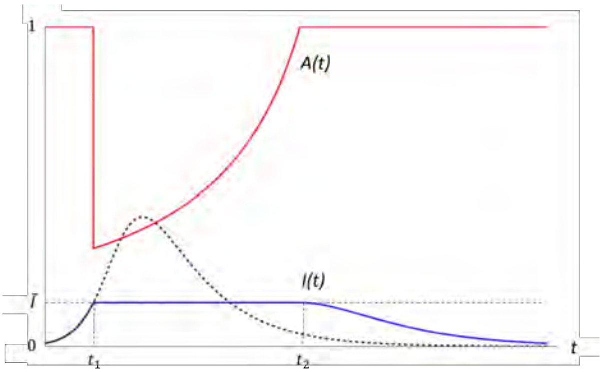

Figure 1: Infection prevalence in standard SIR model without any behavioral change (dotted line), equilibrium infection prevalence $I(t)$ (blue line) and fraction of agents $A(t)$ who are not vigilant (red line) in SIR model with rule-of-thumb vigilance. This is a slightly modified version of Figure 3 in Toxvaerd (2020), used with permission.

Phase #2: Epidemic limbo. Once the mass of infections hits $\overline{I}$, some but not all susceptible agents must choose to be vigilant, just enough so that the mass of infections remains equal to $\overline{I}$. This requires exactly fraction $1 - \frac{\gamma}{\beta S(t_1)}$ of susceptible agents to be vigilant, meaning that fraction $A(t) = \frac{\gamma}{\beta S(t_1)}$ are not vigilant (A is mnemonic for "active"); note that $A(t)\beta S(t_1) = \gamma$. If more susceptible agents than this were vigilant, the mass of infections would fall and none would want to be vigilant, a contradiction. Similarly, if fewer were vigilant, the mass of infections would rise and all would want to be vigilant, another contradiction.

The resulting epidemic dynamics are characterized by the system:

$$S'(t) = -\beta \overline{I} S(t) A(t) = -\gamma \overline{I} \tag{9}$$

$$I(t) = \overline{I} \tag{10}$$

$$A(t) = \frac{\gamma}{\beta S(t_1)} \tag{11}$$

plus the usual adding-up condition $S(t) + I(t) + R(t) = 1$. Since infections clear at rate γ, the flow of agents out of the infected state is $\gamma \overline{I}$. Equilibrium social distancing $1 - A(t)$ is just enough so that the flow of new infections also equals $\gamma \overline{I}$. Note that,

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since the mass of susceptible agents $S(t)$ falls over time, agents distance less and less throughout the "limbo" phase of the epidemic, i.e., activity $A(t)$ is increasing.

Let t_2 be the time at which $S(t) = \frac{\gamma}{\beta}$. This is moment at which the population as a whole achieves "herd immunity," in the sense that the mass of infected agents will henceforth fall over time *even if* no one distances.[14]

Phase #3: Declining epidemic. After time t_2, no one is vigilant and the mass of infections declines over time, with $I'(t_2) = 0$, $I'(t) < 0$ for all $t > t_2$, and $\lim_{t\to\infty} I(t) = 0$.

Vigilance versus self-isolation. Suppose that, instead of deciding whether to take protective actions (such as wearing a mask) to prevent transmission during each given meeting, agents decide whether to avoid such meetings altogether. The effect of such "self-isolation" on others depends on whether isolating oneself reduces the number of encounters that *others* experience.

The most common assumption in the literature, following Geoffard and Philipson (1996), is that isolating yourself causes transmission events that would have happened not to happen at all. For instance, suppose that a susceptible person decides to go for a walk in the park, and that half of all susceptible people stay home (but all infected and recovered people go out). That person will "cross paths" with half as many susceptible people but the same number of infected people, and hence be at the same amount of risk as if no one had stayed home. The overall flow of new exposures in this case when half of susceptible agents stay home is therefore the same as in the earlier "vigilance model" with half of all susceptible agents choosing to be vigilant.

This modeling approach has been widely adopted in the recent Covid-inspired theoretical literature, but misses a key feature of the social context of disease transmission captured originally by Kremer (1996). In many settings, people get *partner-unspecific benefit* from social interactions and, because of this, will seek out alternative partners if the person they would have otherwise matched with is absent. To see the point, suppose that the person going to the park is there to play a game of pickup basketball.[15] Fewer teams will form, but whoever is there will still form teams and play.

[14]Herd immunity is achieved in the SIR model with random meetings once mass $1 - \frac{\gamma}{\beta}$ of hosts have been exposed, leaving mass $\frac{\gamma}{\beta}$ still susceptible. In an uncontrolled epidemic, herd immunity is achieved at the moment when infection prevalence is at its peak. Distancing reduces the overall number of infections by reducing how many people are infected *after* herd immunity is achieved.

[15]The same issues arise in many other contexts. For instance, in Kremer (1996)'s original example,

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Moreover, because only susceptible people stay home, the people playing will be more likely to be infected than if no one had stayed at home. In this way, social distancing by susceptible people makes other susceptible people *more* likely to be infected when not distancing themselves.

In Kremer (1996)'s pioneering model, each agent in an atomless population decides how many interactions they want to have, and then agents are randomly matched in a way so that each agent has the number of interactions that they desire. For example, suppose that the host population consists of two equally-likely types—"high-activity agents (H type)" who are fully active ($a_i = 1$) and "low-activity agents (L type)" who cut back by half ($a_i = 1/2$)—and that, if everyone were fully active, everyone would encounter 6 H types and 6 L types per unit time on average. In Kremer (1996), H types encounter 8 H types and 4 L types per unit time, while L types encounter 4 H types and 2 L types. By contrast, in the more commonly-used approach, H types encounter 6 H types and 3 L types, while L types encounter 3 H types and 1.5 L types.

The key difference is that, in Kremer (1996), people's distancing decisions impact not just how many matches occur, but who matches with whom. In particular, one type of agent staying out of the "matching market" makes it more likely that market participants will match with other types. Social distancing by susceptible agents therefore creates a positive feedback: the more that susceptible people distance, the more that other susceptible people want to distance. The game among susceptible agents therefore exhibits strategic complements and, as such, can possess multiple equilibria.

Extension: economic complementarities. Building on a model introduced in McAdams (2020), McAdams and Song (2020b) explores the impact of economic complementarities on the equilibrium epidemic trajectory. Each agent i is assumed to get flow economic payoff of the form

$$u(a_i; A) = \alpha_0 + \alpha_1 a_i + \alpha_2 a_i A, \tag{12}$$

where a_i is agent i's activity level, A is the population-wide average activity level, and $\alpha_0, \alpha_1, \alpha_2 \geq 0$ are parameters capturing the importance of isolated, public non-social,

someone going to a brothel for sex is going to have sex with *someone*, but the odds that that person is HIV-positive depends on the relative likelihood that HIV-positive and HIV-negative women will being working at the brothel.

and public social activities, respectively, for agent welfare.[16] (Those who are sick incur an additional cost and may or may not be incapacitated.)

Interpretation of parameters: α_0 captures the baseline level of benefits that a well agent gets while quarantined in the home; α_1 captures the extra benefits associated with being able to leave the home, e.g., the extra pleasure and health benefit of walking outside; and α_2 captures the extra benefits associated with sharing the same physical space with others, e.g., hugging a friend rather than just talking on the phone. These parameters can be changed in many ways. For instance, a restaurant service that delivers safely-prepared fresh-cooked meals would increase α_0 and reduce α_2, as would improved virtual-meeting technology that enhances remote collaboration.

The presence of economic complementarities ($\alpha_2 > 0$) changes the qualitative features of the social-distancing game played by agents throughout the epidemic, in two main ways. First and most importantly, there can be multiple equilibrium trajectories. The course of the epidemic may therefore depend on coordinating mechanisms (e.g., public announcements) that induce agents to play one equilibrium rather than another. Second, as people begin to distance, there is a positive feedback as others' inactivity reduces agents' incentive to be active themselves. For instance, entrepreneurs who share an incubator space might have a strong incentive to work in their office so long as everyone else is doing so, to share ideas during impromptu encounters, but not once most other people are working from home. Similarly, there is less reason to go to a shopping area when most stores are closed, less benefit from operating a production facility if suppliers and shut down, and so on.

McAdams and Song (2020b) has forward-looking agents but, to gain intuition, it is helpful to consider the impact of economic complementarities in the SIR model considered above, with rule-of-thumb decision-makers who have perceived harm H from being infected. However, now assume that the cost of self-isolation takes the form $c(A) = \alpha_1 + \alpha_2 A$, where A is the fraction of the overall population that remains socially active. In this context, each agent has a dominant strategy to self-isolate whenever infection prevalence $I(t)$ is greater than $\overline{I} \equiv \frac{c(1)}{\beta H} = \frac{\alpha_1+\alpha_2}{\beta H}$ and a dominant strategy *not* to self-isolate whenever $I(t)$ is less than $\underline{I} \equiv \frac{c(0)}{\beta H} = \frac{\alpha_1}{\beta H}$. When $I(t) \in \left(\underline{I}, \overline{I}\right)$, then are multiple equilibria, including one in which all susceptible agents isolate and another in which no one isolates.

In the equilibrium with the most infection, $I(t)$ increases until time t_1 at which

[16] Assuming linear payoffs simplifies equations but is not essential. The analysis can also be easily modified to allow for congestion effects ($\alpha_2 < 0$).

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$I(t_1) = \overline{I}$, when agents are indifferent whether to self-isolate. Immediately after time t_1, at least fraction $1 - \frac{\gamma}{\beta S(t_1)}$ of susceptible agents must isolate (by the same argument as before). But then the economic benefit of activity falls, from $\alpha_1 + \alpha_2$ to $\alpha_1 + \alpha_2 \frac{\gamma}{\beta S(t_1)}$, causing agents to strictly prefer to self-isolate. Everyone isolates and the equilibrium prevalence of infection falls precipitously right after time t_1—very unlike the "epidemic limbo" that prevails in models without complementarities.

The most extreme version of this phenomenon arises when all of the benefit of public activity comes from social activity, i.e., when $\alpha_1 = 0$ but $\alpha_2 > 0$. Once infection prevalence hits $\overline{I}$ at time t_1, each susceptible agent is indifferent whether to isolate when no one else is doing so. But then as some people start isolating, all agents strictly prefer to isolate and the unique equilibrium has everyone hunkered down in isolation, getting flow utility $u(0; 0) = \alpha_0$ from isolated activities alone. Such sudden collective voluntary isolation stops the virus in its tracks but, so long as there is even a small amount of virus in circulation, it remains an equilibrium for everyone to remain at home. In this context, a social planner can increase welfare by subsidizing some agents to re-engage in social activity, to prod them out of the no-activity equilibrium.

Extension: altruism. Altruism can also have a dramatic effect on equilibrium epidemic outcomes. Suppose that people are willing to pay $B \geq 0$ to avoid causing someone else to be infected, and recall that $d_S(t)$ is the share of susceptible agents who distance. Each infected agent encounters a susceptible agent at rate $\beta S(t)(1 - d_S(t))$, and hence gets expected altruistic benefit $B\beta S(t)(1 - d_S(t))$ when isolating themselves from others. Since self-isolation costs $c > 0$, infected agents strictly prefer to isolate at time t if and only if $S(t)(1 - d_S(t)) > \overline{S} \equiv \frac{c}{\beta B}$.

Early during an outbreak, susceptible agents choose not to isolate because infection is rare (shown earlier); that is, $d_S(t) = 0$. Altruistic agents who become infected early on while infection is rare therefore choose to isolate if and only if $B > \frac{c}{\beta}$. The outbreak will therefore die out with only a few people infected ... and never reach the "epidemic limbo" phase.

Extension: asymptomatic infection. Consider the SCIR model described in Section 1.1. At time t, each susceptible agent who does not distance becomes infected at rate $\beta(C(t) + I(t))$, where $C(t)$ and $I(t)$ are, respectively, the mass of agents with asymptomatic infection ("carriage") and symptomatic infection ("sickness"). Each agent who has not yet gotten sick by time t therefore has an incentive to distance so

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long as $p_S(t)H\beta(C(t)+I(t)) > c$, where $p_S(t) = \frac{S(t)}{S(t)+C(t)+R_C(t)}$ is the likelihood of being susceptible conditional on being not-yet-sick at time t.

For any given prevalence of infection, not-yet-sick agents have less incentive to distance in the SCIR model than susceptible agents do in the SIR model, due to their uncertainty about whether they remain susceptible, i.e., due to the fact that $p_S(t) < 1$. Consequently, (i) a smaller fraction of not-yet-sick agents distance in the SCIR model for any given prevalence of infection, and (ii) agents wait longer in the SCIR model before they begin distancing, i.e., they do not distance until $C(t) + I(t)$ exceeds a threshold strictly higher than $\overline{I}$. This implies, as one would expect, that more people ultimately become infected when the pathogen has asymptomatic spread.

2.2 Forward-looking behavior

The analysis thus far has assumed that agents are (myopic) rule-of-thumb decision-makers, whose behavior depends only on the current prevalence of infection, their own perceived harm from being infected, and, in the SCIR model, their own likelihood of being susceptible. How does agent behavior and the epidemic trajectory change when agents are forward-looking optimizers?

Consider first an SIR model as in Farboodi et al. (2020) and Toxvaerd (2020), in which agents know once they have become infected and there are no economic complementarities. Moreover, for simplicity and to highlight key ideas as clearly as possible, assume that agents make a discrete choice whether to isolate themselves fully or not distance at all. In particular, suppose that agents seek to maximize the expected present value of their future lifetime payoff stream ("continuation welfare"), incur flow cost $s > 0$ while sick, incur flow cost $c > 0$ while self-isolating, and use interest rate $r > 0$ to discount future payoffs. As in the analysis surrounding Figure 1, let $\beta > 0$ be the transmission rate absent any distancing, let $\gamma > 0$ be the infection recovery rate, and assume that agents are not altruistic and self-isolation reduces the risk of transmission to zero.

Equilibrium social distancing. For each epidemiological state $\omega \in \{S, I, R\}$, let $\Pi_\omega(t)$ be the continuation welfare of agents in state ω at time t. Susceptible agents are willing to pay $H(t) \equiv \Pi_S(t) - \Pi_I(t)$ in order to avoid becoming infected. Since they become infected at rate $\beta I(t)$ when not distancing, susceptible agents strictly prefer to distance if and only if $I(t) > \overline{I}(t) \equiv \frac{c}{\beta H(t)}$, much as in the previous rule-of-thumb

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analysis but now with an endogenous time-varying cost $H(t)$ of being infected.

Infected agents' welfare. Once someone has become infected, they will choose thereafter not to distance themselves, earn flow payoff $-s < 0$ while infected, and then earn zero flow payoff once recovered. Since recovery occurs at rate γ, each infection has likelihood $e^{-\gamma L}$ of lasting longer than length of time L. Given discounting at interest rate r, the expected present value of the sickness costs incurred during a given infection is therefore

$$\Pi_I = -s \int_0^\infty e^{-(r+\gamma)L} \mathrm{d}L = \frac{s}{r+\gamma} \tag{13}$$

and does not depend on the time t; in particular, $\Pi_I(t) = \frac{s}{r+\gamma}$ for all t.

Susceptible agents' welfare. The continuation welfare of a susceptible agent varies over time, and in a non-monotone fashion. Early in the epidemic while infection is rare, susceptible agents do not distance and face little immediate risk of exposure. However, as time passes, the risk of soon being infected grows exponentially and the epidemic looms larger in agents' welfare considerations. Over this timeframe, susceptible agents' welfare is declining over time. On the other hand, near the end of the epidemic when infection is once again relatively rare, agents will once again choose not to distance. The difference is that now, as time passes, susceptible agents' *remaining* risk of becoming infected falls as the epidemic continues to fade, causing their continuation welfare to increase.

Equilibrium trajectory. An equilibrium epidemic with forward-looking agents typically follows a similar[17] three-part trajectory as in the previous rule-of-thumb analysis: (i) first, a period of uncontrolled growth in the prevalence of infection until time t_1; (ii) second, an intermediate period until time t_2 in which some but perhaps not all agents self-isolate; and (iii) a final period after t_2 in which no one distances, but the prevalence of infection continues to fall because "herd immunity" has been achieved.

The main difference is that the prevalence of infection $I(t)$ is no longer constant but *falls* over time during the intermediate phase.[18] To gain intuition, note that agents are

[17]Other patterns are possible. For instance, if distancing is only partially effective at limiting transmission events, then there can be periods in which all agents distance, interspersed with periods in which some but not all distance.

[18]The March 2020 version of Toxvaerd (2020) states that the prevalence of infection is constant over the intermediate phase. This is incorrect, as I have confirmed through an email correspondence with the author. Fortunately, the underlying error is easily corrected and his other main qualitative findings remain.

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indifferent whether to incur the cost c to self-isolate. A susceptible agents' continuation welfare at time $t \in (t_1, t_2)$, $\Pi_S(t)$, is therefore the expected present value associated with incurring cost c all the way from time t until t_2 and then getting lump-sum payment $\Pi_S(t_2)$ at time t_2. Moreover, because agents strictly prefer not to distance after time t_2, they are obviously better off than if they had to pay c in perpetuity. Consequently, $\Pi_S(t)$ is strictly *increasing* from time t_1 until time t_2. That implies that the harm of infection $H(t) = \Pi_S(t) - \Pi_I$ is also increasing in t. In order for agents to be indifferent whether to self-isolate, the risk of infection must therefore be decreasing in t, which requires that fewer people are infected over time.

Impact of a vaccine or treatment. Those who are vaccinated are less likely to become infected for any given level of activity and hence will choose to be more active than otherwise. If the vaccine is imperfect, the overall effect of such "risk compensation" can be to increase the amount of infection; see e.g. Hoy and Polborn (2015) and Talamas and Vohra (2018). Similarly, treatments that reduce the harm of infection may lead to greater transmission, as people are less cautious about avoiding infection.

Even before a vaccine or treatment becomes available, the anticipation of its arrival can change behavior. Suppose that agents are forward-looking optimizers and that they expect a *perfect vaccine* to become available at time $T > 0$. Anyone exposed at or after time T will not become infected; so, susceptible agents have no reason to distance and will not become sick, i.e., $\Pi_S(t) = 0$ for all $t \geq T$. Just before time T, the harm of being infected, $H(t) = \Pi_S(t) - \Pi_I(t) \approx \frac{-s}{r+\gamma}$, is therefore as large as it can ever be. This gives agents a relatively strong incentive to distance just before the vaccine becomes available—the intuition being that they have nearly "made it" to the point when they won't need to distance any longer.

What if, instead, a *perfect treatment* becomes available at time $T > 0$. Anyone infected at or after time T will not suffer; so, as with a perfect vaccine, susceptible agents have no reason to distance and $\Pi_S(t) = 0$ for all $t \geq T$. The main difference is that those who are infected shortly before time T now also do not suffer much at all. In particular, $\Pi_I(t) \approx -s(T - t) \approx 0$ for all t slightly less than T, implying that the harm of infection is approximately zero. Thus, agents respond quite differently to news of a coming vaccine versus a coming treatment.

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3 Lockdown policies

In early April 2020, the *Wall Street Journal* reported that "U.S. counties under lockdown orders ... represent nearly 96% of national output" and that "at least one-quarter of the U.S. economy has suddenly gone idle ... an unprecedented shutdown that economists say has never occurred on such a wide scale." Many Americans chafed under these restrictions and called for them to be eased, including President Donald Trump,[19] but the case for government intervention of some kind was strong. States like Florida and Texas whose governors initially resisted public-health measures to slow the virus' spread were soon overwhelmed and forced to follow suit.

Consider the simple example analyzed in Section 2.1. During the "limbo phase" of the epidemic, when some but not all agents distance, agents have a choice between (i) suffering economically by distancing or (ii) facing the risk of infection by not distancing. A key feature of the equilibrium epidemic during this period is that agents are indifferent whether to distance. Indeed, they suffer more than if everyone had been completely locked down since, with a lockdown, there would at least have been less infection when activity is allowed to resume.

What type of lockdown policy is socially optimal? The answer depends on three key questions about the economic-epidemiological environment: (i) can infections be identified?, (ii) is social distancing voluntary?, and (ii) are there economic complementarities associated with economic activity?

What if infections can be identified? If public-health authorities can identify who is infected, then the epidemic can potentially be halted in its tracks by imposing a *targeted lockdown* that only restricts the activity of infected agents.[20]

Suppose for the moment that lockdown reduces an agent's social activity to fraction $0 \leq \phi < 1$ of its normal level and that, absent lockdown, all agents would engage in their normal level of activity. If $\phi < \frac{\gamma}{\beta}$, then locking down all infected agents reduces the basic reproduction number of the virus from $R_0 = \frac{\beta}{\gamma}$ to $R_0 = \frac{\phi\beta}{\gamma} < 1$, extinguishing

[19] After relatively small protests against state-ordered lockdowns in mid-April, Trump tweeted "LIBERATE MINNESOTA" and "LIBERATE MICHIGAN" and criticized the Democratic governors of these and other states. Two weeks later, protesters armed with assault rifles occupied the Michigan statehouse (DeBrabander 2020).

[20] Locking down all infected hosts and no susceptible hosts has the same effect as locking down all susceptible hosts and no infected hosts. Thus, even after most people have become infected, an epidemic's *further* expansion can be stopped if the uninfected hunker down in isolation—a key plot point in most zombie-apocalypse movies.

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the epidemic. What if $\phi > \frac{\gamma}{\beta}$? Locking down infected hosts is then not enough to stop the virus from infecting a substantial fraction of the population. However, since the virus spreads *as if* it has transmission rate $\phi\beta$ rather than β, fewer people will be infected and, if recovery does not confer immunity, the steady-state prevalence of infection will be lower.

Bethune and Korinek (2020) characterize the socially-optimal targeted lockdown policy, assuming that the social planner can dictate each agent's level of activity $a_i \in [0, 1]$ and that agents get concave flow utility $u(a)$ from activity-level a, with $u'(1) = 0$ so that small reductions in activity have a negligible impact on agent welfare. Figure 2 illustrates their findings in the SIS model, the panels on the left showing agents' equilibrium activity as a function of current infection prevalence, for a high-cost disease such as Covid (top) and a low-cost disease such as the common cold (bottom), and the panels on the right showing the corresponding socially-optimal activity levels.

In the decentralized equilibrium without any forced lockdown, only susceptible agents reduce their activity and much more so in the case of a high-cost disease, as expected. For the high-cost disease, the social planner always imposes a sufficiently severe lockdown policy so that the virus' basic reproduction number R_0 is held below one, so that the prevalence of infection falls over time. However, this is achieved through a *combination* of restrictions on infected and susceptible agents, with restrictions on infected and susceptible agents growing more and less severe, respectively, as the prevalence of infection falls over time. In the long run, as infection prevalence vanishes to zero, susceptible agents are unrestricted and only infected agents are restricted.

The most interesting case is when the disease is less severe, as illustrated in the lower panels of Figure 2. If infection is sufficiently rare—for instance, if there is an outbreak of a novel virus—then the social planner finds it optimal to target infected agents with severe restrictions, enough to reduce R_0 below one and drive the prevalence of infection to zero. Although these restrictions are burdensome on those who become infected, the mass of agents who ever become infected is small; so, the overall burden of the lockdown policy is small, relative to the harm that would have been done if the outbreak had been allowed to grow into an epidemic. However, once infection prevalence passes a threshold (about 0.15 in Figure 2), the lockdown "cure" is worse than the disease and the social planner finds it optimal to blunt the epidemic but not stop it.

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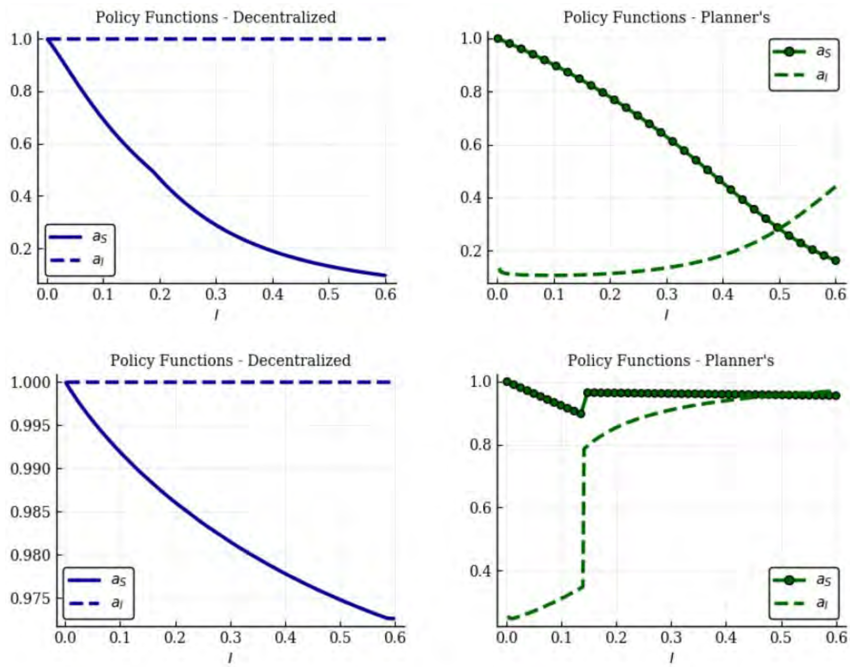

Figure 2: Equilibrium ("decentralized") and socially-optimal activity levels for susceptible and infected agents in the SIS model, for a severe disease (top panels) and a mild disease (bottom panels). Courtesy of Zachary Bethune and Anton Korinek.

What if infections cannot be identified? Suppose that the disease spreads mainly during an early asymptomatic phase and that there is no way to determine who is asymptomatically infected. In this case, the social planner is constrained to uniform lockdown policies. Alvarez et al. (2020), Bethune and Korinek (2020), and Rowthorn and Maciejowski (2020) characterize the optimal uniform lockdown in an SIR model, under various parameter conditions motivated by the Covid-19 outbreak. In Alvarez et al. (2020), "the optimal policy prescribes a lockdown starting four weeks after the outbreak, and covering 45% of the population after 8 weeks." Similarly, in Rowthorn and Maciejowski (2020), "the lockdown lasts 5.3 weeks and brings the disease under control quite soon, although not before millions of people have been infected and many thousands have died." On the other hand, Bethune and Korinek (2020) find that it is optimal not to allow the infection ever to become common. In all three cases, continued "relaxed" restrictions are maintained for an extended period, to keep R_0 close to one and prevent a resurgence of the epidemic.

Two features[21] of optimal lockdown here are worth emphasizing. First, the social planner waits until the outbreak is sufficiently large before imposing any restrictions. To see why, suppose that the social planner were to severely constrain activity while infection is extremely rare. Infection would grow even more rare, but would not disappear entirely. Once the lockdown is eased, the virus will then come roaring back and, since few have been exposed, the population as a whole will then be in the same position as if they had not just locked down their economy.

Second, the social planner applies relatively intense restrictions and then eases up over time. Why? Because lockdowns are costly and must be applied across the board, it is never optimal to maintain such restrictions forever. But then that means that the virus must eventually infect enough people for the population to achieve herd immnuity, after which the rate of new infection declines over time. In an uncontrolled epidemic, the number of people who are infected reaches its peak at the point in time when herd immunity is achieved, and the epidemic blows through the herd-immunity threshold; in the end, many more are infected than needed to be. By constraining activity while the epidemic would otherwise be raging, the social-planner can ensure that relatively few people are infected after herd immunity is reached.

Of course, both of these findings hinge critically on the assumption that there is no way to detect infection. Should testing for asymptomatic infection be available, the social planner typically finds it optimal to isolate those who are found to be infected—not just to slow or smooth out the epidemic trajectory, but to eliminate the virus entirely.

Discussion: nuances around testing and heterogeneity. Testing to discover asymptomatic carriers is essential, as it empowers public-health authorities to get the epidemic under control without a large number of people being infected. However, as Acemoglu et al. (2020b) and Deb et al. (2020) have noted, testing without appropriate incentives can lead to perverse outcomes. As Acemoglu et al. (2020b) explains:

> "Testing enables the isolation of infected individuals, slowing down the infection. But greater testing also reduces voluntary social distancing or

[21] These features are evident in Alvarez et al. (2020) and Rowthorn and Maciejowski (2020), but also present in Bethune and Korinek (2020), just with a very low prevalence threshold for lockdown and a very long time until herd immunity is reached.

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increases social activity, exacerbating the spread of the virus. We show that the effect of testing on infections is non-monotone. This non-monotonicity also implies that the optimal testing policy may leave some of the testing capacity of society unused."

Further nuances arise when agents have heterogeneous types. Brotherhood et al. (2020) and Acemoglu et al. (2020a) analyze an extension of the SIR model allowing for multiple agent types that differ in their health status (e.g., "old" are more likely to die if infected) and/or in their connections with others (e.g., "young" interact mostly with themselves). A shared insight that emerges in these papers is that it may be optimal to allow infection to spread more widely among the young.[22] This can be good for the young, since they are not as burdened economically, but can also be good for the old as herd immunity can be reached with fewer of the old becoming sick.[23]

Are there economic complementarities associated with economic activity? McAdams and Day (2020) explores the implications of economic complementarities on lockdowns. Consider an SCIR model in which a lockdown can be imposed on not-yet-sick agents. In this context, restricting others' activity benefits agents by reducing pathogen transmission ("health spillover") but also harms agents economically, by reducing the benefit that agents get from social activity ("economic spillover"). McAdams and Day (2020) find that, if transmission only occurs during carriage, then the health spillover always dominates the economic spillover, in the sense that agents benefit by having a lockdown imposed *before* they would begin to distance voluntarily. On the other hand, if transmission occurs primarily during infection, then not-yet-sick agents may sometimes benefit by being forced to be active when they would not otherwise voluntarily choose to do so.

4 Pathogen eradication

When can a pathogen be eradicated from a host population? An extensive literature explores the potential to eradicate diseases through vaccination; see e.g., Geoffard and

[22] An earlier literature grapples with the question of how to optimally devote limited infection-prevention resources. In a multi-population SIS model, Anderson et al. (2012) show that it can be optimal to focus entirely on just one population.

[23] As these authors note, this conclusion hinges on the assumption of unlimited hospital capacity. If the young take up limited hospital beds, then more of the old could die even as fewer are infected.

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Philipson (1996) and Chen and Toxvaerd (2014) on vaccination in fully-mixed models and Perisic and Bauch (2009) in a model with transmission over a network. Here I focus on complementary approaches that leverage *treatment* and/or *infection control*.

Section 4.1 follows Rowthorn and Toxvaerd (2012), focusing on the special case of their model in which a highly-effective treatment is available and there are no prevention options. The main finding is that an infectious disease *can* potentially be eradicated through treatment alone, but only if the treatment is introduced while infection remains sufficiently rare.

Section 4.2 follows McAdams et al. (2019) in considering a context in which multiple strains of the same pathogen co-exist, some of which are resistant to antibiotic treatment. The main finding is that resistant strains *can* potentially be eradicated, thereby restoring the effectiveness of existing antibiotics to which resistance has already emerged, but only if (i) diagnostics are available to detect resistant infection and (ii) public-health resources can be deployed specifically to reduce transmission of resistant strains.

4.1 Eradicating a disease

Consider an SIS-model infectious disease for which a costly treatment is available, and suppose that this treatment is sufficiently effective that the disease could be eradicated if every infection were treated. Here I focus on two central questions. First, is it socially optimal to eradicate the disease? Second, can the disease be eradicated in a decentralized (Nash equilibrium) setting in which each infected person incurs the cost of treatment and decides whether to receive treatment?

Epidemiological model. A pathogen circulates among a unit-mass population of hosts according to a standard SIS model. While infected, each host may or may not receive treatment that speeds recovery. Let $S(t)$ and $I(t)$ denote the mass of susceptible and infected hosts, respectively, with $S(t) + I(t) = 1$ because the population has unit mass. Let $I_Y(t)$ and $I_N(t)$ denote the mass of infected hosts who are treated (Y for "yes") or not treated (N for "no"). Infected hosts recover at baseline rate γ_0 if untreated or at faster rate $\gamma_A > \gamma_0$ if treated. The overall flow of newly-recovered agents therefore equals $\gamma_0 I_N(t) + \gamma_A I_Y(t) = \gamma_0 I(t) + (\gamma_A - \gamma_0)I_Y(t)$. The resulting

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epidemiological dynamics are characterized by the differential equation

$$S'(t) = -\beta I(t)S(t) + \gamma_0 I_N(t) + \gamma_A I_Y(t) \tag{14}$$

with $I(t) = I_Y(t) + I_N(t)$ and $S(t) + I(t) = 1$. If all infections are treated, equation (14) simplifies to $S'(t) = I(t)(\gamma_A - \beta(1 - I(t)))$.

Eradication through treatment is possible when $\gamma_A > \beta$, since then $S'(t) > 0$ (and hence $I'(t) < 0$) no matter how many agents are currently infected. I will focus here on the case when $\gamma_A > \beta > \gamma_0$, meaning that the disease will be eradicated if all infections are treated but not if no infections are treated.

Untreated infections last on average for length of time $L_0 = \frac{1}{\gamma_0}$. Each untreated infected person therefore on average exposes $R_0 = \frac{\beta}{\gamma_0} > 1$ others during the course of their infection. Should all infections be left untreated, the prevalence of infection will increase from approximately zero (when the pathogen first enters the host population) to a steady-state level $I_0^\infty \equiv 1 - \frac{\gamma_0}{\beta}$. On the other hand, if all infections are treated, then $R_0 = \frac{\beta}{\gamma_A} < 1$ and the long-run steady state prevalence of infection is zero.

To close the model, it remains to characterize when infected hosts receive treatment. To do so, one needs to overlay an economic model on top of the epidemiological model.

Economic model. Each host i receives flow payoff $\pi_i(t) = 0$ when susceptible, $\pi_i(t) = -s$ when sick and untreated (s is "sickness cost"), or $\pi_i(t) = -s - c$ when sick and treated (c is used here for "treatment cost"), and discounts payoffs with respect to interest rate $r > 0$. While infected, each agent decides whether or not to receive treatment.

Maximizing social welfare. Across the entire population, the disease does harm $sI(t) + cI_Y(t)$ at each time t. Treating more infections at time t raises the costs that are immediately incurred, but reduces the future prevalence of infection. Rowthorn and Toxvaerd (2012) show that the socially-optimal treatment policy is bang-bang. In particular, a threshold $\widehat{I}$ exists such that it is socially optimal to treat all infections whenever $I(t) < \widehat{I}$ but to leave all infections untreated whenever $I(t) > \widehat{I}$.

The bang-bang nature of optimal treatment arises because treatment is more socially valuable when a disease is rarer. To gain intuition, note that the prevalence of infection grows exponentially during the early phase of an outbreak while infection is relatively rare, but that the rate of growth declines as more people become infected.

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Treating any given infection therefore prevents more infections when the overall prevalence of infection is lower.

Nash-equilibrium outcomes. What if individuals decide for themselves whether or not to be treated? The resulting game exhibits strategic complements, with each agent having more incentive to be treated if they believe that others (now and in the future) are more likely to seek out treatment as well. To gain intuition, note that agent i's benefit of recovering from infection depends on the risk of re-infection: the lower the rate of re-infection, the longer that agent i expects to remain infection-free and hence the more valuable it is to recover. If others are more likely to be treated (now and in the future), then fewer people will be spreading infection once agent i eventually recovers, increasing agent i's incentive to be treated herself.

As in any game with strategic complements, there is a maximal and a minimal Nash equilibrium (Milgrom and Roberts 1990). Rowthorn and Toxvaerd (2012) characterize these maximal and minimal equilibria in terms of two additional infection-prevalence thresholds, denoted here as $\underline{I}$ and $\overline{I}$, with $0 \leq \underline{I} \leq \overline{I} \leq \widehat{I}$.

In the maximal equilibrium, all infections are treated at time t if $I(t) < \overline{I}$ but none are treated if $I(t) > \overline{I}$. Similarly, in the minimal equilibrium, all infections are treated at time t if $I(t) < \underline{I}$ but none are treated if $I(t) > \underline{I}$. Note that the disease is eradicated in *all* equilibria if its initial prevalence $I(0)$ is less than $\underline{I}$, and is eradicated in *some* equilibrium if $I(0) \leq \overline{I}$.

A necessary condition for equilibrium eradication. Suppose that agent i is infected but that the disease is exceedingly rare, so that agent i faces negligible re-infection risk. When deciding whether to seek out treatment, agent i will compare the expected present value of the costs associated with her current infection, with and without treatment.

When untreated, agent i incurs flow cost s until recovery, which occurs at rate γ_0. When treated, agent i incurs flow cost $s + c$ until recovery at rate γ_A. Let C_0 and C_A be the expected present value of the costs incurred during an untreated and treated infected, respectively:

$$C_0 = \int_0^\infty s e^{-rt} e^{-\gamma_0 t} dt = \frac{s}{r + \gamma_0} \tag{15}$$

$$C_A = \int_0^\infty (s + c) e^{-rt} e^{-\gamma_A t} dt = \frac{s + c}{r + \gamma_A} \tag{16}$$

If $\gamma_A \leq \frac{s+c}{s}\gamma_0 + \frac{c}{s}r$, then $C_0 \leq C_A$ and agent i is strictly better off being left untreated. In this case, the disease cannot be eradicated in any equilibrium. Otherwise, if $\gamma_A > \frac{s+c}{s}\gamma_0 + \frac{c}{s}r$, then $C_0 > C_A$ and agent i is strictly better off being treated so long as the infection is sufficiently rare. In this case, the disease will be eradicated so long as the treatment becomes available sufficiently early, while infection remains sufficiently rare.

4.2 Restoring antibiotic effectiveness

> "Some experts say we are moving back to the pre-antibiotic era. No. This will be a post-antibiotic era ... an end to modern medicine as we know it."
>
> – Margaret Chan, Director-General of the World Health Organization, 2012

Staphylococcus aureus ("staph"), a bacterium that commonly colonizes the nasal passage, has numerous strains that dwell peacefully within the human microbiome. But some strains long ago acquired the genetic machinery to produce toxins that cause disease and, more recently, to survive exposure to the antibiotics used to treat bacterial infection ("antibiotic resistance"; see Laxminarayan et al. 2013). These staph strains are in a competition[24] that naturally favors the antibiotic-resistant strains, since they are more likely to survive when a person receives antibiotic treatment. For instance, methicillin-resistant staph (MRSA) first emerged in the 1960s but by 2014 accounted for over half of hospital-associated staph infections in the United States (WHO 2014, pg. 118).

Since antibiotic exposure is more effective at killing antibiotic-sensitive bacteria, increased *indiscriminate* antibiotic use advantages resistant strains and hence hastens the rise of untreatable infection. In that context, antibiotics are "exhaustible resources" whose value is diminished by use (Laxminarayan and Brown 2001). As the CDC and

[24] Dall'Antonia et al. (2005) found that colonization by a methicillin-sensitive strain reduced a person's likelihood of subsequently being colonized by a MRSA strain by 78%. Yang et al. (2018) found in mice that a commensal strain suppressed the growth of a MRSA strain and elicited both innate and adaptive immunity against MRSA skin infection.

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the Review on Antimicrobial Resistance (AMR Review) explained: "Because antibiotic resistance occurs as part of a natural evolution process, it can be significantly slowed but not stopped" (CDC 2013); and "Any use of antimicrobials, however appropriate and conservative, contributes to the development of resistance" (AMR Review 2014).

While indiscriminate antibiotic use promotes resistance, increased *targeted* use of any given antibiotic can slow or even reverse the rise of resistance to *other* antibiotics. This point was first made in McAdams (2014) and subsequently elaborated in McAdams (2017) for an obligate pathogen (SIS model) and in McAdams et al. (2019) for an opportunistic pathogen (SCIS model) with incidental antibiotic exposure in carriage. With targeted interventions, antibiotics become *preservable resources* whose value can be maintained even as all patients receive the best-available treatment.[25]

SIS model with competing strains. Consider an SIS model with multiple strains having different antibiotic-resistance profiles. In particular, suppose that there are two antibiotics, drug A and drug B, and four strains in circulation: "strain 0," sensitive to both drugs; "strain A," resistant to drug A but sensitive to drug B; "strain B," resistant to drug B but sensitive to drug A; and "strain AB," resistant to both drugs. For each resistance profile $X \in \{0, A, B, AB\}$, let $I_X(t)$ be the mass of hosts with strain-X infection at time t; so, $I(t) = \sum_X I_X(t)$, and $S(t) + I(t) = 1$, where $S(t)$ is the mass of uninfected hosts.

Let β_X be the transmission rate of strain X. Being resistant to an antibiotic can sometimes disadvantage bacteria in other ways. Such "fitness costs" can be captured by assuming that $\beta_0 > \max\{\beta_A, \beta_B\}$ and $\min\{\beta_A, \beta_B\} > \beta_{AB}$. When there are fitness costs, *withholding treatment* is enough to put resistant bacteria at disadvantage and cause their (relative and eventually absolute) number to dwindle over time. I focus here on the more challenging case without fitness costs, i.e., $\beta_X = \beta > 0$ for all X.

Treatment is assumed to have two sorts of effects: (i) *speedier recovery*, from baseline rate $\gamma_0 > 0$ to $\gamma_A > \gamma_0$ for A-sensitive infections treated with drug A, or $\gamma_B > \gamma_0$ for B-sensitive infections treated with drug B; and (ii) *resistance emergence*,[26] with sensitive

[25] In their final report, citing an early version of McAdams et al. (2019), the AMR Review acknowledged the game-changing potential of rapid diagnostics to reverse the rise of resistance: "The information garnered from rapid diagnostics might eventually allow doctors to improve treatment and infection control to such an extent that this places negative selective pressure on resistance pathogens, thus reducing resistance in older drugs" (AMR Review 2016, pg. 35).

[26] "Resistance emergence" is shorthand for all the various ecological pathways by which a host who is initially infected (only or primarily) by sensitive bacteria can transition to being infected by resistant bacteria. Notably: (i) *treatment-induced mutation*, whereby antibiotic exposure triggers accelerated

infections becoming resistant to the drug being used for treatment at rate $\eta \geq 0$.

Case #1: indiscriminate treatment. Suppose for a moment that all patients are treated with drug A. The resulting flows among epidemiological states are as follows. *New infection ($S \to I_X$)*: Each X-infected host meets a susceptible host at rate $\beta S(t)$, creating flow $\beta S(t) I_X(t)$ from the susceptible state S to the X-infected state I_X. *Treated recovery ($I_0, I_B \to S$)*: 0- and B-infections clear at treated rate γ_A, creating flows $\gamma_A I_0(t)$ from I_0 to S and $\gamma_A I_B(t)$ from I_B to S. *Untreated recovery ($I_A, I_{AB} \to S$)*: A- and AB-infections clear at untreated rate γ_0, creating flows $\gamma_0 I_A(t)$ from I_A to S and $\gamma_0 I_{AB}(t)$ from I_{AB} to S. *Emergence of drug-A resistance ($I_0 \to I_A$, $I_B \to I_{AB}$)*: 0- and B-infections acquire A-resistance at rate η, creating flows $\eta I_0(t)$ from I_0 to I_A and $\eta I_B(t)$ from I_B to I_{AB}. The resulting epidemiological dynamics, expressed as percentage rates of change, are given by the following system of equations:

$$\frac{I_0'(t)}{I_0(t)} = \frac{I_B'(t)}{I_B(t)} = \beta S(t) - \gamma_A - \eta \tag{17}$$

$$\frac{I_A'(t)}{I_A(t)} = \beta S(t) - \gamma_0 + \eta \frac{I_0(t)}{I_A(t)} \tag{18}$$

$$\frac{I_{AB}'(t)}{I_{AB}(t)} = \beta S(t) - \gamma_0 + \eta \frac{I_B(t)}{I_{AB}(t)} \tag{19}$$

Note that strains $0, B$ grow at a slower percentage rate than strains A, AB. The percentage of infections that can be effectively treated with drug A therefore falls over time until, eventually, all infections are resistant to drug A.

Case #2: targeted treatment and no control. A rapid resistance diagnostic enables doctors to identify each infection's resistance profile and prescribe the best-available antibiotic treatment. Suppose that doctors prefer to prescribe drug A when both are effective, perhaps because drug A is less expensive or induces milder side effects. 0- and B-infections will continue to be treated with drug A, but now A-infections will be treated with drug B while AB-infections will be left untreated (to avoid harmful side effects). This leads to quicker clearance and hence less transmission of A-infection, but also faster emergence of multidrug resistance as AB-infections now emerge both from A-infections being treated with drug B and B-infections being treated with drug A.

mutation (via stress response, chemical signaling by other bacteria, etc.), increasing the likelihood of a resistance-conferring mutation; and (ii) *competitive release*, whereby killing off sensitive bacteria promotes explosive growth of resistant bacteria that were already colonizing the host in small numbers.

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In particular, equations (18,19) become

$$\frac{I'_A(t)}{I_A(t)} = \beta S(t) - \gamma_B - \eta + \eta \frac{I_0(t)}{I_A(t)} \tag{20}$$

$$\frac{I'_{AB}(t)}{I_{AB}(t)} = \beta S(t) - \gamma_0 + \eta \frac{I_A(t) + I_B(t)}{I_{AB}(t)} \tag{21}$$

If both drugs are equally effective ($\gamma_B = \gamma_A$), then $\frac{I'_{AB}(t)}{I_{AB}(t)} > \frac{I'_A(t)}{I_A(t)} > \frac{I'_B(t)}{I_B(t)} > \frac{I'_0(t)}{I_0(t)}$. Strains $0, B$ dwindle over time the fastest, and strain A is also eventually overwhelmed by strain AB—a "post-antibiotic world" dominated by untreatable infection.

Case #3: targeted treatment and targeted control. While targeted treatment alone is insufficient to prevent a post-antibiotic world, targeted treatment combined with targeted infection control can be enough to put resistant strains at a disadvantage. "Targeted infection control" can take many forms depending on the pathogen and relevant host population, e.g., requiring a child with resistant pneumoccal infection to stay home from school (Ekdahl et al. 1998), providing skilled wound care (Solberg 2000) or free needles (Bassetti and Battegay 2004) for those with resistant skin staph infection, etc.

For simplicity, I assume here that infection control takes the form of *perfect isolation* of up to mass $\Delta > 0$ of hosts, with prioritized isolation first of those with untreatable AB-infection, then the B-infected, and then the A-infected, but no isolation of the 0-infected or of the uninfected. Moreover, I will assume that (i) isolation capacity is very limited, i.e., $\Delta \approx 0$, (ii) untreatable AB-infections are sufficiently rare *at first* to all be isolated, i.e., $I_{AB}(0) < \Delta$, and (iii) resistance emergence is sufficiently rare[27] that $\eta < \Delta\gamma_0$ and $\eta < \Delta\frac{\gamma_0}{\beta}$.

Under these assumptions, all AB-infections can be isolated in perpetuity. Targeted isolation reduces strain AB's *average transmission rate* from β to $\widehat{\beta}_{AB}(t) \equiv \beta \max\left\{\frac{I_{AB}(t)-\Delta}{I_{AB}(t)}, 0\right\}$. If AB-infection were already sufficiently widespread at time 0 that $\frac{I_{AB}(0)}{\Delta} \gg 1$, then $\widehat{\beta}_{AB}(t) \approx \beta$ and targeted isolation would have a negligible effect on epidemiological dynamics. However, because $I_{AB}(0) < \Delta$, all untreatable infections

[27] Resistance-conferring mutation is rare in bacteria and, so long as resistance to an antibiotic remains rare, competitive release will also tend to be rare as few hosts are colonized by even small numbers of the resistant strain. The assumption here that $\eta \approx 0$ therefore appears reasonable while resistance remains rare, but perhaps not once resistance has become common.

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can be isolated and $\widehat{\beta}_{AB}(0) = 0$. Equation (21) at time 0 then becomes

$$\frac{I'_{AB}(0)}{I_{AB}(0)} = -\gamma_0 + \eta \frac{I_A(0) + I_B(0)}{I_{AB}(0)} \tag{22}$$

Note that $I'_{AB}(0) < 0$ if and only if $I_{AB}(0) < \widehat{I}_{AB}(0) \equiv \frac{\eta}{\gamma_0}(I_A(0) + I_B(0))$. Since $\eta < \gamma_0 \Delta$ (by assumption) and $I_A(0) + I_B(0) < 1$ (obviously), we have $\widehat{I}_{AB}(0) < \Delta$. Consequently, *either* $I_{AB}(0) < \widehat{I}_{AB}(0)$ and $I'_{AB}(0) > 0$ *or* $I_{AB}(0) \in \left(\widehat{I}_{AB}(0), \Delta\right)$ and $I'_{AB}(0) < 0$. Either way, AB-infection prevalence remains strictly less than Δ, allowing all AB-infections to continue to be isolated. Because this logic continues to apply after time 0, all AB-infections can be isolated in perpetuity. Moreover, $\lim_{t\to\infty} \frac{I_{AB}(t)}{I_A(t)+I_B(t)} = \frac{\eta}{\gamma_0} < \Delta \approx 0$ and $\lim_{t\to\infty} I_{AB}(t) \leq \Delta(1 - \gamma_0/\beta)$ (straightforward details omitted), implying that at least $\frac{\Delta\gamma_0}{\beta}$ isolation capacity is available to target other infections.

Since B-infections are equally-well treated as 0-infections (with drug A) and some B-infections are isolated, $\frac{I'_B(t)}{I_B(t)} < \frac{I'_0(t)}{I_0(t)}$. The prevalence of B-infection must therefore eventually fall to zero. What about A-infections? Let $\Delta_A(t) = \max\{\Delta - I_{AB}(t) - I_B(t), 0\}$ denote the isolation capacity available at time t to isolate A-infected hosts. Isolation reduces the flow of new A-infection from $\beta S(t) I_A(t)$ to $\max\{\beta S(t)(I_A(t) - \Delta_A(t)), 0\}$; modifying equation (20) and comparing to (17) yields

$$\frac{I'_0(t)}{I_0(t)} - \frac{I'_A(t)}{I_A(t)} = (\gamma_B - \gamma_A) + \beta S(t) \frac{\Delta_A(t) - \eta I_0(t)}{I_A(t)} \tag{23}$$

Consider the case in which both drugs are equally effective, so that $\gamma_B - \gamma_A = 0$.[28] As discussed previously, $\lim_{t\to\infty} \Delta_A(t) \geq \frac{\Delta\gamma_0}{\beta}$. Since $\eta < \frac{\Delta\gamma_0}{\beta}$ (by assumption) and $I_0(t) < 1$ (obviously), we have $\Delta_A(t) - \eta I_0(t) > 0$ and hence $\frac{I'_0(t)}{I_0(t)} > \frac{I'_A(t)}{I_A(t)}$ for all large t. The prevalence of A-infection must therefore also eventually fall to zero—and, with A-infection and B-infection each vanishing, AB-infection must also vanish.

In the end, the effectiveness of both antibiotics is completely restored, even as all patients receive the best-available antibiotic treatment—a complete *turning of the tables* on resistant bacteria!

What made this possible? First, doctors and public-health officials had access to a rapid resistance diagnostic, to know what treatment to prescribe and where specifically to deploy public-health resources. Second, a highly-effective infection-control option

[28] If $\gamma_A > \gamma_B$, then strain A may grow in number and eventually dominate the bacterial population. However, drug B remains effective in this case and can be used to treat A-resistant infections.

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("isolation") is available that specifically disrupts transmission from targeted infections. Finally, the pathogen in question spreads according to an SIS model, i.e., it is an *obligate pathogen* that causes disease immediately after colonizing the host.

Infection-oriented interventions such as isolation are much less effective against *opportunistic pathogens* that dwell in carriage for extended periods, such as *Streptococcus pneumoniae* (pneumococcus) and *Escherichia coli*. However, other microbiome-oriented interventions can potentially reverse the rise of resistance among such pathogens. For instance, McAdams et al. (2019) argues that (i) an annual "microbiome checkup" to detect resistant bacteria currently colonizing a patient plus (ii) a moderately effective intervention aimed at clearing these bacteria from carriage (e.g., seeding or promoting the growth of competitor bacteria) may be enough to select against resistance.

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Individualism during crises[1]

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Individualism has long been linked to economic growth. Using the COVID-19 pandemic, we show that such a culture can hamper the economy's response to crises, a period with heightened coordination frictions. Exploiting variation in US counties' frontier experience, we show that more individualist counties engage less in social distancing and charitable transfers, two important collective actions during the pandemic. The effect of individualism is stronger where social distancing has higher externality and holds at the individual level when we exploit migrants for identification. Our results suggest that individualism can amplify economic downturns by exacerbating collective action problems.

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1 Introduction

Individualism, the preference for personal freedom and achievement, has long shaped the American culture and its institutions. By awarding social status to personal accomplishments, individualism incentivizes innovation. A large literature documents that such a culture contributes to economic growth (Gorodnichenko and Roland, 2011a,b, 2017). However, individualism also makes collective actions more difficult, as it encourages individuals to pursue their own interests without internalizing the externality of their behaviors. Such a trade-off between growth and coordination can change dramatically during economic crises, when the collective action problem is more acute (Schaal and Taschereau-Dumouchel, 2018). This paper demonstrates this point empirically using the COVID-19 pandemic.

The COVID-19 pandemic is one of the most significant crises facing humankind in recent history. While still unfolding, it has already brought significant economic and human tolls around the globe. Central to this crisis is a collective action problem. To mitigate the spread and the impact of the disease, individuals and regions need to coordinate their efforts, such as social distancing and charitable transfers. However, these socially optimal actions can be deterred by individualism, which prevents the internalization of group interests, leading to worse pandemic response (Bethune and Korinek, 2020).

We employ novel data and methodologies to test this hypothesis at the US county and individual level. Despite sharing common institutions, US counties differ significantly in culture for historical reasons. Bazzi et al. (2020) show that the amount of time a county spent on the US frontier as it expanded in the 18th and 19th centuries powerfully shapes its individualism culture today. Using county-level total frontier experience (TFE) as a measure of local individualism, we find that more individualist counties engage less in social distancing, as measured by Google and SafeGraph mobility data. An interquartile increase in local individualism offsets 41% of the effect of state lockdown orders on social distancing. These effects hold controlling for county and state-day fixed effects.

Another important socially optimal action during crises is redistribution. Crises often hit parts of the economy harder than others. From a social planner's perspective, redistribution can be optimal and help the economy recover faster. Yet, it is hard to achieve on a voluntary basis since individuals may not internalize the social benefits of redistribution. Such a problem could be exacerbated by individualism, which emphasizes self-reliance (Bazzi et al., 2020). To test this idea, we employ data from the world's largest online donation platform—GoFundMe. From March to April of 2020, GoFundMe experienced an increase of more than 100% in funds raised, driven almost exclusively by COVID-19-related campaigns (43,455 campaigns with $232 million raised).[1] We find that more individualistic counties launch fewer COVID-19-related campaigns after state lockdowns, and that these campaigns raise less money. Further, government stimulus from the Coronavirus

[1] Among these, 26.9% of the raised funds are for personal protective equipment (PPE) and 31.5% for are economically vulnerable populations.

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Aid, Relief, and Economic Security (CARES) Act crowds out private redistributions less in more individualistic counties. Local individualism therefore appears to be an important determinant of voluntary redistribution and affects the effectiveness of government redistribution during crises.

One may be concerned that local unobserved shocks such as county-level government policies or local protests may drive our findings. To address this, we use a proprietary individual-level dataset and exploit individuals' migration to tighten identification. Our novel device-level location data tracks the locations of a quarter of the US population up to a frequency of every five minutes, allowing us to accurately measure the mobility of each individual. We focus on residents in 12 large US cities in 2020, and compare migrants who moved to these cities in 2019 with those who have always been in these cities over our sample period. Based on the sociology literature (Richerson and Christiansen, 2013; Giuliano and Nunn, 2017), we measure individuals' culture by their original location rather than their current location. By comparing individuals residing in the same county at the same time but from different cultural backgrounds, we can difference out any remaining local unobserved shocks, such as local policies, news, or unemployment. Our granular sample allows us to include individual fixed effects and residence county-day fixed effects, which rule out many confounding alternative explanations. Using this identification strategy, we find a result of a similar magnitude as our county-level analysis. Our paper is the first to use device-level mobility data to analyze social distancing behaviors.

Our main hypothesized channel is that individualism hinders individuals form internalizing the social benefits of their actions. To shed light on this channel, we exploit cross-sectional variation in the externalities associated with social distancing and charitable transfers. We find that the effect of individualism on social distancing is particularly strong in counties where social distancing poses larger externalities, i.e., counties with a higher population density or more seniors. We also show that, conditioning on fundraising for COVID-19-related reasons, individualism decreases the share of fundraising campaigns for communities (e.g. local hospitals or restaurant workers) as opposed to those for selves. These results suggest that our findings are driven by the externality channel, rather than individualism altering people's perception of the health or economic consequence of COVID-19.

We conduct a variety of robustness tests. First, using Hofstede (1991)'s individualism score and an instrumental variable approach, we show that our within-US results also hold across countries, suggesting strong external validity of our findings. Second, we show that our results are similar when we use the share of infrequent names or non-patronymic/-matronymic names in the 1930 Census as an alternative measure of county-level individualism. Third, our results hold in both Republican and Democratic counties, as well as when controlling for local political beliefs and social capital. Lastly, our results are similar when we use the local number of confirmed cases or Trump's national emergency announcement as alternative shocks to the severity of the pandemic.

Our findings provide important policy implications. Governments often spend substantial resources on interventions during crises to overcome coordination problems (Schaal and Taschereau-

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Dumouchel, 2018). In the current COVID-19 pandemic, such interventions include lockdown orders, stimulus checks, and business subsidies (Meier and Smith, 2020; Granja et al., 2020). Our findings suggest that culture impacts not only the need for intervention, but also policy take-up and compliance conditional on intervention. Government interventions could be more effective if they target areas differentially based on culture (Sakovics and Steiner, 2012). For example, governments may explicitly communicate the externalities of collective actions to areas with higher individualism to improve policy compliance. Moreover, public health models, such as those predicting the spread of disease, would benefit from incorporating culture (Alfaro et al., 2020). Our results also suggest that individualism, while linked to long-run growth, could also affect the cyclicality of growth. Policymakers may consider taking culture into account when formulating macroeconomic policies.

Our paper contributes to the literature on culture and economics. Economists have long recognized culture as an important determinant of economic outcomes (Guiso et al., 2006), ranging from institutions (Alesina and Giuliano, 2015), to trade and investment (Guiso et al., 2009; Ahern et al., 2015), financial development (Guiso et al., 2004; D'Acunto et al., 2019), household decisions (Guiso et al., 2008, 2013), and firm outcomes (Bloom et al., 2012; Guiso et al., 2015). Gorodnichenko and Roland (2011b, 2012) find that, among all cultural dimensions, the individualism-collectivism dimension has the strongest and most robust effect on long-run economic growth. Individualism also affects innovation and risk taking (Gorodnichenko and Roland, 2011a; Li et al., 2013; Kanagaretnam et al., 2014). Different from these papers, our study focuses on the downside of individualism by highlighting its deterring effect on socially optimal actions during crises.

Our paper also relates to the literature on coordination failures and business cycles. Agents' inability to internalize the externalities of their actions often characterizes crises and downturns (Schaal and Taschereau-Dumouchel, 2018; Bianchi, 2011; Hansen and Libecap, 2004; Bethune and Korinek, 2020). Government interventions are therefore necessary (Schaal and Taschereau-Dumouchel, 2018), but often have to confront constrained resources. Sakovics and Steiner (2012) show that, in the presence of coordination problems, optimal subsidies should target agents imposing the highest externalities. Our paper highlights that individualism is an important aspect of such heterogeneity. Optimal policy design should take into account not only formal institutions, but also informal institutions such as culture.

Lastly, we join a fast-growing literature examining the impact and the economics of COVID-19. Bethune and Korinek (2020), Alvarez et al. (2020), Jones et al. (2020), Correia et al. (2020) and Xiao (2020) study optimal policy response to the pandemic. Allcott et al. (2020), Barrios and Hochberg (2020), Barrios et al. (2020), and Durante et al. (2020) examine the role of political ideology and social capital in social distancing. Other papers study responses by the labor market (Coibion et al., 2020b; Kahn et al., 2020; Campello et al., 2020), financial markets (Alfaro et al., 2020; Baker et al., 2020; Gormsen and Koijen, 2020), households (Coibion et al., 2020a; Baker et al., 2020), and firms (Fahlenbrach et al., 2020; Bartik et al., 2020; Hassan et al., 2020). Our paper highlights the importance of culture in shaping regions' response to the pandemic, and provides a powerful explanation of the vast differences in pandemic outcomes across regions.

2 Data and Measures

2.1 Individualism

We follow Bazzi et al. (2020) to measure US county-level individualism by their frontier experience—the amount of time each county spent on the frontier as it expanded westward in the 18th and 19th centuries. The influential historian Frederick Jackson Turner famously argued that the presence of "a continually advancing frontier line" at the "edge of free land" strongly influenced the American culture (Turner, 1893). As described in Bazzi et al. (2020), life at the frontier was rough, lonely, and perilous (Overmeyer, 1944). Frontier settlers faced many challenges (e.g., weather shocks, attacks by Native Americans) with little or no social infrastructure to turn to (Edwards et al., 2017). Such conditions engender self-reliance and personal drive, as well as antipathy to control. At the same time, the abundance of land in an uncharted environment also drives individuals to become more resourceful, non-conformist, and inventive (Stewart, 2006; Shannon, 1977).

Bazzi et al. (2020) find strong empirical support for the frontier thesis. They show that locations exposed to frontier conditions for a longer period exhibit higher contemporary levels of individualism, as well as greater aversion to redistribution and government regulation. Frontier culture persists strongly into modern days for two reasons. First, due to natural selection, self-reliant and innovative individuals are more likely to survive at the frontier, thus passing down their genes to next generations (Shannon, 1977; Kitayama et al., 2010). Second, frontiers attract like-minded people from other locations through selective migration. We follow the methodology in Bazzi et al. (2020) to calculate the total frontier experience (TFE) and divide all counties with information on TFE into 15 bins (same as the 15 bins in Figure 3 of Bazzi et al. (2020)). We also use a continuous measure of TFE in decades and a dummy variable indicating above median TFE in robustness tests. Because our measure is historically determined over a century ago, modern-day covariates, such as recent epidemic experience or institutional changes, are unlikely to confound the relationship between TFE and COVID-19 response.[2]

As a robustness check, we also use infrequent names and non-patronymic/-matronymic names from the 1930 full-count Census as alternative measures of county-level individualism. A rich social science literature shows that infrequent names reflect a desire to stand out, as opposed to common names, which reflect a desire to fit in (Twenge et al., 2010). Bazzi et al. (2020) documents a strong positive link between TFE and the share of children age 0-10 with infrequent names and non-patronymic/-matronymic names. We start with children aged between 0 and 10 with native-born parents in the 1930 Census, and then calculate the shares of infrequent and non-patronymic/-

[2] Our measure aims to isolate the exogenous part of the variation in modern-day individualism. Any culture changes from the frontier period to today can be considered as measurement errors and would therefore attenuate our findings.

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matronymic names in each county. Infrequent names are given names outside the national top 10 most popular names in the 1920s. Non-patronymic/-matronymic share is the share of boys/girls with names that are distinct from those of their fathers/mothers.

2.2 Collective Actions

2.2.1 Social Distancing

We use three large-scale location datasets to measure social distancing compliance around COVID-19.

Google Community Mobility Report. Google publishes data on community mobility during COVID-19 for a wide range of countries and US regions.[3] The project uses Google Map to track visits to different types of locations, such as retail and recreational, groceries and pharmacies, parks, transit stations, workplaces, and residential. The data is from February 15th to April 30th, 2020, and reflects changes in traffic for each day relative to a baseline value, which is the median in the period from January 3 to February 6, 2020, for the same day of the week.

SafeGraph Social Distancing Metrics. SafeGraph provides daily views of social distancing compliance by US Census block group.[4] It determines the home address for each mobile device by its night-time location and tracks daily mobility patterns (e.g., distance to home, travel for job) relative to the home address. We aggregate the data to county-day level and compute several measures of social distancing: the share of devices that travel more than two kilometers in a day, that travel for full-time and part-time work, that stayed at home for more than 75% of a day, and that stay at home for the entire day. Our data runs from January 14th to April 30th, 2020.

High-Frequency Individual-Level Data. To provide more granular evidence, we also use proprietary de-identified individual-level cellular location data. The data comes from a large location data provider that tracks locations from several hundred mobile apps up to every five minute,s or whenever a device moves more than 15 meters. The data covers a quarter of the US population, with 175 trillion records and a data size of 300TB. Using big-data techniques, we extract a representative sample of individuals in 12 cities from January 2019 to April 2020. Our cities include Atlanta, Austin, Boston, Chicago, New York, Omaha, Phoenix, San Francisco, Seattle, Baltimore, Washington DC and Wichita, representing all major regions in the US and a wide spectrum of political and economic conditions. We first identify a set of individuals who migrated to the aforementioned cities in 2019 by tracking their home locations over time. These migrants come from more than 1,600 different counties across the US, and we measure their individualism based on their original locations. We then combine these migrants with local residents who have always been in their respective cities over the sample period. Lastly, we track these individuals' daily activities and calculate social distancing measures at the individual-day level from January 1st to April 30th,

[3]See `https://www.google.com/covid19/mobility`.

[4]See `https://docs.safegraph.com/docs/social-distancing-metrics`.

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2020. Appendix B describes our big data procedure in detail. To the best of our knowledge, our paper are among the first to use *individual-level* cellular location data for COVID-19 research.

2.2.2 Redistribution

GoFundMe. To measure local voluntary redistribution, we use data from GoFundMe, the world's largest online donation platform. We scrape campaign information, including launch date, zip code, category, description, target, and funds raised, of all campaigns listed between January 1st and April 30th, 2020. We identify COVID-related campaigns based on the title and the description of each campaign. We further use supervised text mining to classify COVID-related campaigns based on whether the beneficiaries are fundraisers themselves or a broader community (e.g, procuring PPE for local hospitals, fundraising for restaurant workers). We then map campaign zip codes to counties and collapse the data to county-day level. To the extent that donation-based crowdfunding relies heavily on social network and local donors, our measures capture local redistribution on both the receiving and the giving end.

2.3 Descriptive Statistics

Panels A to C of Table 1 provides summary statistics on our outcome variables at the county-day levels. There is great variation in social distancing measures across counties, as indicated by large standard deviations relative to means. Counties also exhibit dispersion in the number of GoFundMe campaigns. Panel D of Table 1 shows the summary statistics for our individualism measures. The median US county has a TFE value of 5 (corresponding to about 15 years on the frontier) with a standard deviation of 3.2. When converted into decades, the median US county spent 1.6 decades on the frontier with a standard deviation of 1.8 decades. In the average county, 84.6% of children have an infrequent name and 93.2% have an non-patronymic/-matronymic name with standard deviations of 9.0 and 6.3 percentage points, respectively.

Figure 1a shows the spatial distribution of the TFE measure for counties for which frontier experience can be measured. Figure 1b further shows the distribution of social distancing—the share of mobile devices at home based on data in April 2020. Comparing the two maps, we can see a largely negative relationship between individualism and social distancing. This inverse relationship is more evident when we compare our alternative name-based individualism measure with the social distancing map in Figure 2. We investigate these relationships using multivariate panel regressions in Section 4.

Figure 3 maps the original locations of the migrants in our individual-level sample. Our migrants are coming from 1,633 different counties across the nation. We verify that the migration patterns identified in our individual-level data closely match those shown in Census Migration/Geographic Mobility Data from 2013 to 2017. Figure 4 demonstrate this using New York and Seattle as examples. Table 2 reports summary statistics across the 12 cities. The median city in our sample

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Table 1: County-Level Summary Statistics

Panel A: Social Distancing - Percent Change from Pre-COVID Values Post Lockdown

Variable	Obs	Mean	SD	Min	Median	Max
grocery & pharmacy	26,033	-11.6	13.1	-81	-12	106
workplaces	42,124	-38	9.93	-77	-38	15
retail & recreation	28,060	-37.1	13.8	-100	-37	21
transit stations	16,721	-30.8	18.5	-89	-29	47
parks	11,492	0.521	45.8	-90	-7	324
residential	19,317	16.7	4.9	-3	16	36

Panel B: Social Distancing - Share of Devices

Variable	Obs	Mean	SD	Min	Median	Max
travel (>2km)	184,870	51.8	10.4	11.5	52.1	97.1
travel for full-time job	184,870	13.5	6.85	0.669	13.6	44.6
travel for part-time job	184,870	9.6	3.96	1.03	8.84	35.3
home (>75%)	184,870	51.9	10.6	2.72	52.2	108
completely-at-home (=100%)	184,870	26.6	8.44	1.57	25.3	67

Panel C: COVID-Related GoFundMe Campaigns

Variable	Obs	Mean	SD	Min	Median	Max
Total no.	192,654	0.146	1.03	0	0	93
COVID share (%)	192,654	4.41	18.2	0	0	100
no. of personal	192,654	0.0818	0.671	0	0	76
no. of business	192,654	0.0176	0.193	0	0	22
no. of fully funded	192,654	0.0219	0.204	0	0	14
ln (raised amount)	192,654	0.406	1.68	0	0	9.43
share fully funded (%)	12,851	14.8	31	0	0	100

Panel D: Individualism Measures

Variable	Obs	Mean	SD	Min	Median	Max
TFE (15 groups)	1,946	5.94	3.16	1	5	15
TFE (in decades)	1,946	1.83	1.14	0	1.6	6.3
% Infrequent Names	2,769	84.6	9.01	57.1	85	100
% Non-patronymic/-matronymic	2,769	93.2	6.31	66.7	94.4	100

The table presents the summary statistics for variables listed in the first column at the US county-day (Panels A to C) or county-level (Panel D). Panels A and B summarize social distancing measures from Google Community Mobility Report and SafeGraph, respectively. Panel C summarizes COVID-19 related GoFundMe Campaigns. Panel D summarizes county-level individualism measures.

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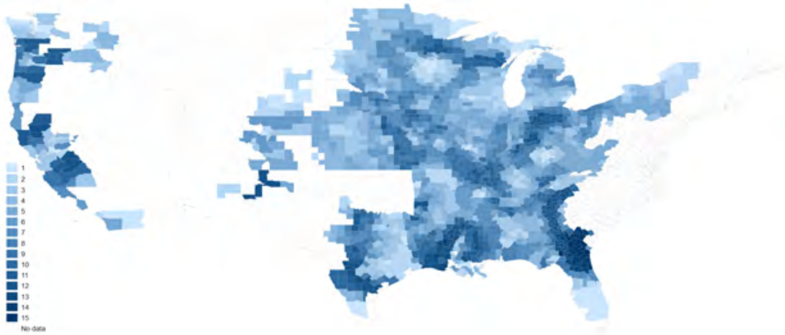
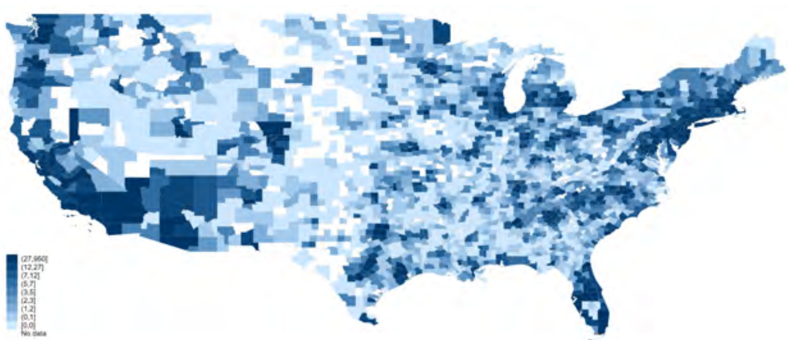
Figure 1: County-level: Individualism, Social Distancing, and Voluntary Redistribution



(a) Total Frontier Experience (15 categories)

(b) Share of Completely-at-home Devices



(c) Number of COVID-19 Campaigns on GoFundMe

Figure 1a shows the total frontier experience in 15 categories for US counties during 1790 and 1890. Total frontier experience is the total number of years the county was within 100 km of the frontier line and its population density was below 6 people per square mile, between 1790 and 1890. Figure 1b shows the share of completely-at-home devices in April, 2020 for US counties. Figure 1c shows the number of COVID-19 campaigns on GoFundMe in April, 2020 for US counties.

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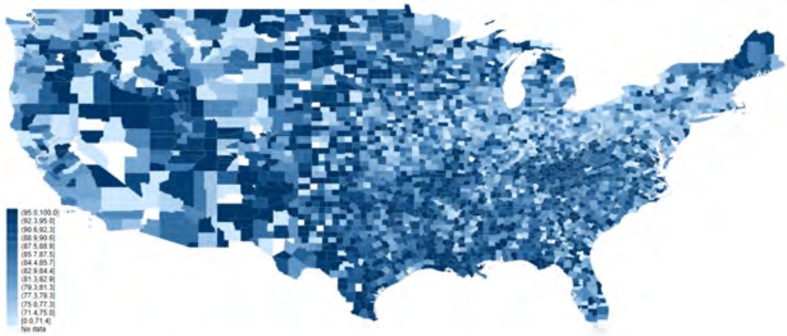
Figure 2: County-level: Individualism and Social Distancing



(a) Share of Infrequent Baby Names

(b) Share of Non-patronymic/-matronymic Baby Names

(c) Share of Completely-at-home Devices

Figure 2 shows the share of babies with names outside of the national top 10 most popular names based on 1930 Census data. Figure 2b shows share of boys/girls with names that are distinct from their fathers/mothers based on 1930 Census data. Figure 2c shows the share of completely-at-home devices in April, 2020 for US counties.

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Figure 3: Individual-level: Migration Origin Counties (12 cities)

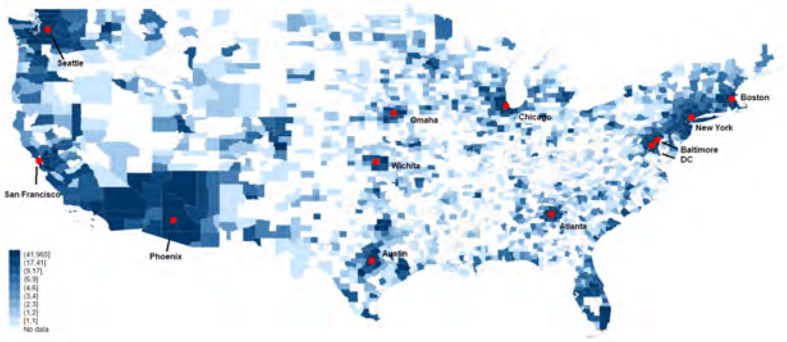
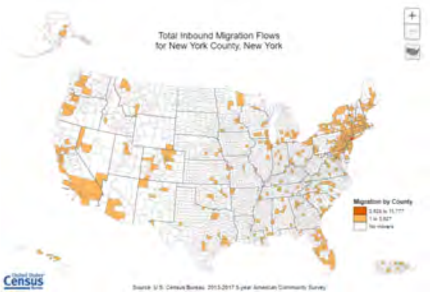


Figure 3 shows the number of migrants from counties across US into the 12 cities in individual-level analysis.

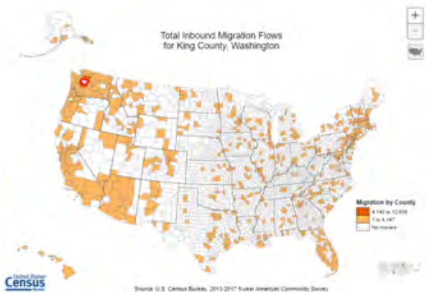
Figure 4: Individual-level: Migration Origin Counties for New York and Seattle

(a) Smartphone Location Data: New York

(b) Smartphone Location Data: Seattle



(c) US Census: New York



(d) US Census: Seattle

Figure 4 compares the migration patterns calculated from the smartphone location data with those from the US Census Migration/Geographic Mobility Data (2013-2017). Figure Figure 4a and Figure 4c show the number of inbound migrants for New York and Figure 4b and Figure 4d are for Seattle. In both examples, we observe similar migration patterns.

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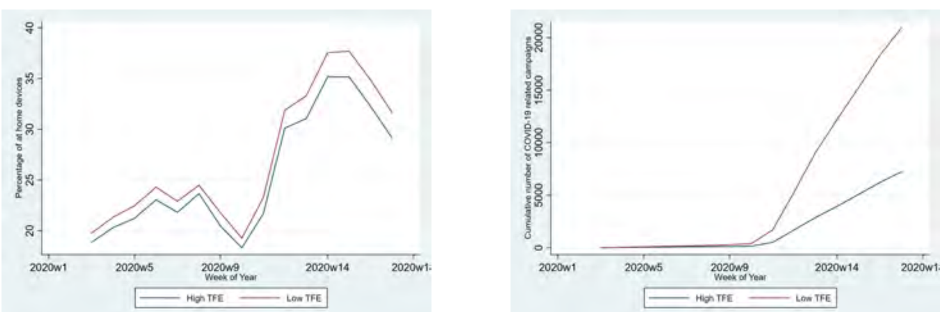
Table 2: Summary Statistics for Individual-Level Sample

Summarized Across 12 Cities						
Variable	Obs	Mean	SD	Min	Median	Max
no. of individuals	12	22,672	21,401	5,535	9,238	60,255
% migrants	12	10.7	4.41	4.64	11.6	17.3
% in-state	12	6.7	4.01	1.3	6.46	13.1
% out-of-state	12	3.98	2.99	1.48	3.13	12.7
no. of origin counties	12	329	208	106	302	807
no. of daily records	12	168	15	152	161	193
% time spent at home	12	66.4	2.42	63.7	65.8	70.9

The table presents summary statistics at the city level for our sample of individual migrants and residents from 12 cities.

Figure 5: Time-series Trend in Social Distancing and voluntary redistribution



(a) Share of Completely-at-home Devices

(b) Number of COVID-related Campaigns

Figure 5 shows the weekly trends in social distancing and voluntary redistribution over time for high- and low-TFE counties. High- (low-) TFE counties have above- (below-) median total frontier experience. Figure 5a shows the shares of completely-at-home devices using SafeGraph data. Figure 5b shows the cumulative numbers of COVID-19-related campaigns on GoFundMe.

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has 22,672 individuals, out of which 11.6% are migrants. About two-thirds of the migrants are in-state, and one-third are out-of-state. The average individual is tracked 168 times a day, i.e., about every 8 minutes.

Figure 5 shows the trends in social distancing and COVID-19 related online donations for high- versus low-TFE counties over the period of week 3 to 18 in 2020. We see that the two groups of counties exhibit parallel trends in these collective actions before COVID-19, and they diverge significantly after COVID-19 hits around weeks 10 to 12. In particular, more individualist counties with high TFE have lower levels of social distancing and charitable donations. This non-parametric evidence lends strong support to our main hypothesis, which we test formally with granular fixed effects in Section 4.

3 Empirical Strategy

We collect information on state-level lockdown orders and use a difference-in-differences approach to examine the effect of individualism on collective actions before and after lockdowns. Lockdowns mark the date when the public's perception of COVID-19 risks becomes discontinuously higher and more salient.[5] Benchmarking against lockdown also allows us to compare the effect of local individualism on social distancing against the effect of lockdown in the absence of individualism influence. Specifically, we estimate the following specification at the county-day level:

$$Y_{c,t} = \boldsymbol{\gamma_c} + \boldsymbol{\alpha_{s,t}} + \beta LockDown_{s,t} \times TFE_c + \theta LockDown_{s,t} \times X_c + \varepsilon_{c,t} \quad (1)$$

where c indexes county, s indexes state, and t indexes day. Since lockdown orders are issued by states, we control for county fixed effects $\boldsymbol{\gamma_c}$, and importantly, state by day fixed effects $\boldsymbol{\alpha_{s,t}}$ to absorb any state-level shocks. Because we are comparing counties within a state, the timing of state-level lockdown is exogenous to individual counties and their residents because they have no control over state-level policies. County-level individualism TFE_c is measured by an index of total frontier experience from 1 to 15. The dependent variables $Y_{c,t}$ include social distancing measures from both Google Community Mobility Report and Safegraph. We also use this specification to examine voluntary redistributions measured from GoFundMe data. The coefficient of interest is β, which captures differential response to lockdown orders in counties with varying levels of individualism. In robustness tests, we also control for the interaction between $LockDown_{s,t}$ and county-level variables, including political belief, social capital, population density, and local demographics.

To further strengthen identification, we conduct an individual-level analysis exploiting inbound migrations to 12 US cities. We measure individuals' individualism by the TFE of their origin county

[5] We obtain US state lockdown dates from Institute for Health Metrics and Evaluation (IHME) (`https://covid19.healthdata.org/united-states-of-america/`).

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rather than the current county of residence. Specifically, we estimate the following specification:

$$Y_{i,c_0,c_1,t} = \boldsymbol{\gamma_i} + \boldsymbol{\alpha_{c_1,t}} + \beta LockDown_{s,t} \times TFE_{i,c_0} + \varepsilon_{i,t} \tag{2}$$

where i indexes individual, c_0 indexes the original county from which an individual i migrates, c_1 indexes current residence county in 2020, s indexes current residence state, and t indexes date. The dependent variables $Y_{i,c_0,c_1,t}$ are social distancing measures calculated from our individual-level cellular location data. TFE_{i,c_0} is the TFE of an individual's origin county. Our individual-level sample allows us to include granular fixed effects, including individual fixed effects $\boldsymbol{\gamma_i}$ and residence county-day fixed effects $\boldsymbol{\alpha_{c_1,t}}$. These fixed effects absorb time-invariant personal traits and time-varying local shocks. We are therefore comparing two individuals living in the same county at the same time, but who come from different culture backgrounds due to migration. This specification greatly limits the set of omitted variables that can plausibly explain our results.

Our empirical strategies address several identification concerns. First, our historically determined individualism measure ensures that the results are not reversely caused by modern-day socioeconomic or institutional factors. Second, our DID design exploits the discontinuous increase in the salience of COVID-19 around state lockdowns and the exogeneity of the timing of these lockdowns relative to individual counties within the state; thus, any alternative stories must *differentially* explain the effects before and after lockdowns. Third, our high-dimensional fixed effects eliminate the explanatory power of any time-invariant county-level factors (e.g., county geography or demographics) as well as state-day-level shocks (e.g., other state-level policies and programs). More importantly, our individual-level migration-based identification further eliminates the explanatory power of fixed individual traits (e.g., demographics) and county-day-level shocks (e.g., city- or county-specific social distancing policies, news, local unemployment rates, or local protests).

4 Results

4.1 Social Distancing

Social distancing is perhaps the most important collective action in the current COVID-19 pandemic. COVID-19 is unique and different from prior pandemics in that it has a moderate mortality rate but a high transmission rate—a perfect combination for large-scale spread. Limiting human-to-human contact through social distancing is therefore critical to mitigating the outbreak. By practicing social distancing, individuals not only protect themselves from being exposed, but, more importantly, also avoid potentially spreading the virus to others. This is made more important by the fact that a significant fraction of COVID-19 carriers are asymptomatic, and that the severity

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of symptoms varies dramatically across demographics.[6] Hence, social distancing carries substantial positive externality (Bethune and Korinek, 2020).

Despite overwhelming evidence on the effectiveness of social distancing in stemming the pandemic (Fang et al., 2020; Correia et al., 2020), individuals may under-engage in it due to a failure to fully internalize its social benefits, or due to a rational belief that its social benefits are smaller if others do not comply (i.e., a network effect). We posit that both these frictions can be significantly altered by the individualism-collectivism culture dimension. High collectivism encourages internalization of group interests, and facilitates coordination, leading to better compliance with social distancing measures. We empirically test this hypothesis in this section.

4.1.1 US County-Level Analysis

Although the United States has the highest individualism among all countries, there is substantial variation in culture within the country for historical reasons. Conducting analysis at the US county level has several advantages. First, we can hold constant many confounders, such as a country's institutions, technological development, and federal relief efforts, which are hard to consistently measure in a cross-country setting. Second, county-level analysis allows us to include state by day fixed effects to absorb regional time-varying shocks, such as state lockdown orders, pandemic relief programs, or changing economic or fiscal conditions. Third, we can exploit local individualism measure that originates from the unique historical features of US territories — their total frontier experience. Because the US frontier expanded gradually over the period of 1790–1890, we are able to obtain rich variation in frontier experiences across US counties. Such a granular, historically based, and empirically validated (Bazzi et al., 2020) individualism measure is unavailable in other countries.

Table 3 examines the effect of local individualism on social distancing using Google mobility data. The specification follows Equation 1. We find that counties higher in individualism (i.e., with more frontier experience) reduce their visits to non-essential places less and stay at home less in response to state-issued shelter-at-home orders. These results hold when we weight the sample by county population, and when we control for state-day fixed effects.[7] An interquartile increase in total frontier experience (a value of 5) offsets 41% of the effect of state lockdown orders on social distancing. This effect is strikingly large, suggesting the importance of culture in mediating collective actions relative to traditional economic factors.

Table 4 examines alternative measures of social distancing based on SafeGraph data, which is more accurate than Google Mobility in tracking individuals' movements away from home. We construct five social distancing measures: the share of mobile devices that travel more than two

[6]The US Center for Disease Control and Prevention (CDC) estimates that 35% of COVID-19 cases are asymptomatic (CDC, 2020). Evidence also shows that the death rate of COVID-19 is much higher among males, seniors, and people with pre-existing conditions.

[7]We weight the regression by population because measurement errors in location tracking and hence social distancing are likely to be greater for counties with smaller populations.

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Table 3: Individualism and Social Distancing (Google Mobility Report)

Panel A: Equal Weighted

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	percent change in visits from pre-COVID-19 value					
	grocery/pharmacy	workplaces	retail/recreation	transit	parks	residential
TFE × Lockdown	0.323***	0.400***	0.443***	0.486***	-0.591	-0.171***
	[0.066]	[0.047]	[0.065]	[0.149]	[0.410]	[0.029]
Lockdown	-11.063***	-7.131***	-10.825***	-10.230***	-9.687***	2.900***
	[0.502]	[0.388]	[0.504]	[1.154]	[2.683]	[0.230]
County FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Obs	93,810	121,240	98,942	43,819	28,448	55,268
Adj. R-sq	0.699	0.916	0.87	0.788	0.412	0.936

Panel B: Weighted by Population

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	percent change in visits from pre-COVID-19 value					
	grocery/pharmacy	workplaces	retail/recreation	transit	parks	residential
TFE × Lockdown	0.526***	0.530***	0.583***	1.114***	0.946*	-0.277***
	[0.081]	[0.096]	[0.089]	[0.223]	[0.565]	[0.047]
Lockdown	-9.830***	-7.711***	-7.600***	-11.962***	-13.180***	3.392***
	[0.596]	[0.732]	[0.748]	[1.307]	[3.195]	[0.344]
County FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Obs	93,810	121,240	98,942	43,819	28,448	55,268
Adj. R-sq	0.82	0.948	0.934	0.87	0.433	0.947

Panel C: Control for State-level Time-varying Trends

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	percent change in visits from pre-COVID-19 value					
	grocery/pharmacy	workplaces	retail/recreation	transit	parks	residential
TFE × Lockdown	0.472***	0.576***	0.422***	0.876***	0.649*	-0.286***
	[0.076]	[0.084]	[0.078]	[0.188]	[0.351]	[0.053]
County FE	YES	YES	YES	YES	YES	YES
State × Date FE	YES	YES	YES	YES	YES	YES
Obs	93,640	121,117	98,794	43,741	28,209	55,110
Adj. R-sq	0.89	0.965	0.965	0.901	0.824	0.966

This table shows how individualism affects social distancing at the US county level using data from Google Mobility Report. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism, TFE, is measured by an index of total frontier experience from 1 to 15. The outcome variables are six social distancing measures from Google Community Mobility Report. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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Table 4: Individualism and Social Distancing (Safegraph)

Panel A: Equal Weighted

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	share of devices				
	travel (>2km)	full-time work	part-time work	home (>75%)	completely-at-home
TFE × Lockdown	0.164***	0.040**	0.026***	-0.166***	-0.304***
	[0.030]	[0.016]	[0.009]	[0.025]	[0.029]
Lockdown	-3.633***	0.265*	-0.243***	2.056***	4.570***
	[0.253]	[0.136]	[0.077]	[0.221]	[0.239]
County FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Obs	184,870	184,870	184,870	184,870	184,870
Adj. R-sq	0.881	0.903	0.838	0.888	0.854

Panel B: Weighted by Population

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	share of devices				
	travel (>2km)	full-time work	part-time work	home (>75%)	completely-at-home
TFE × Lockdown	0.360***	0.036	0.066***	-0.246***	-0.514***
	[0.064]	[0.045]	[0.018]	[0.055]	[0.074]
Lockdown	-4.716***	0.566	-0.235**	2.780***	6.263***
	[0.483]	[0.366]	[0.109]	[0.432]	[0.570]
County FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Obs	184,870	184,870	184,870	184,870	184,870
Adj. R-sq	0.925	0.925	0.909	0.936	0.913

Panel C: Control for State-level Time-varying Trends

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	share of devices				
	travel (>2km)	full-time work	part-time work	home (>75%)	completely-at-home
TFE × Lockdown	0.351***	0.047***	0.081***	-0.237***	-0.451***
	[0.059]	[0.016]	[0.017]	[0.048]	[0.062]
County FE	YES	YES	YES	YES	YES
State × Date FE	YES	YES	YES	YES	YES
Obs	184,775	184,775	184,775	184,775	184,775
Adj. R-sq	0.945	0.969	0.947	0.957	0.946

This table shows how individualism affects social distancing at the US county level using data from SafeGraph. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism, TFE, is measured by an index of total frontier experience from 1 to 15. The outcome variables are five social distancing measures from SafeGraph. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

kilometers in a day, the shares of devices that travel for full-time work and for part-time work, the share of devices at home for more than 75% of a day, and the share of devices completely at home in a day.[8] Across these measures, we find similar results to those in Table 3. High-TFE counties travel more, go to work more, and stay at home less after state-issued lockdowns than before them, suggesting lower social distancing compliance. These results are again robust to population-weighting and state-day fixed effects. The magnitude is almost identical to that reported in Table 3. Based on column 5 of Panel B, an interquartile increase in total frontier experience undoes 40% of the effect of state lockdown orders on social distancing.

4.1.2 Individual-Level Analysis Exploiting Migration

To further mitigate identification concerns related to unobserved county-level shocks, we conduct an individual-level analysis using proprietary data on individual mobile devices. As described in Section 3, our identification strategy exploits migrants in 12 big cities in the United States. In particular, we compare 24,131 individuals who moved to these cities in 2019 with 247,285 residents who have always resided in these cities over our sample period. By measuring culture based on an individual's original location, we are able to include county-day fixed effects for individuals' current residence locations to eliminate all potential local shocks. We also include individual fixed effects to remove individual-level heterogeneities.[9]

Table 5 presents the effect of individualism on social distancing at the individual-day level. Our dependent variable is the percentage of time an individual spends at home on a given day. We measure home address by the most frequent coordinates during the period of 3 a.m.-5 a.m. and use a 76-meter grid to capture the home address. Panel A controls for individual fixed effects and date fixed effects, while Panel B additionally controls for current county-day fixed effects. Panel C weights observations by tracking frequency (the number of tracked records in a day) to mitigate measurement errors. We find a significant and robust negative effect of *personal* individualism on an individual's compliance with stay-at-home orders. The effects hold for the full sample, for individuals that are frequently tracked, for either in-state or out-of-state migrants, as well as for both east and west coast cities. Based on the estimates in Panel A, an interquartile increase in individualism reduces individual-level compliance with lockdown orders by roughly 50%, a magnitude slightly higher than our county-level estimates.

[8] SafeGraph measures full-time (part-time) work by the occurrence of a period of 3 to 6 hours (more than 6 hours) at a location other than a home address between 8 a.m. and 6 p.m. local time.

[9] One may argue that individuals tend to migrate to areas with which they share similar cultural values. As a result, we may overestimate the true variation in individualism among migrants and between migrants and residents, biasing the coefficient on individualism downward. Hence, our estimates are likely to provide a lower bound on the true effects of individualism.

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Table 5: Exploiting Migrants for Identification

Panel A: Equal Weighted

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	share of time spent at home					
TFE_origin × Lockdown	-0.245***	-0.241**	-0.257**	-0.249***	-0.267***	-0.701**
	[0.090]	[0.091]	[0.098]	[0.093]	[0.049]	[0.287]
Lockdown	2.538***	2.441***	2.571***	2.450***	2.951***	4.682***
	[0.607]	[0.620]	[0.624]	[0.629]	[0.544]	[0.756]
Sample	full	tracked per 30min	in-state	out-of-state	east	west
Individual FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Obs	8,874,500	8,240,313	8,653,875	8,625,189	4,854,934	4,019,566
Adj. R-sq	0.496	0.518	0.496	0.49	0.505	0.487

Panel B: Control for County-level Time-varying Trends

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	share of time spent at home					
TFE_origin × Lockdown	-0.576***	-0.588***	-0.729**	-0.623***	-0.210**	-0.856***
	[0.204]	[0.205]	[0.275]	[0.218]	[0.087]	[0.276]
Sample	full	tracked per 30min	in-state	out-of-state	east	west
Individual FE	YES	YES	YES	YES	YES	YES
County × Date FE	YES	YES	YES	YES	YES	YES
Obs	8,874,183	8,240,038	8,653,859	8,624,872	4,854,845	4,019,338
Adj. R-sq	0.498	0.52	0.498	0.492	0.506	0.488

Panel C: Weighted by Tracking Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	share of time spent at home					
TFE_origin × Lockdown	-0.610**	-0.607**	-0.765**	-0.661**	-0.124	-0.949***
	[0.244]	[0.243]	[0.317]	[0.258]	[0.089]	[0.305]
Sample	full	tracked every 30min	in-state	out-of-state	east	west
Individual FE	YES	YES	YES	YES	YES	YES
County × Date FE	YES	YES	YES	YES	YES	YES
Obs	8,874,183	8,240,038	8,653,859	8,624,872	4,854,845	4,019,338
Adj. R-sq	0.589	0.593	0.589	0.586	0.595	0.582

This table shows how individualism affects social distancing using individual-level data. The unit of observation is an individual-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism in the original county, TFE_origin, is measured by an index of total frontier experience from 1 to 15. The outcome variable is the share of time spent at home using individual-level smartphone location data. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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4.2 Redistribution

Another important socially optimal action during crises is redistribution. Crises often hit individuals or areas unequally. From a social planner's perspective, wealth transfers could be optimal in helping with economic recovery. This is especially the case when crises do not originate from incentive problems within the system (e.g., risk-taking or too-big-to-fail), such as the current pandemic. Since individualism prizes self-reliance and personal efforts, it presents a force against welfare-improving redistributions, especially when such redistributions are voluntary and not enforced by the government.

Table 6 employs GoFundMe data to test this. We construct county-day level measures of voluntary redistributions from individual fundraising campaigns. The specification is the same as that in Tables 3 and 4. We find that after state lockdowns, which significantly hurt employment and business revenues, there is a surge in COVID-19-related campaigns, but not in non-COVID-related ones (columns 1 to 3). The null result on non-COVID campaigns provides a useful placebo test that ensures that our results are not driven by selection into the platform or unobserved shocks to offline donations. More importantly, increases in COVID-19-related campaigns are significantly weaker in more individualist counties: they launch fewer campaigns, and conditional on launching, these campaigns raise less money and are less likely to be fully funded. An interquartile increase in TFE mitigates 45% to 48% of the increases in redistribution around lockdowns. The results hold for both personal and small business campaigns and are robust to various specifications.

We further examine how individualism affects the substitution between government redistribution and private redistribution in Table 7. The Coronavirus Aid, Relief, and Economic Security (CARES) Act approved billions of stimulus payments to Americans. The first wave of payments were sent out from the week of April 13 and offer checks of $2,400 per married couple, $1,200 per individual, and $500 per child. We interact a post-April-13 dummy $CARES$ with $TFE \times Lockdown$. The interaction term captures the effect of TFE on private redistribution after the stimulus relative to before it (but after lockdown).[10] The positive interaction suggests that government stimulus crowds out private redistribution less in high individualism counties, because such counties did not have much private redistribution before the intervention. This result implies that, were the government to adopt a differential policy, it should prioritize areas with higher individualism, where private redistribution was less and hence crowding out would be smaller.

4.3 Channels

What explains the mitigating effect of individualism on collective actions? Our main hypothesis is that individualism prevents individuals from internalizing the externality of their actions. Alternatively, it could be that individualism shapes people's beliefs about the returns to collective

[10] All state lockdowns predate the distribution of stimulus checks. South Carolina was the last state to issue a lockdown order, having done so on April 7, 2020.

Table 6: Individualism and Voluntary Redistribution (GoFundMe)

Panel A: Equal Weighted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	Non-COVID-19	COVID-19 campaigns					
	# total	# total	share	# personal	# business	ln ($ raised)	share fully funded
TFE × Lockdown	-0.001	-0.053***	-0.590***	-0.029***	-0.006***	-0.092***	-0.516***
	[0.003]	[0.010]	[0.080]	[0.005]	[0.001]	[0.011]	[0.181]
Lockdown	0.011	0.557***	7.722***	0.311***	0.074***	1.026***	3.183**
	[0.023]	[0.096]	[0.688]	[0.055]	[0.015]	[0.095]	[1.416]
County FE	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES
Obs	192,654	192,654	192,654	192,654	192,654	192,654	12,530
Adj. R-sq	0.697	0.365	0.15	0.316	0.159	0.304	0.042

Panel B: Weighted by Population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	Non-COVID-19	COVID-19 campaigns					
	# total	# total	share	# personal	# business	ln ($ raised)	share fully funded
TFE × Lockdown	-0.047*	-0.419***	-1.266***	-0.232***	-0.047***	-0.285***	-0.451**
	[0.025]	[0.136]	[0.205]	[0.073]	[0.015]	[0.045]	[0.210]
Lockdown	0.621	4.348***	12.527***	2.504**	0.627***	2.352***	1.889
	[0.384]	[1.625]	[1.754]	[0.977]	[0.204]	[0.255]	[1.182]
County FE	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES
Obs	192,654	192,654	192,654	192,654	192,654	192,654	12,530
Adj. R-sq	0.76	0.445	0.416	0.382	0.294	0.566	-0.005

Panel C: Control for State-level Time-varying Trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	Non-COVID-19	COVID-19 campaigns					
	# total	# total	share	# personal	# business	ln ($ raised)	share fully funded
TFE × Lockdown	-0.003	-0.061***	-0.610***	-0.034***	-0.007***	-0.095***	-0.395*
	[0.003]	[0.011]	[0.087]	[0.006]	[0.002]	[0.012]	[0.234]
County FE	YES	YES	YES	YES	YES	YES	YES
State × Date FE	YES	YES	YES	YES	YES	YES	YES
Obs	192,555	192,555	192,555	192,555	192,555	192,555	12,172
Adj. R-sq	0.702	0.389	0.171	0.332	0.198	0.333	0.108

This table shows how individualism affects voluntary redistribution at the US county level using data from GoFundMe. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism, TFE, is measured by an index of total frontier experience from 1 to 15. Column (1) examines non-COVID-19 related campaigns. Columns (2) to (7) examine COVID-19 related campaigns, including the total number of COVID-19 campaigns, the share of COVID-19 campaigns in all campaigns, the number of personal-driven (business-driven) COVID-19 campaigns, log of dollar amount raised for COVID-19 campaigns, and the share of fully funded COVID-19 campaigns in all COVID-19 campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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Table 7: Individualism, Voluntary Redistribution, and Federal Aid

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	COVID-19 campaigns						
	# total	share	# personal	# business	# fully funded	ln ($ raised)	share fully funded
TFE × Lockdown	-0.435***	-1.331***	-0.258***	-0.060***	-0.083***	-0.282***	-0.757**
	[0.117]	[0.262]	[0.070]	[0.018]	[0.021]	[0.045]	[0.363]
TFE × Lockdown × CARES	0.152**	0.377**	0.115***	0.036***	0.050***	0.038**	0.582*
	[0.062]	[0.179]	[0.043]	[0.014]	[0.013]	[0.018]	[0.322]
County FE	YES	YES	YES	YES	YES	YES	YES
State × Date FE	YES	YES	YES	YES	YES	YES	YES
Obs	192,555	192,555	192,555	192,555	192,555	192,555	12,172
Adj. R-sq	0.619	0.462	0.582	0.473	0.529	0.625	0.085

This table studies how individualism differentially affects voluntary redistribution at the US county level before and after the federal financial aid under the Coronavirus Aid, Relief, and Economic Security (CARES) Act became available. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism, TFE, is measured by an index of total frontier experience from 1 to 15. $CARES$ is a dummy variable that equals one after April 13, when the federal government started to distribute CARES support widely. Columns (1) to (7) examine COVID-19 related campaigns, including the total number of COVID-19 campaigns, the share of COVID-19 campaigns in all campaigns, the number of personal-driven (business-driven) COVID-19 campaigns, the number of fully funded COVID-19 campaigns, log of dollar amount raised for COVID-19 campaigns, and the share of fully funded COVID-19 campaigns in all COVID-19 campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

actions. For example, high individualism people may believe that social distancing is not effective in preventing COVID-19 spread, or that COVID-19 has limited health or economic consequences. To distinguish between these channels, we explore cross-sectional heterogeneities in our results. If the externality channel is at work, we should see individualism having a stronger effect on collective actions when the externalities of these actions are larger. These variations in externalities, however, should be largely independent of individuals' beliefs about the health or economic consequences of COVID-19.

We use county-level population density and the fraction of senior populations to capture the externalities of social distancing. Social distancing has a larger impact on COVID-19 transmission in more densely populated areas, and has larger consequences when the exposed population is more vulnerable. For charitable transfers, we exploit variation in the beneficiaries of COVID-19-related GoFundMe campaigns. Specifically, we use machine learning techniques to classify campaigns into those for communities (e.g., local hospitals or schools) versus those fundraising for selves — we expect the former group to generate more positive externalities and social benefits than the latter.

Table 8 presents the heterogeneity tests using the externality measures above. In Panel A, we focus on social distancing and interact $TFE \times Lockdown$ with a county-level variable *Externality* that is indicated in the column header. The dependent variable is the share of devices that are completely at home on a given day. Consistent with our hypothesis, we find that the mitigating effect of individualism on social distancing is stronger in more urban counties, counties with higher population density, or counties with more senior people. Panel B focuses on COVID-19-related GoFundMe campaigns. The dependent variable is a dummy equal to one if the beneficiary of a campaign is a community rather than a fundraising individual. The sample is at the campaign level. We find that, individualism decreases the share of COVID-19-related campaigns fundraising for communities as opposed to those for selves. These findings suggest that individualism impacts collective actions by reducing the tendency to internalize the externalities of these actions.

4.4 Robustness

4.4.1 Cross-Country Evidence

To establish the external validity of our results, we further conduct a cross-country analysis. We use Hofstede (1991)'s individualism score to measure individualism at the country level. The score measures the extent to which individuals believe they are supposed to take care of themselves as opposed to being strongly integrated and loyal to a cohesive group.[11] Following Gorodnichenko and Roland (2017), we also collect information on blood type distance to instrument country-level individualism.

Table A.1 provides summary statistics. In our sample, the United States has the highest individualism score of 91, while Ecuador has the lowest score of 6.[12] Figure A.1 shows the relationship between the percentage changes in visits to different types of locations and a country's Hofstede individualism score. We see a clear negative relationship between individualism and social distancing. Relative to low-individualism countries, countries higher in individualism visited retail, recreational, and public transit locations more and stay at home less in the period between February 15 and April 30, 2020 relative to the base period between January 3 and February 6, 2020. Consistent with this, these countries also experienced higher growths in COVID-19 cases and deaths, as shown in Figure A.2. On a univariate basis, individualism explains 22% of the variation in infection and death growth rates across countries.

Table A.2 shows statistical evidence using a regression specification in the same spirit as Equation 1.[13] We first find that country-level lockdowns significantly reduce traffic to non-essential locations such as grocery and pharmacy stores, workplaces, retail and recreational places, public transit stations, and parks (columns 1 to 5) and increases people's tendency to stay at home (column 6), as indicated by the coefficient on the post-lockdown dummy. Moreover, the interaction between the post-lockdown indicator and Hofstede's individualism measure, IDV, is significantly positive in columns 1 to 5 (except column 3) and negative in column 6. This suggests that more individualist countries comply less with social distancing orders. The mitigating effect of individualism on social distancing is similar to that at the county level: an interquartile increase in IDV offsets 30% to 50% of the effect of national lockdown orders on various social distancing outcomes.

[11] This variable, among other cultural dimensions, was constructed from responses to a survey of 117,000 IBM employees across 70 countries between 1967 and 1973; this survey was later expanded to 80 countries.

[12] To facilitate interpretation of coefficients, we divide the individualism score by 100.

[13] We obtain country-level lockdown dates from Wikipedia (`https://en.wikipedia.org/wiki/COVID-19_pandemic_lockdowns`). For countries with staggered regional lockdowns, we use the date of the first lockdown.

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Table 8: The Externality Channel

Panel A: Social Distancing (Safegraph)

	(1)	(2)	(3)	(4)
Dep. Var.	social distancing: share of completely-at-home devices			
Interaction term	urban	pop density	age>70 share	age>80 share
TFE × Lockdown × Externality	-0.263***	-0.039***	-0.042**	-0.138***
	[0.065]	[0.015]	[0.017]	[0.046]
TFE × Lockdown	-0.107**	0.190*	0.036	0.096
	[0.043]	[0.106]	[0.202]	[0.194]
Lockdown × Externality	6.724***	1.602***	-0.440***	-0.814***
	[0.393]	[0.104]	[0.088]	[0.260]
County FE	YES	YES	YES	YES
State × Date FE	YES	YES	YES	YES
Obs	184,775	184,775	184,775	184,775
Adj. R-sq	0.951	0.956	0.95	0.95

Panel B: Voluntary Redistribution (GoFundMe)

	(1)	(2)
Dep. Var.	community campaign dummy	
TFE	-0.008***	-0.008***
	[0.002]	[0.002]
State FE	YES	Absorbed
Date FE	YES	Absorbed
State × Date FE	YES	YES
Obs	22,473	22,034
Adj. R-sq	0.056	0.065

Panel A shows how individualism differentially affects social distancing in densely populated and more senior communities. Panel B shows how individualism affects the likelihood of community-based versus individual fund-raising campaigns. The unit of observation is a county-day in Panel A and a campaign in Panel B. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism, TFE, is measured by an index of total frontier experience from 1 to 15 of the origin county. *Externality* is a dummy for urban areas (population more than 50,000) in column (1), population density in column (2), the share of population of age 70 or above in column (3), and the share of population of age 80 or above in column (4). In Panel A, the outcome variable is the share of completely-at-home devices based on data from SafeGraph. In Panel B, the outcome variable is a dummy variable which equals one if the campaign is organized for community and zero if the campaign is organized for an individual. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

The similar magnitude suggests that TFE, though a historical measure, captures useful variations in more recent individualism.

Because culture is slow-moving and the Hofstede cultural scores were measured 50 years ago, reverse causality is unlikely to be an identification concern. However, omitted variables, such as a country's political institutions or healthcare system, may account for our finding. To address this, we first show that our results remain robust if we include the interaction between *Lockdown* and several country-level controls, such as population density, total population, and political regime (Table A.3). We then employ an instrument variable approach following Gorodnichenko and Roland (2017), using distance in blood type frequencies as an instrument. Specifically, we measure the Mahalanobis distance between the frequencies of blood types in a given country and those in the United Kingdom, the second most individualistic country in our sample.[14] Panel B of Table A.2 presents the first-stage results. We find a strong F-statistic of 28.3. Panel C presents the 2SLS results. The coefficients are largely similar to the OLS coefficients in Panel A. For instance, the IV estimate for the effect of individualism on stay-at-home is only slightly higher than the OLS estimate. Other coefficients also have similar magnitudes. These results suggest that the effect of individualism on social distancing has broad external validity and is not just a US phenomenon.

4.4.2 Alternative County-Level Individualism Measures

We demonstrate that our county-level results are robust to using alternative measures of individualism. We consider two alternative measures (Bazzi et al., 2020): (i) infrequent names, and (ii) the absence of parents passing down their given names to children (non-patronymic/matronymic names). A rich social science literature motivates the names-based measures of individualism. The foundational contributions of Hofstede (1991) and Triandis (1995) associate individualism with self-independence and regulation of behavior by personal attitudes rather than social norms. Consistent with these traits, infrequent names reflect a desire to stand out, as opposed to common names, which reflect a desire to fit in (Twenge et al., 2010). Patronymic/matronymic names, which reflect an emphasis on interdependence, provide a useful complementary measure (Brown et al., 2014).

Specifically, we use the 1930 full-count Census to measure the share of babies with names outside of the national top 10, and the share of boys/girls with names that are distinct from their fathers/mothers for each county. Figure 2 maps these name shares and contrasts them with the map on social distancing. These maps reveal a clear inverse relationship. Table 9 further confirms our main results: Counties with more infrequent names or more non-patronymic/matronymic names engage in less social distancing and voluntary redistribution. An interquartile increase in these name shares mitigate 11% of the effect of lockdowns on social distancing and redistribution. The smaller magnitudes suggest that individualism only partially manifests itself in infrequent names or non-patronymic/matronymic names. Our individual-level results are also robust to using these

[14] The advantage of using blood type distance to the UK is that UK's population is genetically more homogeneous than that in the US (the most individualistic country in the world).

two alternative measures of individualism (see Table A.4).

Finally, in Table A.5, we also show that our results are similar when we use a continuous measure of TFE (the number of decades spent on the frontier) or a dummy indicating above-median frontier experience.

4.4.3 County-Level Control Variables

Political Belief. Several recent studies (Allcott et al., 2020; Barrios and Hochberg, 2020; Simonov et al., 2020) have documented the role of political beliefs in individuals' social distancing behaviors. In particular, Republicans are much less likely to comply with social distancing than Democrats. To the extent that individualism may impact political beliefs (Bazzi et al., 2020), we examine whether our results are fully explained by political beliefs. In Table 10, we first show that our main results hold in both Republican and Democratic counties as defined by the 2016 presidential election outcomes. The offsetting effect of individualism is quantitatively similar in these two groups of counties. Further, we show that our results are robust to controlling for county-level measures of political stance. In columns 1 and 4 of Table 11, we include as a control the interaction between county-level Trump vote share and the lockdown dummy, and show that our results remain qualitatively significant, albeit with a smaller magnitude.[15] This suggests that political beliefs cannot fully explain the magnitude of our results.

Social Capital. A few other studies document the positive role of social capital in compliance with social distancing (Barrios et al., 2020; Durante et al., 2020). We show that our results are not driven by the potential correlation between local individualism and social capital. In Table 11, we include as a control the interaction between county-level social capital and the lockdown dummy. We employ two common measures of social capital: voter turnout (columns 2 and 5) and Census response rate (columns 3 and 6). Our results remain similar with a slightly smaller magnitude. Social capital therefore does not drive our results.

Other Controls. In Table A.6, we further control for the interactions between the lockdown dummy and three county-level demographic variables: population density, the percentage of White populations, and the percentage of males. The results remain robust, suggesting that our findings are not driven differences in local demographics.

4.4.4 Alternative Shocks to Pandemic Severity

Lastly, we demonstrate robustness to using alternative shocks to the severity or the salience of the pandemic, such as the March 13, 2020 declaration of national emergency by President Trump or the number of confirmed COVID-19 cases in each county. Table A.7 reproduces our main results, replacing the lockdown dummy with the national emergency dummy (columns (1) and (3)) or

[15] According to column 6 of Panel B, an interquartile increase in frontier experience offsets 25% of the effect of state lockdown orders on social distancing.

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Table 9: Robustness to Alternative Individualism Measures

Panel A: Social Distancing (Safegraph)

	(1)	(2)	(3)	(4)
Dep. Var.	share of completely-at-home devices			
Infrequent Names × Lockdown	-0.083***		-0.037***	
	[0.010]		[0.009]	
Non-patronymic/-matronymic × Lockdown		-0.154***		-0.090***
		[0.018]		[0.015]
Lockdown	9.547***	16.845***		
	[0.885]	[1.756]		
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	263,055	263,055	262,960	262,960
Adj. R-sq	0.834	0.835	0.883	0.883

Panel B: Voluntary Redistribution (GoFundMe)

	(1)	(2)	(3)	(4)
Dep. Var.	share of COVID-19 campaigns			
Infrequent Names × Lockdown	-0.211***		-0.146***	
	[0.025]		[0.024]	
Non-patronymic/-matronymic × Lockdown		-0.435***		-0.264***
		[0.046]		[0.041]
Lockdown	21.870***	44.505***		
	[2.212]	[4.357]		
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	274,131	274,131	274,032	274,032
Adj. R-sq	0.17	0.172	0.202	0.203

This table shows how individualism affects social distancing and voluntary redistribution at the US county level using data from SafeGraph and GoFundMe. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. Infrequent names capture the share of babies with names outside of the national top 10 most popular names, and non-patronymic/-matronymic is the share of boys/girls with names that are distinct from their fathers/mothers. In Panel A, the outcome variable is the share of completely-at-home devices out of all devices based on data from SafeGraph. In Panel B, the outcome variable is the share of COVID-19 related campaigns out of all GoFundMe campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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Table 10: Republican versus Democrat Counties

Panel A: Social Distancing (SafeGraph)

	(1)	(2)	(3)	(4)
Dep. Var.	share of completely-at-home devices			
TFE × Lockdown	-0.208***	-0.583***	-0.193***	-0.485***
	[0.027]	[0.087]	[0.030]	[0.085]
Lockdown	3.634***	7.219***		
	[0.229]	[0.698]		
2016 Presential Election Outcome	Republican	Democrat	Republican	Democrat
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	161,690	23,180	161,405	22,990
Adj. R-sq	0.855	0.874	0.896	0.923

Panel B: Voluntary Redistribution (GoFundMe)

	(1)	(2)	(3)	(4)
Dep. Var.	share of COVID-19 campaigns			
TFE × Lockdown	-0.340***	-1.081***	-0.362***	-0.794***
	[0.070]	[0.273]	[0.080]	[0.263]
Lockdown	5.082***	12.141***		
	[0.582]	[2.307]		
2016 Presential Election Outcome	Republican	Democrat	Republican	Democrat
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	168,498	24,156	168,201	23,958
Adj. R-sq	0.1	0.326	0.118	0.383

This table shows how individualism affects social distancing and voluntary redistribution in Republican versus Democrat counties using data from Safegraph and GoFundMe. Republican (Democrat) counties are counties where the republican (democrat) party won in the 2016 presidential election. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. County-level individualism, TFE, is measured by an index of total frontier experience from 1 to 15. In Panel A, the outcome variable is the share of completely-at-home devices out of all devices based on data from SafeGraph. In Panel B, the outcome variable is the share of COVID-19 related campaigns out of all GoFundMe campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 11: Robustness to Control Variables—Political Belief and Social Capital

Panel A: Social Distancing (SafeGraph)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	share of completely-at-home devices					
TFE × Lockdown	-0.194***	-0.300***	-0.246***	-0.183***	-0.273***	-0.246***
	[0.027]	[0.028]	[0.027]	[0.030]	[0.030]	[0.029]
Trump Vote Share × Lockdown	-1.625***			-1.471***		
	[0.119]			[0.120]		
Voter Turnout × Lockdown		0.896***			1.383***	
		[0.090]			[0.168]	
Census Response Rate × Lockdown			1.309***			1.597***
			[0.096]			[0.113]
Lockdown	3.912***	4.526***	4.065***			
	[0.211]	[0.231]	[0.231]			
County FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	Absorbed	Absorbed	Absorbed
State × Date FE	NO	NO	NO	YES	YES	YES
Obs	184,870	184,870	184,870	184,775	184,775	184,775
Adj. R-sq	0.86	0.856	0.858	0.897	0.895	0.897

Panel B: Voluntary Redistribution (GoFundMe)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	share of COVID-19 campaigns					
TFE × Lockdown	-0.278***	-0.583***	-0.474***	-0.294***	-0.581***	-0.516***
	[0.073]	[0.078]	[0.077]	[0.082]	[0.086]	[0.083]
Trump Vote Share × Lockdown	-4.646***			-4.497***		
	[0.337]			[0.375]		
Voter Turnout × Lockdown		1.884***			3.140***	
		[0.244]			[0.370]	
Census Response Rate × Lockdown			2.618***			3.707***
			[0.188]			[0.255]
Lockdown	5.898***	7.653***	6.734***			
	[0.584]	[0.667]	[0.654]			
County FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	Absorbed	Absorbed	Absorbed
State × Date FE	NO	NO	NO	YES	YES	YES
Obs	192,654	192,654	192,654	192,555	192,555	192,555
Adj. R-sq	0.16	0.152	0.153	0.177	0.172	0.175

This table shows how individualism affects social distancing and voluntary redistribution at the US county level with control variables. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. *Trump Vote Share* measures the share of Trump voters in the 2016 presidential election in each county. *Voter Turnout* and *Census Response Rate* measure the social capital of each county. *Trump Vote Share*, *Voter Turnout*, and *Census Response Rate* are standardized to have a mean of 0 and a standard deviation of 1. In Panel A, the outcome variable is the share of completely-at-home devices out of all devices based on data from SafeGraph. In Panel B, the outcome variable is the share of COVID-19 related campaigns out of all GoFundMe campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

county-day-level logarithmic number of confirmed cases (columns (2) and (4)). We observe similar findings.

5 Policy Implications

Our results provide several policy implications. First, government interventions, such as those enforcing collective actions or redistribution, could be more effective if they include local culture as a targeting parameter. Culture not only affects the need for intervention, but also take-up and compliance conditional on intervention. As culture-based explanations are increasingly integrated into economics (Guiso et al., 2006), they should also be incorporated into policymaking. Such an integration is made easier as more data and techniques become available to measure culture and quantify its impact. Second, local culture should be incorporated into public health models, such as those predicting the spread of disease.[16] Third, individualism, which has long been linked to higher economic growth, could also affect the cyclicality of growth. Given that collective action problems are more acute during downturns (Schaal and Taschereau-Dumouchel, 2018), individualism could amplify negative shocks and business cycles. Policymakers should take culture into account when formulating macroeconomic policies.

6 Conclusion

The COVID-19 pandemic is one of the most acute public health and economic crises in recent history. Vastly different responses across regions underscore the potential importance of culture in explaining this disparity. This paper tests the idea that individualism impacts an economy's response to crises by affecting agents' tendency to engage in socially optimal actions. Using multiple levels of analyses and different identification strategies, we find strong and robust results that individualism discourages social distancing and charitable redistribution, two most important collective actions during the current pandemic. These effects are driven by individualism altering people's tendency to internalize the externalities of their actions. These findings suggest that culture, in addition to traditional economic factors, can affect the severity of a crisis and the speed of recovery; it also affects the returns to policy interventions. As big data and better techniques become increasingly available to quantify culture and its effects, culture should be integrated into policymaking and macroeconomic analysis.

[16]To the best of our knowledge, Alfaro et al. (2020) and Durante et al. (2020) are the only papers that incorporate culture and other preferences into epidemiological models.

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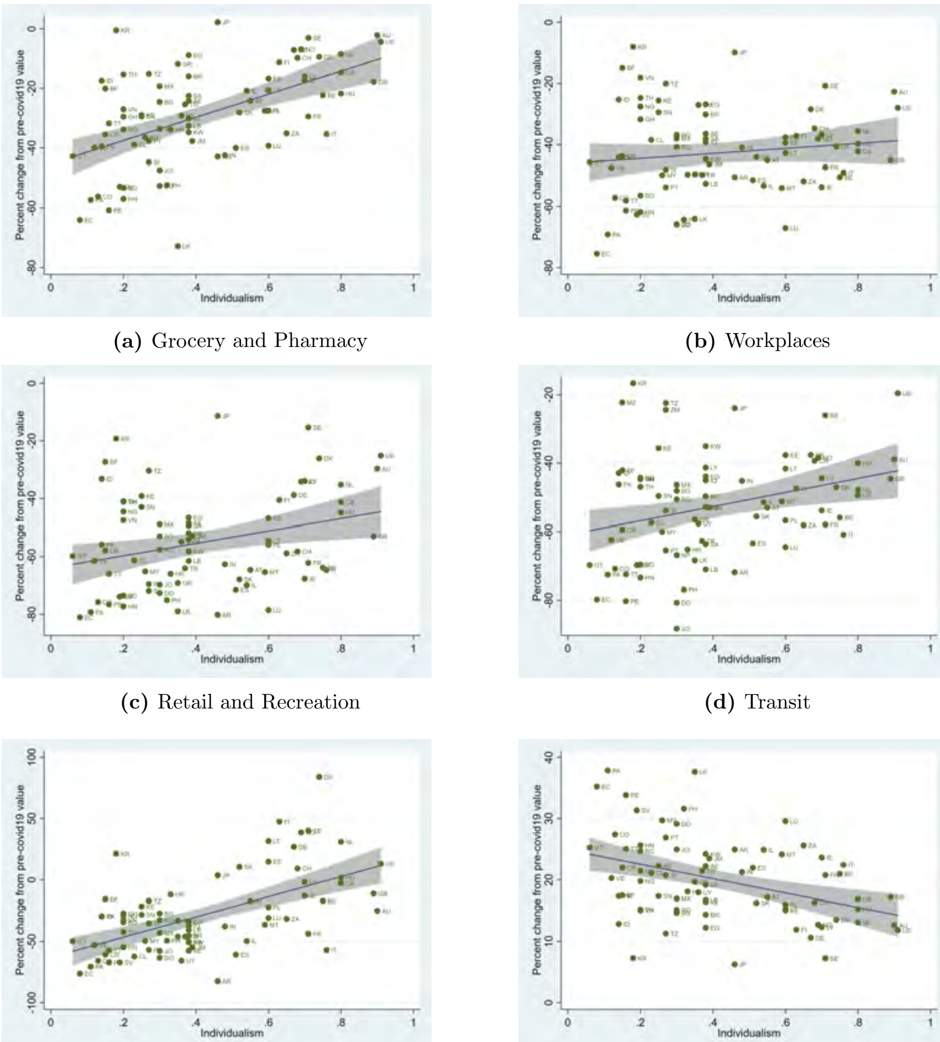
A Additional Figures and Tables



(a) Grocery and Pharmacy

(b) Workplaces

(c) Retail and Recreation

(d) Transit

(e) Parks

(f) Residential

Figure A.1: Country-level: Individualism and Social Distancing

These figures illustrate country-level individualism (x-axis) against social distancing measures (y-axis). Figure A.1a to Figure A.1e show the percentage change in trips to different places compared to a baseline pre-COVID-19 value. Figure A.1f shows the percentage change in time spent in places of residence compared to a baseline pre-COVID-19 value.

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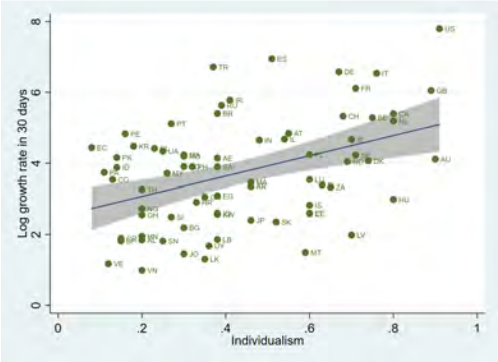
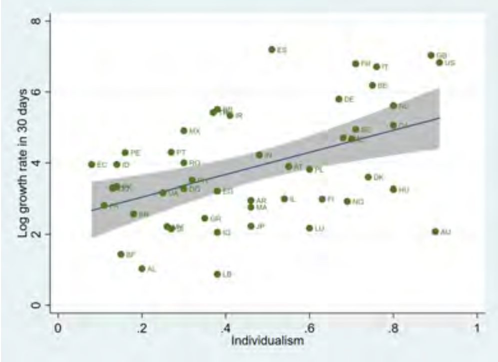


(a) From the 100th confirmed case



(b) From the 10th death

Figure A.2: Country-level: Individualism and 30-day Growth Rate of COVID-19 Cases

These figures illustrate the relationship between country-level individualism (x-axis) and growths in COVID-19 infections and deaths (y-axis). Figure A.2a shows 30-day log growth rate in the number of confirmed COVID-19 cases from the 100th case. Figure A.2b shows 30-day log growth rate in the number of COVID-19 deaths from the 10th death.

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Table A.1: Summary Statistics - Country Level

Panel A: Social Distancing - Percent change from pre-COVID-19 value (after lockdown)

Variable	Obs	Mean	SD	Min	Median	Max
grocery & pharmarcy	2,806	-34.5	22.4	-95	-34.5	85
workplaces	2,806	-49	17.9	-92	-49.5	11
retail & recreation	2,806	-61.8	18.8	-96	-65	1
transit stations	2,806	-62.3	16.4	-95	-64	3
parks	2,806	-32.9	39	-93.5	-42.2	198
residential	2,806	22.6	8.55	-4	22	52

Panel B: Individualism Measure

Variable	Obs	Mean	SD	Min	Median	Max
IDV (Hofstede)	83	0.406	0.227	0.06	0.36	0.91

The table presents the summary statistics for variables listed in the first column at the country level. Panel A summarizes social distancing measures from Google Community Mobility Report. Panel B summarizes the country-level Hofstede individualism measure.

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Table A.2: Country Level: Individualism and Social Distancing

Panel A: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	percent change in visits from pre-COVID-19 value					
	grocery/pharmacy	workplaces	retail/recreation	transit	parks	residential
IDV × Lockdown	31.021***	12.449**	10.145	18.711***	67.176***	-9.696***
	[6.972]	[5.880]	[7.762]	[6.114]	[16.531]	[3.039]
Lockdown	-28.482***	-21.869***	-24.922***	-27.276***	-42.877***	10.362***
	[4.060]	[3.438]	[4.180]	[3.624]	[6.702]	[1.749]
Country FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Obs	6,306	6,306	6,306	6,306	6,306	6,306
Adj. R-sq	0.7	0.835	0.867	0.889	0.653	0.844

Panel B: IV—First Stage

	(1)
Dep. Var.	IDV × Lockdown
DistanceUK × Lockdown	-0.154***
	[0.029]
Lockdown	0.648***
	[0.055]
Country FE	YES
Date FE	YES
F-stat	28.324
Obs	6,230
Adj. R-sq	0.901

Panel C: IV—Second Stage

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	percent change in visits from pre-COVID-19 value					
	grocery/pharmacy	workplaces	retail/recreation	transit	parks	residential
IDV × Lockdown	36.960***	3.844	8.454	13.147	50.175*	-10.924**
	[14.021]	[10.451]	[13.391]	[10.872]	[25.618]	[5.537]
Lockdown	-31.393***	-18.690***	-24.854***	-25.124***	-36.388***	11.084***
	[6.535]	[5.196]	[6.289]	[5.323]	[10.023]	[2.694]
Country FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
F-stat	28.324	28.324	28.324	28.324	28.324	28.324
Obs	6,230	6,230	6,230	6,230	6,230	6,230
Adj. R-sq	0.699	0.835	0.868	0.888	0.652	0.844

This table shows how individualism affects social distancing at the country level. Panel A reports results from OLS regressions. In Panel B and C, we use an instrumental variable—the Mahalanobis distance between the frequency of blood types in a given country and the frequency of blood types in the United Kingdom, or DistanceUK. The unit of observation is a country-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective country-day. It equals one if the respective country has instituted a lockdown and zero otherwise. *IDV* is Hofstede individualism score. The outcome variables are six social distancing measures from Google Community Mobility Report. Robust standard errors clustered at country level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.3: Country Level: Robustness to Control Variables

Panel A: Country level

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	percent change in visits from pre-COVID-19 value					
	grocery/pharmacy	workplaces	retail/recreation	transit	parks	residential
IDV × Lockdown	30.141***	11.351*	10.671	18.813***	64.093***	-10.369***
	[7.232]	[6.447]	[7.663]	[6.488]	[15.286]	[3.169]
Lockdown	16.869	-3.225	20.778	-3.485	14.337	0.778
	[19.001]	[16.681]	[18.689]	[17.112]	[38.415]	[8.358]
Controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Obs	5,698	5,698	5,698	5,698	5,698	5,698
Adj. R-sq	0.713	0.835	0.873	0.889	0.673	0.847

This table shows how individualism affects social distancing with control variables. The unit of observation is a country-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective country-day. It equals one if the corresponding country has instituted a lockdown and zero otherwise. Country-level individualism, IDV, is the Hofstede individualism score. Control variables include the interaction terms between $LockDown$ and population density, ln(pop), and Polity score. The outcome variables are six social distancing measures from Google Community Mobility Report. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.4: Individual Level: Robustness to Alternative Individualism Measures

	(1)	(2)	(3)	(4)
Dep. Var.	share of time spent at home			
Infrequent Names × Lockdown	-0.158***		-0.142*	
	[0.052]		[0.071]	
Non-patronymic/-matronymic × Lockdown		-0.272***		-0.218*
		[0.065]		[0.117]
Lockdown	14.400***	25.189***		
	[4.449]	[5.744]		
Individual FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
City × Date FE	NO	NO	YES	YES
Obs	17,692,884	17,692,884	17,692,499	17,692,499
Adj. R-sq	0.5	0.5	0.502	0.502

This table shows how individualism affects social distancing using individual-level data. The unit of observation is an individual-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. Infrequent names capture the share of babies with names outside of the national top 10 most popular names, and non-patronymic/-matronymic is the share of boys/girls with names that are distinct from their fathers/mothers. The outcome variable is the share of time spent at home using individual-level smartphone location data. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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Table A.5: US County Level: Robustness to Alternative TFE measures

Panel A: Social Distancing (SafeGraph)

	(1)	(2)	(3)	(4)
Dep. Var.	share of completely-at-home devices			
TFE (in decades) × Lockdown	-0.825***		-0.795***	
	[0.077]		[0.086]	
TFE (above median) × Lockdown		-1.568***		-1.422***
		[0.191]		[0.188]
Lockdown	4.271***	3.494***		
	[0.215]	[0.179]		
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	184,870	184,870	184,775	184,775
Adj. R-sq	0.854	0.854	0.894	0.893

Panel B: Voluntary Redistribution (GoFundMe)

	(1)	(2)	(3)	(4)
Dep. Var.	percentage of COVID-19 campaigns			
TFE (in decades) × Lockdown	-1.551***		-1.665***	
	[0.216]		[0.238]	
TFE (above median) × Lockdown		-3.543***		-3.461***
		[0.515]		[0.529]
Lockdown	7.045***	5.872***		
	[0.617]	[0.504]		
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	192,654	192,654	192,555	192,555
Adj. R-sq	0.15	0.15	0.17	0.17

This table shows how individualism affects social distancing and voluntary redistribution at the US county level using data from SafeGraph and GoFundMe. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. Total frontier experience is expressed in decades in columns (1) and (3). In columns (2) and (4), TFE (above median) is a dummy variable that equals one (zero) if the respective county has above (below) median total frontier experience. In Panel A, the outcome variable is the share of completely-at-home devices out of all devices based on data from SafeGraph. In Panel B, the outcome variable is the share of COVID-19 related campaigns out of all GoFundMe campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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Table A.6: Robustness to Control Variables

	(1)	(2)	(3)	(4)
Dep. Var.	share of completely-at-home devices		share of COVID-19 campaigns	
TFE × Lockdown	-0.201***	-0.179***	-0.321***	-0.225***
	[0.024]	[0.026]	[0.064]	[0.070]
Population Density × Lockdown	6.542***	5.712***	20.056***	18.067***
	[0.878]	[0.808]	[2.171]	[2.014]
Pct White × Lockdown	0.452***	0.306**	-0.043	-0.506
	[0.082]	[0.126]	[0.209]	[0.309]
Pct Male × Lockdown	-0.310***	-0.499***	-0.973***	-1.328***
	[0.068]	[0.081]	[0.139]	[0.187]
Lockdown	4.209***		7.045***	
	[0.207]		[0.573]	
County FE	YES	YES	YES	YES
Date FE	YES	Absorbed	YES	Absorbed
State × Date FE	NO	YES	NO	YES
Obs	184,870	184,775	192,654	192,555
Adj. R-sq	0.862	0.9	0.167	0.185

This table shows how individualism affects social distancing and voluntary redistribution at the US county level with additional control variables. The unit of observation is a county-day. *Lockdown* is a dummy variable that indicates the lockdown status in the respective county-day. It equals one if the corresponding state has instituted a lockdown and zero otherwise. *Pct White* (*Pct Male*) measures white (male) population share in each county. *Population Density*, *Pct White*, and *Pct Male* are standardized to have a mean of 0 and a standard deviation of 1. In columns (1) and (2), the outcome variable is the share of completely-at-home devices out of all devices based on data from SafeGraph. In columns (3) and (4), the outcome variable is the share of COVID-19 related campaigns out of all GoFundMe campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.7: Alternative Shocks to the Severity of COVID-19

Panel A: Social Distancing (SafeGraph)

	(1)	(2)	(3)	(4)
Dep. Var.	share of completely-at-home devices			
TFE × Trump Speech	-0.244***		-0.304***	
	[0.029]		[0.030]	
TFE × ln (cases)		-0.064***		-0.034***
		[0.009]		[0.009]
ln (cases)		1.905***		1.834***
		[0.066]		[0.059]
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	184,870	182,924	184,775	182,830
Adj. R-sq	0.849	0.868	0.895	0.912

Panel B: Voluntary Redistribution (GoFundMe)

	(1)	(2)	(3)	(4)
Dep. Var.	share of COVID-19 campaigns			
TFE × Trump Speech	-0.574***		-0.749***	
	[0.084]		[0.088]	
TFE × ln (cases)		-0.117***		-0.037
		[0.022]		[0.023]
ln (cases)		5.336***		5.082***
		[0.170]		[0.160]
County FE	YES	YES	YES	YES
Date FE	YES	YES	Absorbed	Absorbed
State × Date FE	NO	NO	YES	YES
Obs	192,654	190,708	192,555	190,610
Adj. R-sq	0.148	0.189	0.172	0.206

This table shows how individualism affects social distancing and voluntary redistribution using alternative shocks to the severity of COVID-19. The unit of observation is a county-day. *Trump Speech* is a dummy variable that equals one after Mar 13, 2020, when President Trump announced the State of National Emergency, and zero otherwise. ln (cases) equals log number of confirmed COVID-19 cases in the respective county-day. In Panel A, the outcome variable is the share of completely-at-home devices out of all devices based on data from SafeGraph. In Panel B, the outcome variable is the share of COVID-19 related campaigns out of all GoFundMe campaigns. Robust standard errors clustered at county level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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B Processing Individual-Level Location Data via Big-Data Infrastructure

This section describes the big-data architecture used to identify migration patterns and calculate social distance metrics from individual-level cellular location data.

B.1 Geo-Computing Infrastructure

Because our individual-level cellular location data covers a quarter of the US population with each individual tracked up to every five minutes, the number of records exceeds 175 trillion with a data size of more than 300 TB. This creates a big data issue: the size of the data is beyond the computing capability of traditional data management technologies. Hence, we employ a distributed cluster computing framework named Spark. This framework significantly speeds up computation by distributing data and computing across up to thousands of computers.

We first transform all computing logic to be parallel-computing-friendly. We then build a distributed computing infrastructure on the cloud computing platform Amazon Web Services (AWS). This infrastructure includes 97 computers (AWS EC2 c4*xlarge instances with 32 GB RAM and 16-core CPU). One computer is the master node supervising all the distributed data storage and computing processes. The distributed storage for geo-location data is accomplished by automatically splitting coordinates into thousands of small grids. The remaining 96 computers (slave nodes) then perform distributed computing on these geo-grids (mapping) and later merge them into one dataset (reducing). This infrastructure equates to computing 1,536 processes simultaneously. This process speeds up the computing time from more than 100 days in a non-distributed environment to just one day.

B.2 Computing Logic for Migration Patterns and Social Distancing Measures

Step 1: Identifying residents in 12 selected cities in 2020

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(a) We extract all the location records within the geo-bounds of the 12 cities. To alleviate measurement errors, we require individuals to be tracked at least 1,440 times per month, i.e., at least once every 30 minutes on average.

(b) For each individual, we use data within every month to determine their monthly home address. Hence, each individual has four identified home addresses from January 2020 to April 2020. For each individual-day, we identify the most frequent geo-coordinates between 3 a.m. and 5 a.m., and group all geo-coordinates within a geohash-7 (76m) into one. If an individual's night-time geo-coordinates are 50% similar within the month, we consider this coordinate as the individual's home address during that month.

(c) Using county-level polygons from the geojson files available at `https://eric.clst.org/tech/usgeojson/`, we find the corresponding county for each home address.

(d) If an individual's home addresses in all four months (from January 2020 to April 2020) are within a city's geo-bounds, we consider him/her that city's resident.

Step 2: Identifying the migration history in 2019

(a) For all residents within a city, we extract their location records across the United States in 2019.

(b) Following 1b, we find their home addresses each month. If multiple addresses in 2019 are identified for an individual, the address that shows up most frequently and for at least 70% of the months is regarded as the home address. We drop potential travelers with no home address that show up for more than 70% of the months.

(c) Following 1c, we find the corresponding county of the home address.

(d) If an individual's county of residence in 2019 is different from that in 2020, we consider him/her to be a migrant. Summary statistics of migration patterns from the 12 cities are in Table 2. The identified migration patterns are consistent with those from the US Census Migration/Geographic Mobility Data (2013-2017). Figure 4 highlights this similarity for New York City and Seattle.

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Step 3: Calculating social distancing at the individual-day level

(a) For each individual on a given day, we find the number of his/her records within Geohash-7 (76m) of the home address.

(b) Since the tracking time is evenly distributed, we use the number in 3a divided by the total number of records on that day to yield the percentage of at-home time.

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Entrepreneur debt aversion and financing decisions: Evidence from COVID-19 support programs[1]

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We find that an entrepreneur's negative personal attitude towards debt – debt aversion – affects the financing decisions of the businesses they run. We conduct a large-scale survey of entrepreneurs and link it to their firms' registry-based financial information. After controlling for a range of observable traits, firms run by highly debt averse entrepreneurs are about nine percentage points less likely to use debt, compared to baseline debt usage of just under 50%. The same entrepreneurs are also almost 25% less likely to take up government-guaranteed debt during the COVID-19 crisis. We also conduct a set of experiments to strengthen a causal interpretation. The experiments randomize the framing of otherwise identical, hypothetical COVID-19 support policies as debt or grants. Framing policies as debt significantly decreases interest.

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1 Introduction

There is a disconnect between the way debt is discussed in standard finance textbooks and in everyday use. In textbooks, debt is presented as a value-neutral instrument, with an emphasis on the benefits of intertemporal substitution. In everyday use, however, debt is more likely to be presented as an evil to de be avoided. Traditional literary sources strongly advise against taking on debt for reasons of self-reliance ("A man in debt is so far a slave"), self-restraint ("Never spend anything before thou have it; for borrowing is the canker and death of every man's estate") or threat to social ties ("Neither a borrower nor a lender be; for loan oft loses both itself and friend").[1] The word *debt* is even etymologically connected to the concepts of guilt and sin in several world languages.[2]

As a consequence, it appears plausible that people have some level of debt aversion, i.e. a generalized negative attitude toward the idea of borrowing. This has been documented in a number of contexts. For example, Field (2009) studies the impact of psychological responses to debt on career choices and finds that framing tuition support as debt, instead of a financially identical tuition waiver, makes it significantly less appealing. Zinman (2009) shows that individuals with a combined debit/credit card often prefer to use the debit card, even when the credit card amounts to an interest-free loan when paid at the end of the month. Almenberg, Lusardi, Säve-Söderbergh, and Vestman (2019), using a survey of households in Sweden, show that 56% of people find taking debt as unpleasant and that these attitudes are passed on within families. While risk-averse individuals may avoid debt when debt increases risk, debt aversion also includes psychological and cultural components that are not captured by classical notions of payoff uncertainty and risk aversion.

In this paper, we study whether an entrepreneur's personal attitude towards debt has an effect on the financing policy of the firm they manage.[3] We find that a large share of entrepreneurs are debt averse, i.e., they report being uncomfortable with taking on debt. Debt-averse entrepreneurs are less likely to use debt within their firm or to use debt-based rescue packages offered in response to the COVID-19 pandemic. We also conduct experiments which show that debt averse entrepreneurs are less interested in a hypothetical COVID-19 rescue package if it is labelled as debt, compared to a financially equivalent alternative not labelled as debt. Finally, in a follow-up survey, we ask entrepreneurs about their actions if they were offered a direct subsidy or a loan worth one month's revenue, and find that entrepreneurs are twice as likely to invest if offered a direct grant compared to a loan.

[1] Quotes from Emerson (1871, p. 39), Raleigh (1632, p. 61), and Shakespeare (1623, p. 156), respectively.
[2] See, e.g., The Economist (2015).
[3] Our sample consists of owner-managers of Finnish SMEs, which may include second-generation owner-managers. We refer to all owner-managers in our sample as entrepreneurs for conciseness.

We conduct a large-scale survey of approximately a thousand small- and medium-sized enterprises (SMEs) in Finland.[4] We exclude firms where the survey respondent is a hired manager, leaving us with a sample of 916 owner-managers (whom we shall refer to as entrepreneurs).[5] The firms are generally small, with about half the sample employing five or fewer people, and the other half employing between six and 250 people. In the survey, we ask respondents about their attitude towards debt, their subjective assessment of several personality traits, including optimism, financial literacy, risk aversion, and trust in people and banks, their expectations for their business, as well as the measures they have taken in response to COVID-19. We link survey responses to financial and other registry information about the firms.

The Finnish government's COVID-19 rescue packages for SMEs were similar to those implemented in most of Northern Europe (for example, Germany, Switzerland, the UK and Sweden) and focused on government credit guarantees. The credit guarantee scheme was administered through the private banking system, with banks screening loans and applying for the government credit guarantee on behalf of the firms. The guarantees generally covered 50-80% of the loan amount. Government ministers have stated that the take-up of government-guaranteed debt used has been substantially lower than expected (Kukkonen, 2020). The low take-up of loans is not just a Finnish phenomenon—for example, *The Economist* notes that the take-up of partially guaranteed loans has been poor in both the UK and Spain (The Economist, 2020). Given the pressures on liquidity caused by the COVID-19 pandemic, why are firms still so reluctant to use government-guaranteed debt? Our hypothesis is that individual-level debt aversion is correlated with the decision not to take up government-guaranteed debt.

The entrepreneurs in our sample are generally uncomfortable with debt. On a scale of 0-10, with 0 being disagree completely and 10 agree completely, 63% of entrepreneurs answered over 5 to the question “Do you agree with the following statement?: I consider taking on debt to be unpleasant”. Approximately 45% gave an answer of 8, 9 or 10, which we group as *High debt aversion* in our main analysis. We operationalize debt aversion in a

[4]A natural worry is whether Finnish respondents are internationally sufficiently representative. Perhaps they are more risk averse? We show evidence suggesting the levels of debt aversion in our sample are comparable or lower than those of respondents of the US Survey of Consumer Expectations (SCE). The SCE included as a one-time question items related to debt aversion (Hundtofte, 2018). When asked "What were you taught as a child about debts?", 52% of SCE respondents agreed with the non-exclusive option "Something to be avoided", 29% with "A necessary evil", and only 9% with "A useful way to shift money from periods when you have it to periods when you do not". We ask the same questions from our respondents, and obtain 25%, 10%, and 8%, respectively. This suggests that our respondents are less debt-averse than US SCE respondents, which is possibly because our respondents are entrepreneurs.

[5]We present results including non-owner managers, such as hired CEOs or CFOs, in the Internet Appendix.

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second way by asking five questions on "What were you taught about debt as a child?".[6] We find significant correlations between the directly self-reported debt aversion and four of the six possible answers to what the entrepreneur has been taught about debt as a child. The strongest positive correlation with debt aversion is for the question "Should be avoided", and the strongest negative correlation with "Useful to split large purchases".

We find that high entrepreneur debt aversion is associated with a significantly lower likelihood of the firm using debt, both currently and in the past. High-debt-aversion entrepreneurs are approximately nine percentage points less likely to have used debt in the past five years. In addition, a one-standard-deviation increase in debt aversion is associated with an approximately seven percentage points lower likelihood of currently having debt. We include in the analysis a separate measure of general risk aversion.[7] The results show that debt aversion and risk aversion both have a significant association with the decision to apply for a new loan: high debt aversion decreases the likelihood of applying for a new loan, while low risk aversion increases the likelihood. The effect size is approximately three times larger for debt aversion than for risk aversion when both are used simultaneously.

The analysis above describes a correlation between high debt aversion and low debt usage, and we next turn to whether a causal interpretation can be made. Our goal is first to compare firms that are as similar as possible, both in terms of their need for external finance as well as other managerial traits that may affect debt use, and control for the effect of these traits. Using our survey, we are able to control for many firm characteristics, including industry and size. We are also able to control for the size of the coronavirus shock (in terms of % of revenue lost) and the subjective expectations of the entrepreneur on the time to recovery for their firm. Most firms in our sample expect the impact of the virus to be temporary – more than half of the firms expect revenue to recover to pre-COVID levels within six months of our survey (conducted at the end of May), in line with Landier and Thesmar (2020) who show that analysts expect the impact of the virus to be temporary for US public firms.

A number of confounding managerial traits can also be directly controlled for. For example, if debt-averse people are more drawn to certain industries, any observed correlation may simply be a function of selection into industries with different financing needs. We control for this with industry fixed effects. Further, in addition to debt aversion and risk aversion, we include three control variables related to individual attitudes, namely optimism, distrust

[6]The possible (non-exclusive) answers are "Should be used in moderation", "A promise to be kept", "Should be avoided", "A necessary evil", "Useful to split large purchases", and "Useful to transfer money over time"

[7]The measure is based on subjective self-reported risk aversion. Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011) find that self-reported risk aversion is strongly correlated with choices in experimental lotteries and real-world behavior

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of other people, and distrust of banks. However, there remains a possibility that high debt aversion does not actually cause low debt usage, if the correlation is due to some unobservable factor. To mitigate this possibility, we first use the specificity of the COVID-19 context, and second, include a randomized experiment in our survey.

Our first analysis uses the fact that the COVID-19 pandemic caused a severe unexpected liquidity shock for a large number of firms. The timing of the shock was largely unanticipated and hit most firms at the same time. This provides us with a setting in which firms face unexpected financing needs, alleviating concerns about debt-averse managers self-selecting to low-financing-need firms. The magnitude of the liquidity shock in our sample is correlated by industry, but we control for this. In case high debt aversion is associated with low willingness to take on new debt even in this exceptional context, we would expect that our results reflect a lower bound on the effect size. We find not only that high-debt-aversion entrepreneurs were less likely to use debt before the crisis, but also that high-debt-aversion entrepreneurs are five percentage points less likely to have applied for a new bank loan during the crisis, relative to a sample average of 16%.

However, there may still be concerns that, for example, unobservable characteristics of firms run by non-debt averse managers caused a larger liquidity shock.[8] To mitigate this we conduct a three-part experiment to see whether simply labeling a contract as debt makes entrepreneurs less interested in it. The experimental design partially resembles that of Caetano, Palacios, and Patrinos (2019) for student loans. We have three "pairs" of financing options, and each respondent is randomly shown one from each pair, and asked to evaluate how interested they would be in using it, on a scale of one to ten. Both the order of the three questions and the alternative to be evaluated by the respondent are randomized. The pairs consist of identical or nearly identical policies, where one is framed as more loan-like and the other either as a direct grant, or debt but with some debt-like features made more salient. We find that across all policy pairs, respondents are more willing to take up support framed as direct support rather than a loan, or where the loan-like features are made less salient.

The first experiment asks the respondents about their interest in either a loan out of which 75% is forgiven if the firm does not lay off workers (somewhat similar to the US CARES Act Paycheck Protection Program), or a grant covering 75% of the firm's personnel expenses.[9]

[8]Another potential concern might be that applying for debt during the crisis lowered debt aversion, causing us to observe an *ex post* relationship between debt aversion and use of debt even when non-existed at the time of applying

[9]In this case, the loan actually objectively dominates the grant option, as we do not specify, unlike the Paycheck Protection Program, that the loan amount is restricted by the amount of personnel expenses. In principle, in our wording, the forgiven loan amount could be larger than the direct grant. Despite this, the respondents are more interested in the grant.

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The respondents are significantly more interested in taking up the support framed as direct grant instead of loan forgiveness. This implies that governments primarily motivated by limiting lay-offs might want to formulate their payroll support as a partial grant rather than a loan that can be forgiven.

The second experiment is a much more subtle framing of a policy relevant to the EU area, where governments have lent back to firms the value-added tax (VAT) that they paid earlier in 2020. We call the two options either "VAT loan" or "VAT return", with exactly identical financial terms used in the description, i.e. the VAT return is temporary, carries an interest and has the same maturity as the loan. As one might expect, the differences are much smaller than with the first experiment. We do not find a statistically significant difference in the overall average level of interest between the two alternatives. However, there is an interesting statistically significant difference in the subsample of high-debt-aversion entrepreneurs. For the high-debt-aversion group, simply changing the name of the support to "loan" is enough to increase the zero-interest the responses by 14–16 percentage points.

The last experiment is about making the loan-like characteristics more salient. One policy alternative is a normal government-guaranteed loan, while the other is a government guaranteed loan where 80% is forgiven if the firm becomes insolvent as a result of COVID-19. The explicit mention of forgiving 80% of the loan in bankruptcy significantly increases interest relative to a regular loan and reduces zero-interest responses by 16 percentage points. Among high-debt-aversion entrepreneurs, there is an additional reduction in zero-interest responses of 10–11 percentage points. Given that in the event of bankruptcy, equityholders are unlikely to receive any payoff, it is not clear how forgiveness of 80% of the loan has any real impact on the entrepreneur.[10] If interpreted as an increase in the likelihood of the entrepreneur receiving some non-zero amount at the bankruptcy, it might be perceived as a reduction in the downside risk of the loan.

In an additional analysis conducted as part of a follow-up survey (answered by roughly 10% of our original sample), we ask firms about how they would respond to hypothetical offers of either a direct grant or a loan worth one month of revenue. We find that almost all firms would spend the grant on their business, with almost half of firms replying that they would invest the grant.[11] This suggests that most firms see profitable investment opportunities. However, the share of firms investing if offered a loan is less than half of the share investing a grant. One justification for favoring debt-based support programs has been the fact that firms with profitable investment opportunities can always fund them with debt. Our results

[10]Bankruptcy in the Finnish context means a Chapter 7-style liquidation.

[11]Other common responses included paying off debts to suppliers, landlords etc. during the crisis and paying employees a bonus

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suggest that this may not be the case. Instead, firms are significantly more likely to invest out of equity (a grant) than debt.

There are limitations to our analysis. First, the survey was conducted between May 27 and June 8, 2020, when local infections had fallen from their peak and some restrictions were being lifted. Thus, the answers to questions on the viability of the firm and recovery times may be less pessimistic than the attitudes at the peak of the crisis. In addition, there may be some selection bias in the firms that participated in our survey.[12] However, it is not clear how this would bias our cross-sectional results. While the survey was clearly framed as an academic survey, entrepreneurs might also have viewed it as an opportunity to lobby for direct support for firms. However, it is unlikely that entrepreneurs would have used the "personality trait" questions (our variable of interest) as their instrument for lobbying. Finally, the survey was carried out at a time when there was media speculation that direct support (grants) might be provided to firms.[13] It is possible that anticipation of direct support affected our results. Given that our survey mostly asks firms about their use of debt in the past months and explicitly includes a question about "anticipation of better support programs in the future" as a reason for not applying for debt-based relief, we do not think this would influence our results significantly.

Our study builds upon, and contributes to, several strands of literature. First, our study is related to recent work in household finance on individual-level attitudes towards debt. Almenberg et al. (2019) find that more than half of households report being uncomfortable with taking on debt and that these attitudes are correlated with their use of debt. In the context of US student loans, experimental and quasi-experimental studies (e.g., Field, 2009; Caetano et al., 2019) show that student loans with loan forgiveness enjoy lower take-up than financially equivalent grant programs. There is also broader literature on the psychology of debt (e.g., Almenberg and Karapetyan, 2014; Prelec and Loewenstein, 1998; Meissner, 2016). Prior literature also shows that social and cultural norms are important determinant of borrower behavior (see, e.g., Guiso, Sapienza, and Zingales, 2013).

Second, we contribute to the growing a growing literature showing evidence that managerial attitudes affect corporate policy (e.g. Graham, Harvey, and Puri, 2013; Cronqvist, Makhija, and Yonker, 2012; Cronqvist and Yu, 2017; Korkeamaki, Liljeblom, and Pasternack, 2017). For reviews of how managerial attitudes, biases, and experiences play a role in behavioral corporate finance, see Guenzel and Malmendier (2020) and Malmendier (2018). The managerial attitudes approach has helped explain why there is considerable heterogene-

[12] For example, it could be that entrepreneurs of failed firms are not interested in answering surveys, or entrepreneurs with struggling firms might not have the time to do so.

[13] Such direct support was indeed decided on after the survey had been concluded, later in June.

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ity in observed capital structures beyond what is predicted by traditional models such as trade-off theory and pecking order theory. However, one persistent puzzle that remains is that the observed leverage levels of firms tend to be substantially lower than predicted by traditional models (Graham, 2000) and a large number of firms have no debt at all (Korteweg, 2010; Strebulaev and Yang, 2013; El Ghoul, Guedhami, Kwok, and Zheng, 2018). We take findings from the household finance literature on the psychology of debt and link these to the financial policies of SMEs, showing that many entrepreneurs' personal views towards debt affect financial policy in the firms they manage.

Third, our results also have implications for the entrepreneurial finance literature. Debt aversion may act as a constraint to entrepreneurship, as new firms often depend on personally guaranteed debt (Robb and Robinson, 2014), and a partial explanation for the link between personal wealth and entrepreneurship (e.g., Hurst and Lusardi, 2004). In an argument that is close to ours, Nguyen, Nguyen, Troege, and Nguyen (2020) find evidence that many Vietnamese SMEs do not apply for loans and show that this is correlated with a survey answer response stating that they "do not want to incur debt". While plausible, it is not clear to what extent this survey response measures managerial debt aversion, as oppose to just not wanting debt for business-related reasons or because of risk aversion. Our survey directly asks about attitude toward debt, providing a more plausible empirical measure of debt aversion. Our use of COVID-19 as a setting and our experimental analyses mirroring prior experimental work also provide a more plausible causal interpretation.

We also add to the emerging literature on the effectiveness of government policies when response to policies is shaped by imperfect information, lack the capability to process information, or are affected by attitudes and social norms (D'Acunto, Hoang, Paloviita, and Weber, 2020b,a; Coibion, Gorodnichenko, and Kumar, 2018). Much of this literature has focused on individuals rather than firms, while a growing strand of the literature has shown that the expectations and actions of firms often deviate from the full information rational expectations framework (e.g., Bachmann and Elstner, 2015; Coibion et al., 2018). Finally, we contribute to the literature on the impact of COVID-19 on SMEs and the design of government rescue packages. The pandemic has significantly impacted firms around the world (Barrero, Bloom, and Davis, 2020; Humphries, Neilson, and Ulyessea, 2020; Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020) and underscored the importance of effective government policies.

A big picture implication of our results is that governments should incorporate insights from behavioral economics into their dealings with firms. Even with "nudge units" existing around the world to incorporate behavioral economics into policy, government policy often presumes that firms operate in a profit-maximizing framework. For this reason, rescue

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policies for firms struggling due to the pandemic may not be as widely adopted as assumed.

The next section provides some background information on the coronavirus in Finland and measures taken by the government to help firms and SMEs. We then describe the data (our survey + key variables construction). The section "Main results" presents summary statistics from our sample and the main results documenting the impact of debt aversion on the use of debt, the use of debt-based government programs during COVID-19 and on the perceived attractiveness of hypothetical rescue policies (our experimental results). The next section, "Additional analysis" presents several descriptive analyses showing the measures taken during the crisis by high-debt-aversion firms as well as a brief look at which demographic traits and childhood "stories" about debt are correlated with debt aversion.

2 Background information

We use Finland as the institutional setting for research because government policy early on in the COVID-19 crisis aimed to help firms by improving access to credit and because even small Finnish SMEs are required to prepare annual accounts which are publicly available. In this section, we provide a brief overview of the impact of the COVID-19 pandemic on Finland as well as measures taken by the government to curb the spread of the disease and to help firms.

Overall, the coronavirus did not spread widely in Finland compared to other Western European countries. Because testing was not widespread at the beginning of the outbreak, we use death rates as a proxy for the spread of the disease. As of 3 August, Finland had 329 deaths (population = 5.5 million). The virus did not spread evenly across Finland, with the province of Uusimaa (including the capital city, Helsinki) having a death rate double the national average (other hard hit areas include the border region with Sweden). The first documented case was found relatively early, on 29 January when a Chinese tourist tested positive. In early March the number of documented cases started to rise rapidly. Finland imposed (once again, compared to Western Europe) a relatively light set of social distancing measures. The first measures were enacted on 16 March when the government announced that schools and non-essential government services would be closed, over 70 year olds were encouraged to limit contacts, borders were closed to non-Finns/non-residents[14] and gatherings of more than 50 people were banned. On 20 March, Finland saw its first death from the virus, on 27 March internal borders between the province of Uusimaa and the rest of country were closed to non-essential traffic and on 30 March bars and restaurants were ordered to close (takeaway and delivery were still possible). The travel ban on the Uusimaa

[14]Excluding certain essential traffic

province was lifted on 15 April and other restrictions were lifted starting from May as the rate of new infections fell (on 4 May libraries and other government services were allowed to reopen, on 14 May schools reopened for 2 weeks before the summer holidays and on 1 June restaurants and certain bars were allowed to reopen, with restrictions). Between June and July the government eased capacity restrictions on restaurants and bars.

The government announced its first support package for firms on 20 March. This support package consisted of two elements, chosen mainly because they could be deployed fast: credit guarantees administered through Finnvera, a government-owned body that normally provides export credit and other credit guarantees, and direct "development support" grants administered through Business Finland, a government entity that normally administers direct grants to firms such as R&D subsidies. The government did not loan out money directly but instead Finnvera guarantees were offered via the private banking system. The guarantees typically covered 80% of the loan amount meaning that banks retained some credit risk and hence screened applicants. The annual cost of the credit guarantee was capped at 1.75% of the loan amount plus a 0.1% one-time administrative fee.

The second element of the support package was direct support in the form of development grants offered by Business Finland (for firms with over 5 employees) or grants from local municipalities or regional economic development authorities (for firms under 5 employees). The Business Finland development grants ranged from 10,000 euros to 100,000 euros and required firms to submit a plan for a new product or service or a development to an existing product or service - they could not be used to for instance retain staff or compensate for lost revenue. In addition, they required the firms themselves to contribute 20% of the costs. The development grants were widely criticized as being poorly targeted and inaccessible for the firms that needed them the most. However, our survey suggests that the various forms of direct support were fairly popular, with 44% of firms having applied for these grants, including over half of surveyed firms in the hospitality (restaurants and hotels) industry.

Finally, following the release of a report recommending direct grants to firms in May, the government announced direct support for hard-hit firms in hard-hit industries, consisting of grants for past expenses. The details of direct support to firm were not yet available to the public while our survey was conducted but the firms responding to our survey knew that the government was working to pass the scheme and some preliminary details (such as the fact that support would be contingent on both a drop in revenues for the firm as well as for the industry the firm operates in).

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3 Data and methodology

3.1 Description of the data

Our data come from a survey of Finnish SMEs that we commissioned, conducted between 27 May and 8 June 2020 by TNS Kantar (a firm specializing in market research) and aimed to survey 1,000 Finnish SMEs. The survey was sent to member firms of the Federation of Finnish Enterprises, a trade body for entrepreneurs, as well as firms whose contact details were available in the Bisnode Finland database. We aimed to oversample firms with over 5 employees in the survey. In total, 1,008 firms answered the survey[15]. The respondents were mainly entrepreneurs (91%), with 6.3% being non-entrepreneur CEOs and 2.6% being CFOs or other management (0.1% declined to answer this question). In our results, we focus on the sample of entrepreneurs. All of the firms in our sample are private firms - this makes analysis of non-owner managed firms difficult as it is not clear whether the key decision-maker on financial policy is the hired CEO / CFO or the owner.[16]

Of the firms in our sample, 61% had fewer than 5 employees while 0.5% had over 50 employees, meaning that most firms were extremely small. Median sales (self-reported) in 2019 were 203,000 euros with the 10th and 90th percentile firms having sales of 19,000 and 2,100,000 euros, respectively. About half (48%) of the firms reported having debt. Summary statistics on our sample are presented in Table 1.

Most firms in our sample report that they either will survive or probably survive the crisis. Fewer than 10% of firms report that they are likely to fail or will fail, though this may be a function of the fact that our survey was conducted relatively late into the first wave of the crisis. However, more than half of the firms in our sample report that they would not survive longer than 6 months without additional financing or assistance.

Filling out the survey took on average eight minutes. The first part of the survey asked for background information, such as the size of the firm, the position of the respondent (entrepreneur, hired CEO, other management etc.), the age, gender and education of the respondent and the firm's 2019 sales and industry. We then asked firms for the impact of COVID on their revenue (increased, decreased, stayed the same etc.) and an estimate of the size of the effect. About 63% of firms responded that revenues had fallen because of COVID, with the average change in revenues being a negative 25%. We also asked whether the firm currently has debt / whether the firm has had debt in the past five years as well as whether the owners of the firm had been required to offer guarantees or post collateral for this debt.

We asked firms about the damage caused by COVID to their firm and the measures taken

[15] We had 1009 responses but one firm responded twice

[16] We present results using the full sample of firms in the appendix

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Table 1
Summary statistics

Summary statistics for the sample.

	Mean	Std	p10	p50	p90	N
Firm						
1 employee	0.386	0.487	0.000	0.000	1.000	917
2-4 employees	0.238	0.426	0.000	0.000	1.000	917
5-9 employees	0.209	0.407	0.000	0.000	1.000	917
10-50 employees	0.141	0.348	0.000	0.000	1.000	917
51-250 employees	0.023	0.150	0.000	0.000	0.000	917
250+ employees	0.003	0.057	0.000	0.000	0.000	917
Sales ('000) (self-r.)(w.)	1117.488	3711.959	19.000	203.500	2100.000	804
Firm debt ('000) (self-r.)(w.)	251.922	865.931	0.000	40.000	425.000	515
Has debt	0.480	0.500	0.000	0.000	1.000	917
Had debt last 5y	0.606	0.489	0.000	1.000	1.000	917
Accounting ratios						
Debt/assets	0.143	0.211	0.000	0.000	0.514	564
Net debt/EBIT	-0.797	3.883	-5.000	-0.924	5.044	450
Net debt/turnover	-0.063	0.237	-0.346	-0.051	0.246	537
Cash/assets	0.305	0.263	0.016	0.242	0.742	542
Attitudes						
High debt aversion	0.449	0.498	0.000	0.000	1.000	899
Debt aversion	6.337	2.894	2.000	7.000	10.000	899
Risk appetite	5.976	2.169	3.000	6.000	9.000	904
Optimism	7.255	1.923	5.000	8.000	9.000	901
Distrust people	5.406	2.653	2.000	6.000	9.000	903
Distrust banks	5.132	2.769	1.000	5.000	9.000	907
Firm actions						
Applied new bank loan	0.156	0.363	0.000	0.000	1.000	917
Applied any loan	0.184	0.388	0.000	0.000	1.000	917
Applied direct support	0.534	0.499	0.000	1.000	1.000	917
Applied equity	0.098	0.298	0.000	0.000	0.000	917
Has laid off	0.060	0.238	0.000	0.000	0.000	917
Has furloughed	0.273	0.446	0.000	0.000	1.000	917
Canceled inv.	0.171	0.377	0.000	0.000	1.000	917
Unpaid ent. comp.	0.209	0.407	0.000	0.000	1.000	917
Unpaid taxes	0.128	0.334	0.000	0.000	1.000	917
Unpaid wages	0.009	0.093	0.000	0.000	0.000	917
N	917					

in response. In particular, we asked whether firms had furloughed or laid off employees (and what proportion of workers had been laid off and furloughed) – 29% and 6% had done so, respectively. In addition, we asked whether the firm had cut or postponed investments,

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Figure 1: Expectations on firm survival

Distribution of firms by entrepreneur expectations of firm survival.

missed payments to customers (and whether customers had missed payments) or skipped other payments such as taxes or the entrepreneur's salary.

We also included multiple questions about the respondent's expectations regarding their firm and the economy in general. First, we asked respondents whether their firm will survive the crisis or not, how many months their firm would survive without any external assistance or financing and their expectation of when revenue will return to 2019 levels. We also included more "neutral" expectations questions such as estimates of Finnish GDP in 2020 and 2021 and the probability of GDP falling by more than 15% (an extremely pessimistic estimate compared to most forecasts at the time) and the probability of their firm's revenue falling by more than 30% over the entire year.

The next section included a range of questions on the financing / assistance options used by the firm. In particular, we asked firms what types of financing / assistance they had applied and received for during the crisis. Direct support programs were most popular, with

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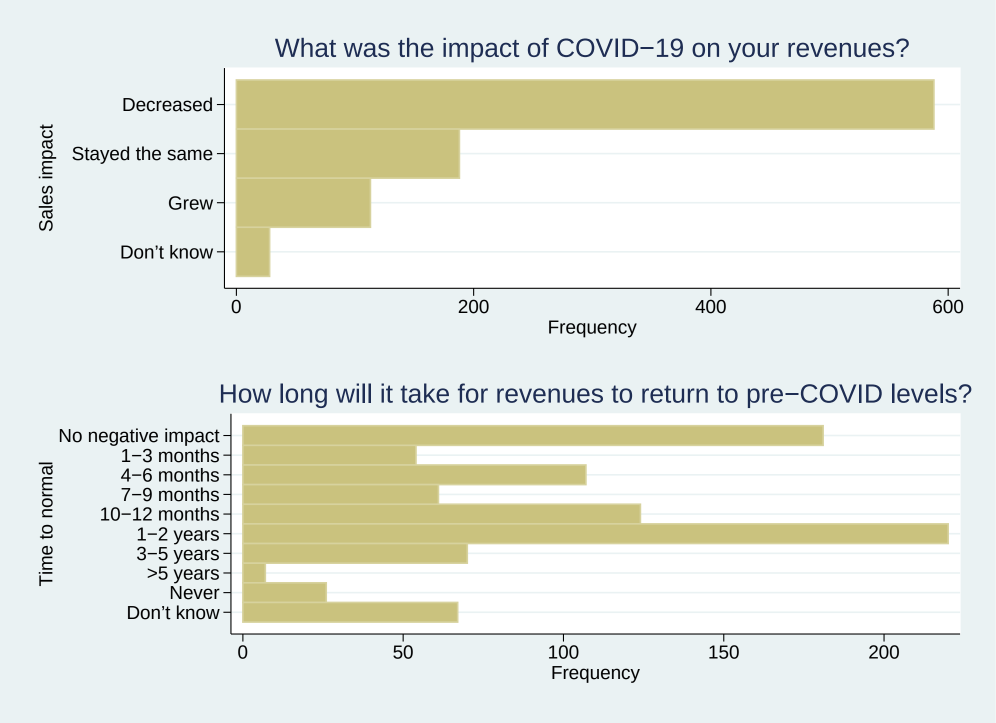
Figure 2: Corona impact on firm sales

Distribution of firms by the reported impact of COVID-19 on firm sales.



over 44% of firms having applied for at least one. Only about 16% of firms had applied for new bank loans and 19% had applied for payment extensions on current loans (with overlap between the two options). We also asked firms how much they had applied for and for the firms that received loans, what the interest rate on these loans was (on average, 2.8%) and whether personal collateral or guarantees were required. We also ask the firms that did not apply for a loan why they did not do so (over 50% responded that they did not need a loan, with the second most common reason being that taking on new debt would increase the riskiness of the firm)

We then conducted an experiment (described above) where all respondents received three questions, but the content of these questions was randomized. There were three "pairs" of questions, with each respondent receiving one of the two questions in each pair. The questions described a hypothetical policy option offered by the government and asked the respondent to rate (on a scale of 0-10) how likely they would be to use it if it had been offered at the beginning of the crisis. The first pair of policy options included a loan with a standard guarantee from Finnvera, with the randomization affecting the way the guaranteed portion of the loan is treated in bankruptcy - half of respondents received a policy with no special treatment while half received a policy where the guaranteed portion is written off in bankruptcy if the firm can show it became insolvent because of COVID-19. The second and third policy options involved various policies being framed either as debt or a grant.

Finally, we asked respondents for their subjective assessments of their risk and financial risk appetite (0-10 scale), whether they consider themselves optimistic, whether they consider themselves good in financial matters (subjective financial literacy), whether they feel people can be trusted, whether they feel banks can be trusted and two questions on debt aversion. The first debt aversion question asked respondents what they had been taught about debt as a child (over 60% had been taught that it is something to be used in moderation, 10% that it was a necessary evil and only 7% that it was a tool for transfering wealth from periods when wealth is high to those when it is low) as well as whether they agree/disagree with the statement "I consider taking debt unpleasant." We also asked whether the respondent knew anyone who had declared bankruptcy and whether they wanted their kids to take over their business after they retired.

3.2 Follow-up survey

About 2 months after our survey, in August, we sent a follow-up report to firms. In this report, we provided industry-level information (for the industry the firm was operating in) on the size of the coronavirus shock and measures taken in response. In addition, we linked to a policy report we had created and posted on the Aalto University website detailing the impact of the coronavirus across the entire economy (along with some industry-level figures for all industries). We asked the firms receiving the report to fill out a small survey, and roughly 110 firms did (about 20% of the roughly 500 firms that elected to receive the industry reports). In this survey, we asked them whether they thought the firms they managed had too much, too little or the right amount of debt. In addition to this, we asked firms about their responses to hypothetical government-backed loans (with either a 3% market interest rate or 1% subsidized interest rate) or grants of 1 month of revenue.[17] We presented the respondents with 9 options for both debt and equity. A graph presenting the percentage of respondents choosing each (non-exclusive) option is presented in Figure 9.

[17] We randomized the order of the debt and grant questions and did not allow respondents to move back in the survey.

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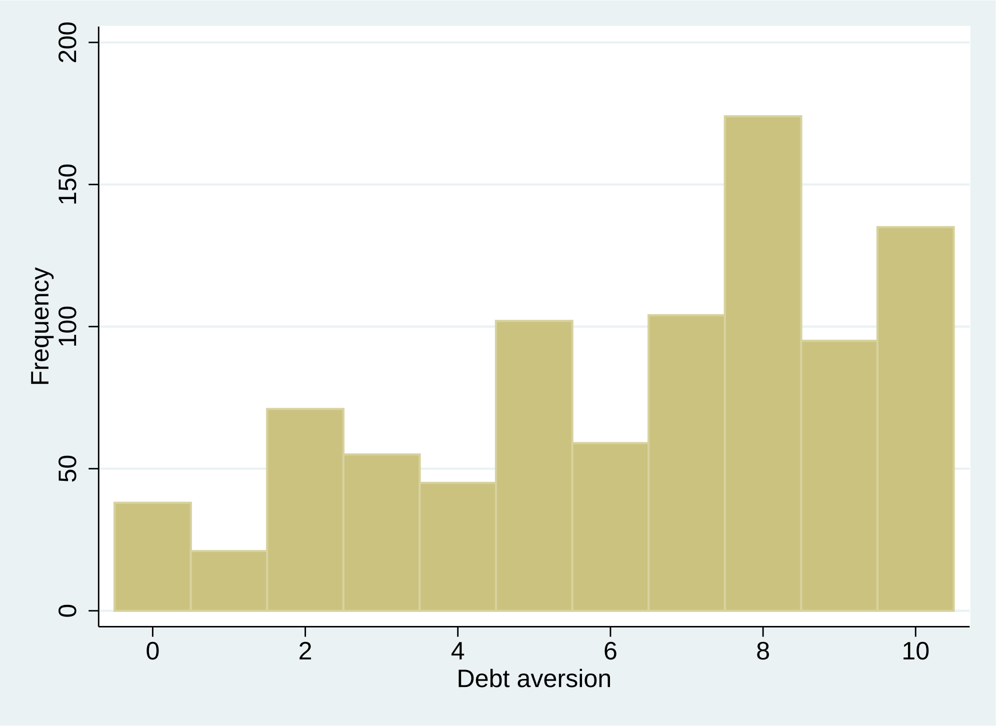
3.3 Key variable definitions

Our main variables of interest are attitudes towards debt (debt aversion) and the use of debt. We look at use of debt in two contexts. First, we look at the firm's use of debt-based rescue packages during the COVID-19 pandemic. Second, we study the use of debt prior to the pandemic, which we obtain from both the survey as well as from linked financial information. Below, we briefly discuss the key measures we use in our analysis and the survey questions they are based on.

- ***Debt aversion:*** *How well does the following argument describe your relationship with debt? "I consider taking debt unpleasant" (0-10 scale)*
  61% of respondents answered above 5 and 43% answered 8, 9 or 10. We define *high debt aversion* as a dummy that takes the value one if a respodent answers either 8, 9 or 10. The distribution of responses to the question is presented in Figure 3.
- ***Debt use during COVID-19:*** *Has your company applied for new financing during Covid-19 from some of the following..?*
  Firms are then presented with a list of potential financing sources (loans, direct-support, deferred payments on existing loans) and answer options (No, No but will use if the crisis continues, Yes, we have applied but not heard back, Yes, we have applied by been rejected and Yes, we have applied and received this). We create a dummy variable that takes the value of 1 if a firm has applied for a loan (regardless of result), encompassing the answers to several financing options (loan from a bank, loan-back of mandatory pension contributions and loan from other sources). 18.4% of firms have applied for a loan of any sort during the crisis.
- ***General debt use:*** *How much debt does your company have?*
  Given the variation in debt use across firm size and industry, we generally use a dummy specification where firms that have any debt are assigned one and others zero. Just under half of firms report having debt. This may be an underestimation as many firms may have debt-like liabilities (such as deferred payments or trade credit) which they do not consider debt. Firms which report having zero debt are presented with an extra question asking them whether they have had any debt in the past five years. In robustness tests, we combine these two measures into a dummy variable that takes the value of one if a firm has debt now or has had debt at any point in the past five years.

Figure 3: Debt aversion

Distribution of entrepreneur responses to the question: "Do you agree with the statement: I consider taking on debt to be unpleasant?". The scale is from zero ("disagree completely") to ten ("agree completely").



4 Main results

4.1 Debt aversion and the use of debt

We begin our analysis by studying the relationship between entrepreneur debt aversion and the general use of debt prior to the pandemic. We construct two outcome dummy variables, *Has debt* and *Had debt 5y*, indicating whether the firm has debt currently and whether it has had debt at some point during the last five years. We then perform a regression analysis of the following form:

$$Has\ debt_i = \alpha_0 + \alpha_1 \times High\ debt\ aversion_i + \beta \times X_i + \epsilon_i \tag{1}$$

where *High debt aversion* is a dummy taking the value one if the entrepreneur has a

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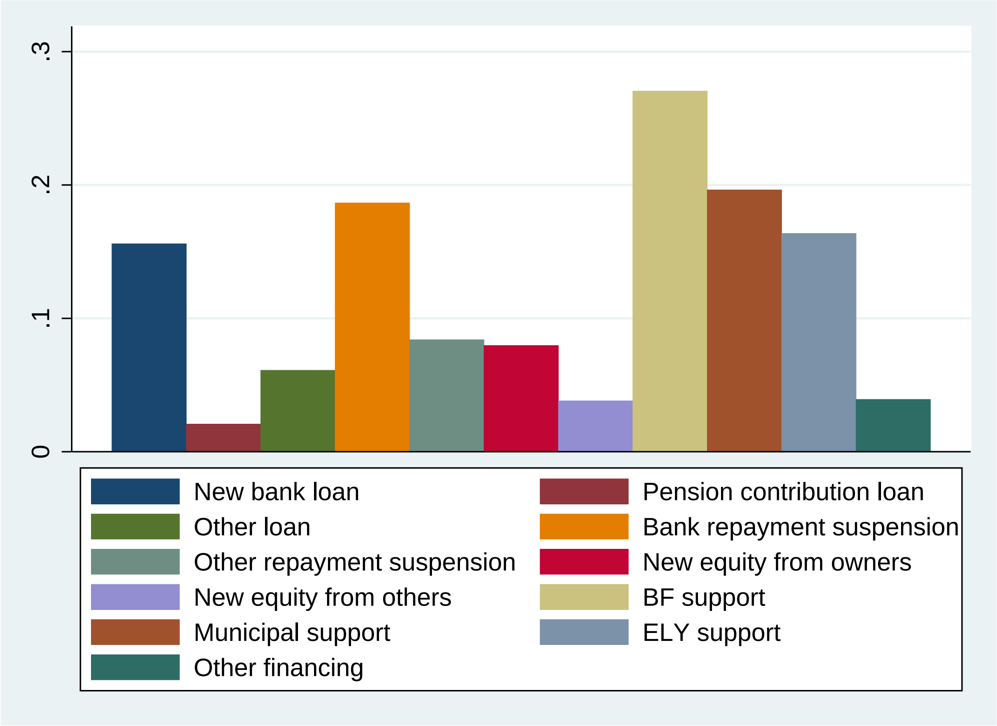
Figure 4: Financing options applied for

Proportion of people answering yes to the question: “Has your firm applied for the following?”.



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debt aversion score of 8,9, or 10, i.e., the highest tertile in our sample, and X is a vector of controls, including risk appetite, optimism, trust in people and banks, firm size-category fixed effects, industry fixed effects. We also include subjective survival probability fixed effects and “survival time” category fixed effects (based on the response options we gave entrepreneurs, e.g. less than 1 month, 1-2 months, 3-4 months, etc.), to control for firm cash flow and liquidity characteristics at the outset of the pandemic.

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Figure 5: Reasons for not applying for new debt

Reasons stated for not having applied for new debt financing. (Choose all that apply)

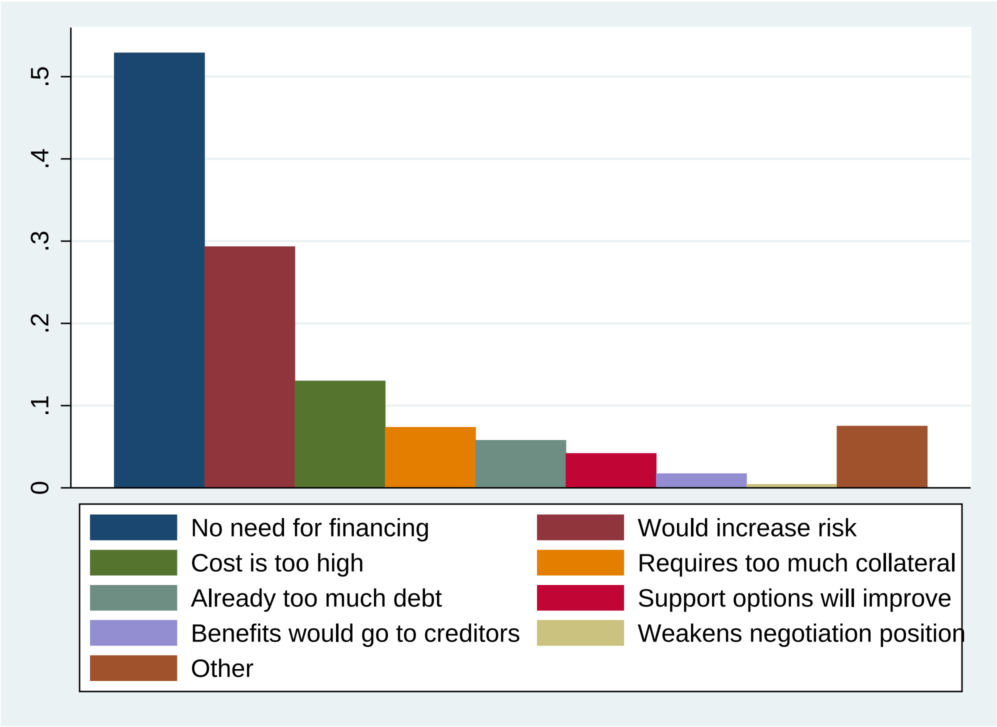

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Table 2
Debt use and cash holdings vs. debt aversion

The dependent variable is shown above each column. *Has debt* is a dummy taking the value one if the firm reported having existing debt. *Had debt 5y* is a dummy taking the value one if the firm reported having had debt at some point during the last five years. In Panel B, the dependent variables are calculated based on financial statement data matched to our survey. The samples consist of all firms where the dependent variable is available. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

Panel A: Current and historical debt use

	Has debt				Had debt 5y			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High debt aversion	−0.1350***	−0.0983**			−0.1275***	−0.0915***		
	(0.0367)	(0.0398)			(0.0350)	(0.0317)		
Debt aversion			−0.0253***	−0.0203***			−0.0245***	−0.0198***
			(0.0061)	(0.0065)			(0.0064)	(0.0053)
Risk appetite		0.0164**		0.0142**		0.0134		0.0110
		(0.0065)		(0.0065)		(0.0094)		(0.0094)
Optimism		0.0072		0.0066		−0.0011		−0.0016
		(0.0127)		(0.0124)		(0.0111)		(0.0110)
Distrust people		0.0115		0.0114		0.0079		0.0080
		(0.0069)		(0.0069)		(0.0074)		(0.0074)
Distrust banks		−0.0058		−0.0052		−0.0073		−0.0067
		(0.0058)		(0.0054)		(0.0046)		(0.0044)
Firm size FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Survival FE	No	Yes	No	Yes	No	Yes	No	Yes
Survival time FE	No	Yes	No	Yes	No	Yes	No	Yes
N	899	883	899	883	899	883	899	883
R^2	0.018	0.192	0.021	0.195	0.017	0.219	0.021	0.223

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 2
Debt use and cash holdings vs. debt aversion (cont'd)

Panel B: Debt and cash holdings

	Debt/assets		Net debt/EBIT		Net debt/turnover		Cash/assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High debt aversion	−0.0389**		−0.5828*		−0.0373*		0.0389	
	(0.0159)		(0.2968)		(0.0180)		(0.0265)	
Debt aversion		−0.0079**		−0.1086		−0.0060		0.0063
		(0.0030)		(0.0697)		(0.0049)		(0.0054)
Risk appetite	0.0062	0.0058	0.1168	0.1127	0.0027	0.0028	−0.0041	−0.0043
	(0.0054)	(0.0052)	(0.1219)	(0.1214)	(0.0057)	(0.0057)	(0.0039)	(0.0041)
Optimism	0.0032	0.0024	0.0402	0.0302	0.0079	0.0072	−0.0062	−0.0055
	(0.0053)	(0.0053)	(0.0747)	(0.0762)	(0.0062)	(0.0062)	(0.0077)	(0.0080)
Distrust people	0.0027	0.0029	−0.0064	−0.0047	−0.0000	0.0000	−0.0009	−0.0010
	(0.0034)	(0.0033)	(0.1015)	(0.1012)	(0.0036)	(0.0036)	(0.0042)	(0.0043)
Distrust banks	−0.0037	−0.0033	−0.0703*	−0.0668	−0.0004	−0.0003	−0.0040	−0.0041
	(0.0033)	(0.0032)	(0.0373)	(0.0400)	(0.0027)	(0.0026)	(0.0038)	(0.0038)
Firm size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	543	543	436	436	516	516	521	521
R^2	0.147	0.150	0.153	0.153	0.161	0.160	0.281	0.280

Significance levels: * 0.1, ** 0.05, * 0.01.**

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Table 3
New bank loans during COVID-19 pandemic vs. debt aversion

The dependent variable is *Applied new bank loan*, a dummy taking the value one if the firm reported having applied for a new bank loan during the COVID-19 crisis. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
High debt aversion	−0.0581**	−0.0526***	−0.0500**			
	(0.0223)	(0.0177)	(0.0188)			
Debt aversion				−0.0067	−0.0067**	−0.0066*
				(0.0039)	(0.0032)	(0.0034)
Risk appetite		0.0114**	0.0119**		0.0117**	0.0121**
		(0.0047)	(0.0047)		(0.0046)	(0.0045)
Optimism		−0.0083	−0.0090		−0.0090	−0.0097
		(0.0067)	(0.0066)		(0.0067)	(0.0067)
Distrust people		0.0047	0.0045		0.0044	0.0043
		(0.0032)	(0.0032)		(0.0031)	(0.0031)
Distrust banks		0.0046	0.0044		0.0045	0.0044
		(0.0044)	(0.0046)		(0.0044)	(0.0045)
Firm size FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Survival FE	No	Yes	Yes	No	Yes	Yes
Survival time FE	No	Yes	Yes	No	Yes	Yes
Sales impact FE	No	No	Yes	No	No	Yes
Time to normal FE	No	No	Yes	No	No	Yes
N	899	883	883	899	883	883
R^2	0.006	0.173	0.181	0.003	0.171	0.180

Significance levels: * 0.1, ** 0.05, * 0.01.**

The results are shown in Panel A of Table 2. We find a significant negative relationship that is slightly mitigated by the inclusion of control variables. Highly debt averse entrepreneurs are 10-14 %-points less likely to have debt, compared to a baseline of about 48% of firms having debt. This difference is statistically significant and economically large. We find similar results when including debt aversion as a continuous variable.

Using financial statement data for those firms for which it is available, we then construct a number of ratios indicating the use of debt and the level of cash holdings and study the effect of debt aversion on those measures.[18] The results are shown in Panel B of Table 2. Firms run by high-debt-aversion entrepreneurs have significantly lower levels of debt, with nearly 4 %-points lower debt/assets ratio, representing 27% decrease relative to the sample average of 14%. Similarly, high-debt-aversion entrepreneurs have on average 0.58 lower net debt/EBIT ratio and 0.04 lower net debt/revenue ratio. These effects are equivalent to 15% and 16% of the sample standard deviation, respectively. Directionally, our results also

[18]To limit the impact of outliers, we winsorize these variables at the 5% level at both tails.

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suggest that high-debt-aversion entrepreneurs may have higher average cash/assets ratios, although this difference is not statistically significant.

As discussed above, the COVID-19 pandemic provides a setup where many firms unexpectedly needed liquidity and debt is the main option on offer. Hence, we study firms' decisions to take-up new loans during the pandemic, depending on the manager's debt aversion. We define a dummy variable *Applied new bank loan*, taking the value one if the firm has applied for a new bank loan during the pandemic. We then perform a similar regresseion as above. We include some additional controls to better capture firm-level heterogeneity in exposure to the pandemic. These include sales impact fixed effects (once again, based on response options, e.g. sales decreased, sales stayed the same, sales grew) and time to normality fixed effects (response options, e.g. sales were not impacted, less than 1 month, 1-2 months.).

The results are shown in Table 3. The coefficient of high debt aversion is consistently negative and significant at either 5% or 10% level, depending on the specification. Entrepreneurs that are highly debt averse are approximately 5 percentage points less likely to have applied for a new bank loan during the crisis, compared to a baseline rate of 16% that applied for bank loans. Risk appetite is also significantly negatively correlated with the used of debt during the pandemic, suggesting that more risk-averse entrepreneurs are less likely to take on new debt. Optimism and trust are not significantly correlated with the use of debt. We also note that the relationship between debt aversion and take-up of new loans during the pandemic appears non-linear. The results are statistically more significant for a dummy indicating high levels of debt aversion than when including debt aversion as a continuous variable.

4.2 Experiments on framing

In this section, we conduct a set of experiments to study the impact of debt aversion on the take-up of government support for SMEs. We compare the level of interest in three "pairs" of hypothetical policies, and each respondent is randomly shown one from each pair. The pairs consist of identical or nearly identical policies, where one is framed as more loan-like and the other either as a direct grant or debt but with making some debt-like features more salient. In each pair, the respondent is asked to rate (on a 0-10 scale) how likely they would be to use the presented policy if it was offered and they were at the beginning of the COVID-19 crisis. For each question, we create a *Treated* dummy variable that takes the value one if the respondent was shown the policy option where the policy is framed as being debt-based, or in the case of experiment 3, where the debt-like features are more salient.

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The framing of the questions is as follows:

- **Common introduction:**
  In this question, we will present one support option that has been a subject of public conversation. Considering your company's state at the beginning of Covid-19 crisis, would you have applied for support with the following terms?
- **Experiment 1:**
  Control: *The government will pay 75% of salaries if employees are not temporarly laid off or permanently dismissed.*
  Treatment: *The government offers a loan of which 75% will be forgiven if employees are not temporarly laid off or permanently dismissed.*
- **Experiment 2:**
  Control: *A VAT-refund, where VATs paid at the beginning of this year would be temporarily refunded to companies. The refund would have to be paid back in 2 years with a 3% annual interest.*
  Treatment: *A VAT-loan, where VATs paid at the beginning of this year would be temporarily lent back to companies. The loan would have to be paid back in 2 years with a 3% annual interest.*
- **Experiment 3:**
  Control: *A bank will lend with 6% interest. The loan is 80% guaranteed by Finnvera. The cost of Finnvera's guarantee is 1.75% of the loan amount. You will need the other 20% to be collateralized by something else. 80% of the loan amount is forgiven if your company will face a permanent insolvency due to Covid-19 crisis.*
  Treatment: *A bank will lend with 6% interest. The loan is 80% guaranteed by Finnvera. The cost of Finnvera's guarantee is 1.75% of the loan amount. You will need the other 20% to be collateralized by something else*

A graphical presentation of the results is shown in Figures 6 and 7. Table 4 shows the corresponding regression results. In these analyses, there are two aspects of interest. First, general debt aversion would suggest generally higher interest for the support alternatives that are framed as non-debt, or less debt-like. Second, we might expect the difference in interest to be larger for entrepreneurs that are more debt averse. These two aspects are illustrated by Figure 7. The level difference between the treated and control lines indicates general debt aversion, regardless of the self-reported debt aversion of the entrepreneur. A difference in slopes of the fitted lines implies different sensitivity to the debt framing depending on entrepreneur debt aversion.

The first experiment asks the respondents about their interest in either a loan, of which 75% is forgiven if the firm does not lay off workers, or a grant covering 75% of the firm's personnel expenses. In this case, the loan actually objectively dominates the grant option, as we do not specify that the loan amount is restricted to the amount of personnel expenses. So in principle, the forgiven loan amount could be larger than the direct grant. Figure 6 shows a clearly visible difference in the level of interest between these two options, notably in favor of the grant covering 75% of personnel expenses. Figure 7 shows the average level of interest conditional on the debt aversion of the entrepreneur. Across all levels of self-reported debt aversion, the grant is clearly more popular than the loan alternative. These findings are supported by the regression analysis in Table 4. There is significantly less interest for the debt alternative, but this difference is not statistically larger for high-debt-aversion entrepreneurs.

The second experiment is a much more subtle framing of a policy discussed in the Finnish media, whereby the government would lend back to firms the VAT that they have paid earlier in the year. We call this option either "VAT loan" or "VAT return", with identical financial terms in the description. As one might expect, the differences are much smaller than with the first experiment. In this case, as shown in Figure 7, there is no general difference in interest level, but a visible difference in the slope. In other words, more debt-averse entrepreneurs are sensitive to the debt framing, while low-debt-aversion entrepreneurs are not. The regression results in Table 4 provide some support for this interpretation. The likelihood of reporting zero interest for the debt option, relative to refund option, is significantly higher for high-debt-aversion entrepreneurs. For this high-debt-aversion group, simply changing the name of the support to "loan" is enough to increase the zero-interest responses by 14-16 % points. Directionally, the results are similar for the average interest level measured as a continuous variable, but the difference is not statistically significant.

The last experiment is about making the loan-like characteristics more salient. One policy is a normal government-guaranteed loan and the other is a government guaranteed loan where 80% is forgiven if the firm becomes insolvent as a result of COVID-19. The explicit mention of forgiving 80% of the loan in bankruptcy significantly increases interest relative to a regular loan and reduces zero-interest responses by 16 %-points. Among high-debt-aversion entrepreneurs, there is additional reduction in zero-interest responses of 10-11 %-points. Given equityholders generally receive nothing in a Finnish bankruptcy, it is not clear that this forgiveness of 80% of the loan has any real impact. If interpreted as an increase in the likelihood of the entrepreneur to receive some non-zero amount at the bankruptcy, it might be perceived as a reduction in the downside risk of the loan.

Based on Figure 7, the results appear somewhere between the first two experiments. There seems to be a general level difference favoring the alternative with explicit write-off in bankruptcy, as well as a slight difference in the slope of the line. The regression analysis in

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Table 4 shows a significant difference in the general level of interest, with the average level of interest being significantly higher with the explicit forgiveness alternative. This is also true in the case of zero interest responses. The interaction term between treated and high debt aversion is not significantly different from zero, but high-debt-aversion entrepreneurs are generally more likely to have zero interest in *either* version of the loan. This makes sense, as both options are explicitly framed as loan, so one might expect debt aversion to reduce interest in both.

5 Additional analysis

5.1 Other consequences of debt aversion

In addition to looking at whether *high debt aversion* affects the probability of taking a loan, we test its correlation with other measures taken during the crisis. If entrepreneur debt attitudes lead to lower take-up of loans, firms may take other costly measures to deal with the liquidity shock of COVID-19. The results are shown in Table 5. We find that debt averse entrepreneurs are more likely to apply for direct support, in column 3 (though this is not statistically significant) and are more likely to cancel investments (column 7). In other measures, such as raising new equity, laying off or furloughing workers or leaving wages unpaid, *high debt aversion* firms are not significantly different from other firms.

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Figure 6: Framing of support as debt vs. other – response distribution

Distribution of expressed level of interest in each alternative on a scale of 0 (no interest at all) to 10 (highest level of interest).

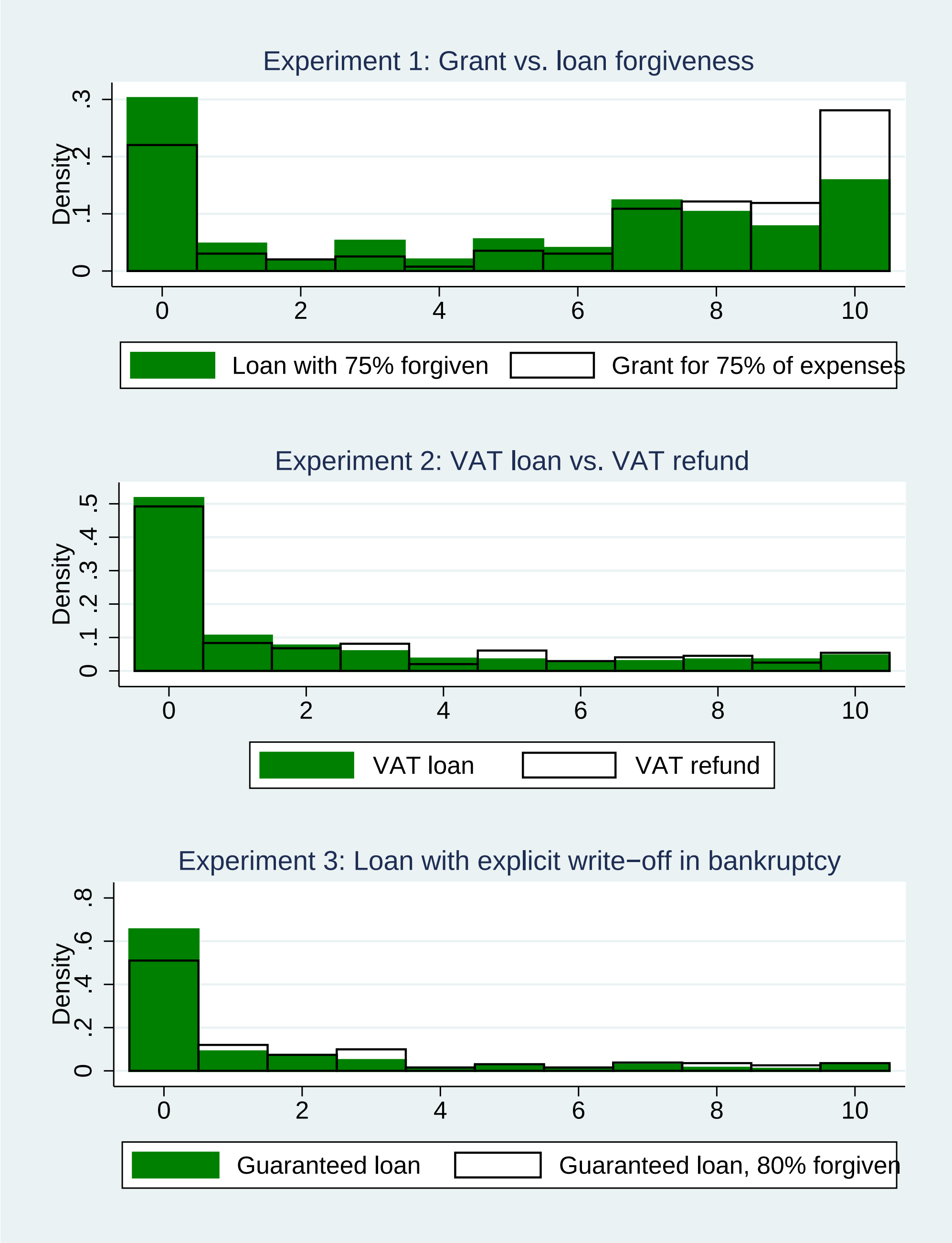

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Figure 7: Framing of support as debt vs. other – interest vs. debt aversion

Average level of interest in each alternative on a scale of 0 (no interest at all) to 10 (highest level of interest), plotted against the respondent debt aversion.

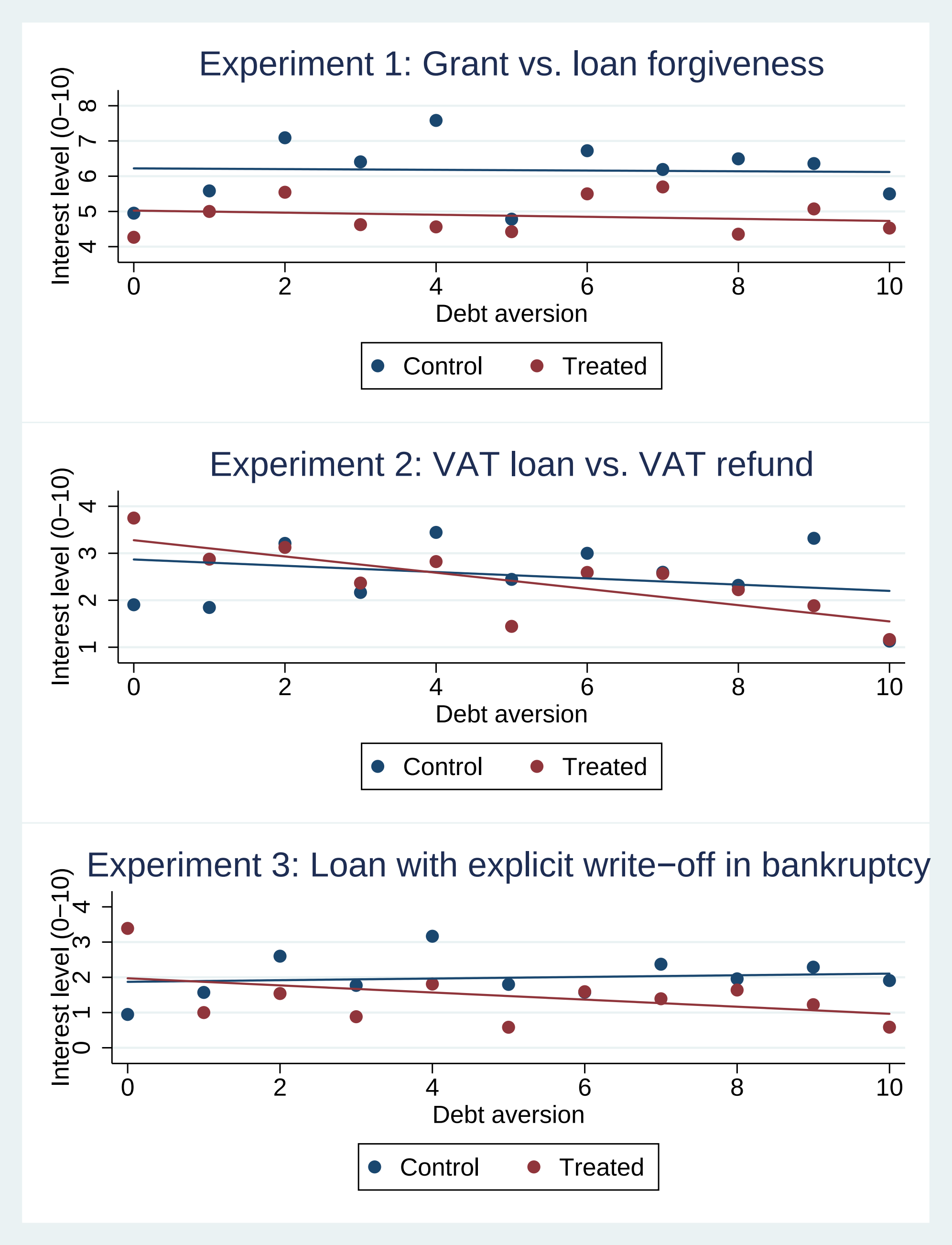

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Table 4
Experiments – framing as debt

The dependent variable is shown above each column. *Interest level* is the reported level of interest on a scale of zero (lowest interest) to ten (highest interest). *Zero interest* is a dummy taking the value one if the respondent has no interest at all in this form of supprt. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

Panel A: Grant vs. loan forgiveness of 75% employee costs

	Interest level (0-10)			Zero interest (dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	−1.3307***	−1.1049**	−0.8178**	0.0820*	0.0306	0.0004
	(0.3587)	(0.3943)	(0.3575)	(0.0445)	(0.0534)	(0.0456)
Treated x High debt a.		−0.4653	−0.6552		0.0999	0.1113
		(0.7044)	(0.6852)		(0.0855)	(0.0797)
High debt aversion		−0.0174	0.4850		0.0167	−0.0264
		(0.4003)	(0.3663)		(0.0485)	(0.0446)
Controls	No	No	Yes	No	No	Yes
Firm size FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Survival FE	No	No	Yes	No	No	Yes
Survival time FE	No	No	Yes	No	No	Yes
N	792	789	779	792	789	779
R^2	0.028	0.030	0.260	0.009	0.017	0.225

Panel B: VAT loan vs. VAT refund

	Interest level (0-10)			Zero interest (dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	−0.2665	−0.1507	−0.0509	0.0251	−0.0377	−0.0510
	(0.2239)	(0.3177)	(0.3462)	(0.0397)	(0.0541)	(0.0601)
Treated x High debt a.		−0.2867	−0.2809		0.1463**	0.1545***
		(0.4132)	(0.3956)		(0.0568)	(0.0540)
High debt aversion		−0.4752*	−0.4588*		0.0389	0.0392
		(0.2488)	(0.2651)		(0.0409)	(0.0410)
Controls	No	No	Yes	No	No	Yes
Firm size FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Survival FE	No	No	Yes	No	No	Yes
Survival time FE	No	No	Yes	No	No	Yes
N	851	847	835	851	847	835
R^2	0.002	0.012	0.117	0.001	0.018	0.144

Significance levels: * 0.1, ** 0.05, * 0.01.**

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Table 4
Experiments (cont'd)

Panel C: Loan with explicit write-off in bankruptcy

	Interest level (0-10)			Zero interest (dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	−0.6865***	−0.5599***	−0.5260**	0.1446***	0.1756***	0.1634***
	(0.1431)	(0.1967)	(0.2176)	(0.0248)	(0.0254)	(0.0333)
Treated x High debt a.		−0.2780	−0.2067		−0.0778	−0.0715
		(0.3229)	(0.3235)		(0.0491)	(0.0558)
High debt aversion		0.0052	−0.1274		0.1013*	0.1090*
		(0.3070)	(0.2938)		(0.0551)	(0.0527)
Controls	No	No	Yes	No	No	Yes
Firm size FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Survival FE	No	No	Yes	No	No	Yes
Survival time FE	No	No	Yes	No	No	Yes
N	815	810	797	815	810	797
R^2	0.016	0.017	0.128	0.022	0.027	0.117

Significance levels: * 0.1, ** 0.05, * 0.01.**

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Table 5
Outcomes vs. high debt aversion

The dependent variable is shown above each column. *Bank loan* indicates having applied for a new bank loan, similar to our main results in Table 3. *Any loan* indicates having applied for any new loan. *Direct support* indicates having applied for direct support. *Equity* indicates having sought new equity. *Layoffs* and *Furloughs* indicate having laid off or furloughed employees, respectively, during the crisis. *Canceled investments* indicates having canceled investments. *Entrepreneur compensation* indicates having reduced entrepreneur compensation. *Taxes* and *Wages* indicate having left taxes or wages unpaid, respectively. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	(1) Bank l.	(2) Any l.	(3) Dir. s.	(4) Eqt.	(5) Layoffs	(6) Furloughs	(7) Canc. inv.	(8) Ent. comp.	(9) Taxes	(10) Wages
High debt aversion	−0.0526***	−0.0582***	0.0453	−0.0136	−0.0251	0.0095	0.0665**	0.0031	−0.0099	0.0017
	(0.0177)	(0.0163)	(0.0305)	(0.0176)	(0.0157)	(0.0282)	(0.0277)	(0.0209)	(0.0211)	(0.0062)
Risk appetite	0.0114**	0.0190***	0.0023	0.0042	0.0004	−0.0032	0.0123*	0.0127*	0.0059	0.0029
	(0.0047)	(0.0055)	(0.0059)	(0.0060)	(0.0049)	(0.0073)	(0.0060)	(0.0068)	(0.0044)	(0.0018)
Optimism	−0.0083	−0.0059	0.0304***	0.0144**	0.0069	0.0081	0.0016	−0.0118*	0.0060	−0.0024
	(0.0067)	(0.0062)	(0.0102)	(0.0059)	(0.0040)	(0.0069)	(0.0073)	(0.0061)	(0.0066)	(0.0018)
Distrust people	0.0047	0.0069*	0.0052	0.0039	−0.0018	0.0051	0.0031	0.0018	−0.0019	0.0018
	(0.0032)	(0.0039)	(0.0060)	(0.0034)	(0.0032)	(0.0036)	(0.0044)	(0.0037)	(0.0051)	(0.0016)
Distrust banks	0.0046	0.0047	−0.0027	0.0033	0.0028	0.0002	0.0103**	0.0037	0.0041	0.0012
	(0.0044)	(0.0049)	(0.0053)	(0.0027)	(0.0027)	(0.0032)	(0.0045)	(0.0047)	(0.0036)	(0.0007)
Firm size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	883	883	883	883	883	883	883	883	883	883
R^2	0.173	0.181	0.257	0.080	0.133	0.351	0.190	0.179	0.174	0.052

Significance levels: * 0.1, ** 0.05, * 0.01.**

5.2 Subsample analysis

We then focus on subsamples in Table 6. We look at firms where entrepreneurs had not pledged personal assets as collateral in the past, limited liability firms (for these firms, new debt is less likely to increase the risks faced by the entrepreneur), firms that applied for any form of financing (i.e. firms that need financing), excluding firms that said they did not apply for debt because they did not need it (an alternative way to define a group of firms that need finance) and firms with/without prior debt.

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Table 6
Applied for new bank loan vs. debt aversion – subsamples

The dependent variable is *Applied new bank loan*, a dummy taking the value one if the firm reported having applied for a new bank loan during the COVID-19 crisis. Each column represents a separate subsample. *No pledges* includes only the firms where the management has not provided any personal guarantees for firm liabilities. *Limited* includes only limited companies. *App. fin.* includes only the firms that applied for some type of financing during the pandemic. *Ex. no need* excludes the firms that report not needing new financing. *No debt* and *Has debt* include only firms that do not have existing debt and have existing debt, respectively. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	(1) No pledges	(2) Limited	(3) App. fin.	(4) Ex. no need	(5) No debt	(6) Has debt
High debt aversion	−0.0712***	−0.0555*	−0.0786**	−0.0710**	−0.0324	−0.0290
	(0.0198)	(0.0307)	(0.0279)	(0.0254)	(0.0199)	(0.0375)
Risk appetite	0.0060	0.0118	0.0191**	0.0283***	0.0045	0.0109
	(0.0058)	(0.0073)	(0.0088)	(0.0072)	(0.0031)	(0.0102)
Optimism	0.0031	−0.0095	−0.0267**	−0.0179	−0.0069	−0.0118
	(0.0055)	(0.0098)	(0.0114)	(0.0110)	(0.0050)	(0.0141)
Distrust people	0.0063*	0.0097**	0.0080	0.0023	−0.0036	0.0084
	(0.0034)	(0.0043)	(0.0057)	(0.0048)	(0.0036)	(0.0056)
Distrust banks	−0.0001	0.0001	0.0041	0.0049	0.0075**	0.0014
	(0.0050)	(0.0052)	(0.0072)	(0.0058)	(0.0034)	(0.0072)
Firm size FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Survival FE	Yes	Yes	Yes	Yes	Yes	Yes
Survival time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	557	600	547	531	452	429
R^2	0.194	0.171	0.185	0.192	0.174	0.170

Significance levels: * 0.1, ** 0.05, * 0.01.**

The effect is negative, economically significant and usually statistically significant in most of these subsamples, with the magnitude being about double the baseline effect in the no collateral pledged subsample and the two subsamples of firms that plausibly need financing. The effect is significantly smaller among firms with no past debt and not statistically significant.

5.3 Determinants of debt aversion

In this section, we provide a brief descriptive analysis of the determinants of debt aversion. First, we focus on attitudes about debt that the respondents were taught as children. We perform a regression analysis with debt aversion as the dependent variable, using indicators for various statements about debt attitudes that the respondent was passed on as a child. The results are shown in Panel A of Figure 8. Those that were taught that debt is "something to be used in moderation" or "should be avoided" are more likely to view taking on debt as unpleasant whereas those who were taught that debt is "useful for splitting large purchases" or "useful for transfering money over time" are less likely to view taking on debt as unpleasant.

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Figure 8: Perceptions about debt

Which of the following statements describe what you were taught about debt when you were a child? Respondents could choose multiple options.

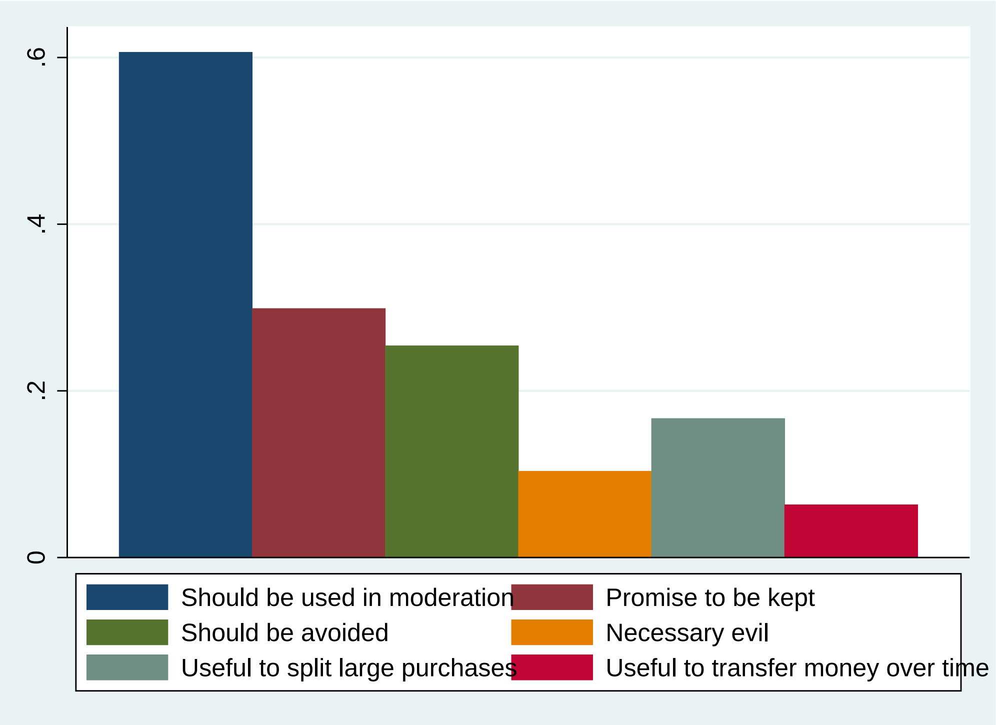

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Table 7
Determinants of debt aversion

The dependent variable is *Debt aversion*, ranging from 0 (lowest) to 10 (highest). In Panel A, the independent variables are dummies indicating chosen answers to the question "Which of the following statements best describe what you were taught about debt when you were a child?" Heteroscedasticity-consistent robust standard errors are shown in parentheses.

Panel A: Debt aversion and childhood debt attitudes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Should be used in moderation	0.3753*						0.6408***
	(0.2048)						(0.1991)
Promise to be kept		−0.2777					−0.1003
		(0.2137)					(0.2053)
Should be avoided			1.8199***				1.7897***
			(0.2002)				(0.2094)
Necessary evil				0.5085*			0.5625*
				(0.3003)			(0.2944)
Useful to split large purchases					−1.7754***		−1.2666***
					(0.2560)		(0.2582)
Useful to transfer money over time						−1.5782***	−0.8896**
						(0.4136)	(0.4076)
N	899	899	899	899	899	899	899
R^2	0.004	0.002	0.075	0.003	0.053	0.017	0.132

Significance levels: * 0.1, ** 0.05, * 0.01.**

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Table 7
Determinants of debt aversion (cont'd)

Panel B: Debt aversion and entrepreneur characteristics

	(1)	(2)	(3)	(4)	(5)
ln(Age)	−0.8248*				−0.7876*
	(0.4829)				(0.4742)
Female		0.8345***			0.6359***
		(0.1914)			(0.2005)
Risk appetite			−0.3601***		−0.3468***
			(0.0453)		(0.0467)
Optimism			0.0693		0.0571
			(0.0541)		(0.0559)
Distrust people			0.0547		0.0435
			(0.0421)		(0.0427)
Distrust banks			0.1119***		0.1249***
			(0.0404)		(0.0410)
Vocational				0.1770	0.0321
				(0.3190)	(0.3187)
Polytechnic				0.5273*	0.4568
				(0.3078)	(0.3094)
University				−0.2487	−0.1986
				(0.3105)	(0.3086)
N	880	899	884	899	865
R^2	0.003	0.019	0.083	0.011	0.110

Significance levels: * 0.1, ** 0.05, * 0.01.**

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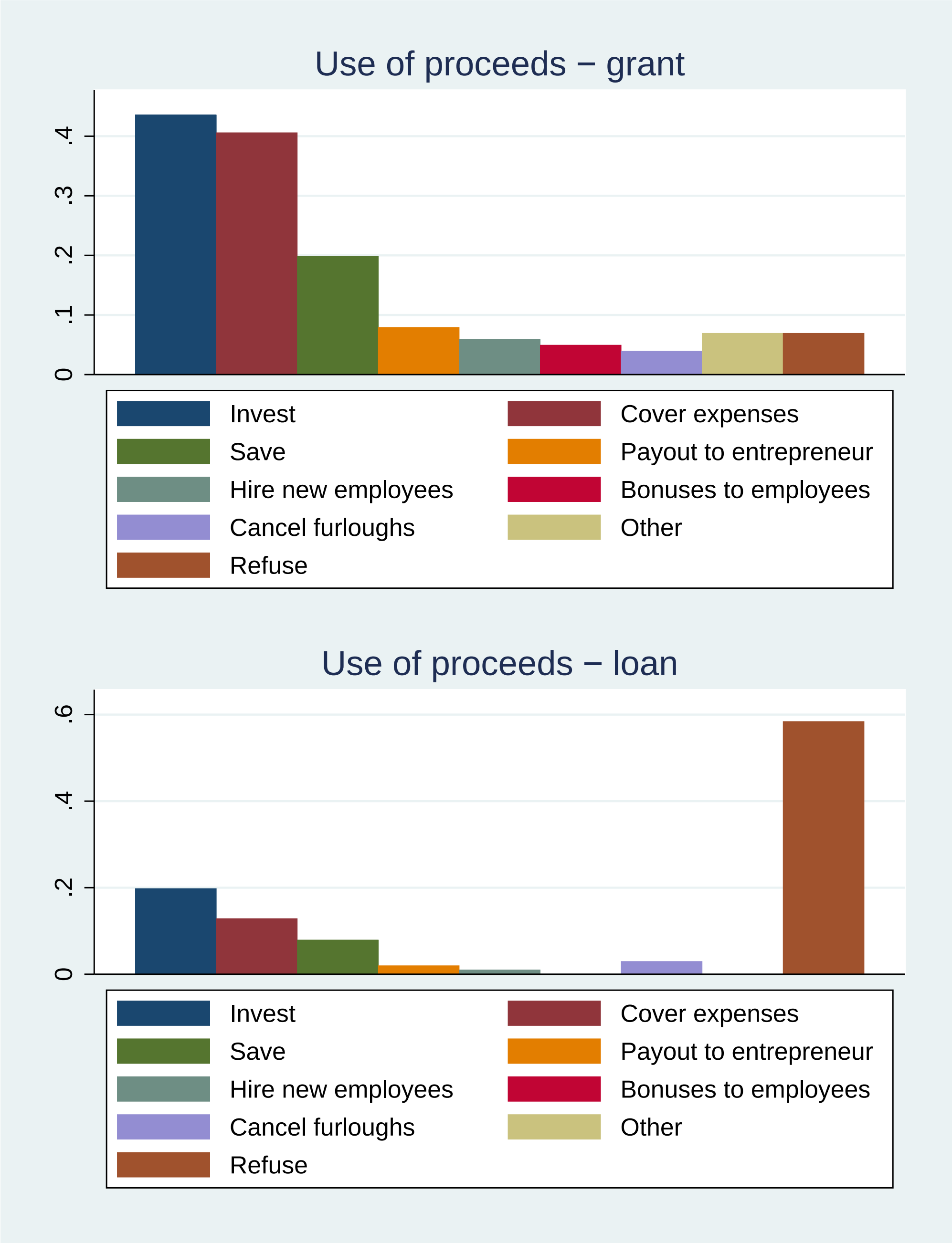
We then study the level of debt aversion across different demographic groups. The results are shown in Panel B of Figure 8. We find that higher entrepreneur age is associated with lower levels of debt aversion, while female entrepreneurs exhibit higher levels of debt aversion. There is also a significant negative correlation between risk appetite and debt aversion, while entrepreneurs who distrust banks are also more debt averse. The differences across different levels of education are not large, but those who studied at a polytechnic appear slightly more debt averse than others.

5.4 Use of proceeds from a grant vs. loan

In an additional analysis conducted as part of a follow-up survey (answered by roughly 10% of our original sample), we ask firms about how they would respond to hypothetical offers of either a direct grant or a loan worth one month of revenue. The responses are presented in Figure 9. Almost all firms would spend the grant on their business, with almost half of firms replying that they would invest the grant. Other common responses include covering expenses during the crisis, hiring new employees, and paying employees a bonus. This suggests that most firms see profitable investment opportunities. However, the share of firms investing if offered a loan is less than half of the share investing a grant, while most firms would actually choose to decline the loan if offered.

Figure 9: Use of proceeds from a grant vs. loan

The share of respondents selecting each option for the use of proceeds from a hypothetical grant or a loan amounting to one month's revenue. Respondents could choose multiple options.



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6 Conclusion

Our results support the idea that entrepreneur attitudes towards debt affect the use of debt within the firms they manage. This has implications for government policy, which has aimed to "freeze the economy" during the COVID-19 pandemic by providing liquidity to firms facing revenue shortfalls. While the use of debt-based packages has many advantages (it is less costly for governments, they help screen out bad firms etc.), we document that widely-held entrepreneurial attitudes may hinder the effectiveness of these policies.

The statistical significance of our results varies, but the economic magnitudes are consistent within analyses and our various analyses all support the same conclusion. Cross-sectional analysis, "natural experiment"-style analysis around the COVID-19 pandemic and experimental results all suggest that debt averse entrepreneurs are less likely to use debt within their firm. We show that firms run by debt-averse entrepreneurs have less debt in general, are less likely to use debt-based COVID-19 rescue packages, and in an experimental setting prefer policies framed as grants.

Our findings have important policy implications. SME support programmes may struggle to have an impact if they are structured as debt instead of other forms of support. Our experimental analyses suggest that simply framing support policies in non-debt terms may to some extent help increase their effectiveness.

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A Internet appendix

A.1 Results including non-entreneurs

In this section, we replicate our main analysis, but include all respondents, including hired managers (CEOs, CFOs, and other) that are now owners of the firm.

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Table A.1
Current and historical debt use vs. debt aversion – incl. non-entrepreneurs

The dependent variable is shown above each column. *Has debt* is a dummy taking the value one if the firm reported having existing debt. *Had debt 5y* is a dummy taking the value one if the firm reported having had debt at some point during the last five years. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	Has debt				Had debt 5y			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High debt aversion	−0.1272***	−0.0887**			−0.1271***	−0.0887***		
	(0.0342)	(0.0336)			(0.0323)	(0.0266)		
Debt aversion			−0.0262***	−0.0213***			−0.0260***	−0.0216***
			(0.0052)	(0.0051)			(0.0057)	(0.0044)
Risk appetite		0.0156**		0.0128*		0.0117		0.0087
		(0.0063)		(0.0063)		(0.0087)		(0.0088)
Optimism		0.0063		0.0061		0.0001		−0.0000
		(0.0138)		(0.0133)		(0.0105)		(0.0102)
Distrust people		0.0139*		0.0141*		0.0082		0.0084
		(0.0070)		(0.0070)		(0.0080)		(0.0080)
Distrust banks		−0.0084		−0.0077		−0.0071		−0.0064
		(0.0057)		(0.0053)		(0.0051)		(0.0049)
Firm size FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Survival FE	No	Yes	No	Yes	No	Yes	No	Yes
Survival time FE	No	Yes	No	Yes	No	Yes	No	Yes
N	989	974	989	974	989	974	989	974
R^2	0.016	0.178	0.023	0.184	0.017	0.206	0.023	0.213

Significance levels: * 0.1, ** 0.05, * 0.01.**

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Table A.2
New bank loans during COVID-19 pandemic – incl. non-entrepreneurs

The dependent variable is *Applied new bank loan*, a dummy taking the value one if the firm reported having applied for a new bank loan during the COVID-19 crisis. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
High debt aversion	−0.0511**	−0.0401**	−0.0380**			
	(0.0197)	(0.0167)	(0.0182)			
Debt aversion				−0.0044	−0.0036	−0.0034
				(0.0033)	(0.0024)	(0.0027)
Risk appetite		0.0117**	0.0122**		0.0123***	0.0128***
		(0.0044)	(0.0046)		(0.0041)	(0.0044)
Optimism		−0.0057	−0.0062		−0.0065	−0.0069
		(0.0068)	(0.0068)		(0.0068)	(0.0068)
Distrust people		0.0031	0.0030		0.0026	0.0027
		(0.0043)	(0.0045)		(0.0042)	(0.0044)
Distrust banks		0.0024	0.0025		0.0023	0.0023
		(0.0034)	(0.0035)		(0.0034)	(0.0035)
Firm size FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Survival FE	No	Yes	Yes	No	Yes	Yes
Survival time FE	No	Yes	Yes	No	Yes	Yes
Sales impact FE	No	No	Yes	No	No	Yes
Time to normal FE	No	No	Yes	No	No	Yes
N	989	974	974	989	974	974
R^2	0.005	0.162	0.166	0.001	0.160	0.165

Significance levels: * 0.1, ** 0.05, * 0.01.**

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Covid-19 supply chain disruptions[1]

Matthias Meier[2] and Eugenio Pinto[3]

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We study the effects of international supply chain disruptions on real economic activity and prices during the Covid-19 pandemic. We show that US sectors with a large exposure to intermediate goods imports from China contracted significantly and robustly more than other sectors. In particular, highly exposed sectors suffered larger declines in production, employment, imports, and exports. Moreover, input and output prices moved up relative to other sectors, suggesting that real activity declines in sectors with a high China exposure were not particularly driven by a slump in demand. Quantitatively, differences in China exposures accounts for about 9% of the cross-sectoral variance of industrial production growth during March and April 2020. The estimated effects are short-lived effects and dissipate by July.

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3 Federal Reserve Board.

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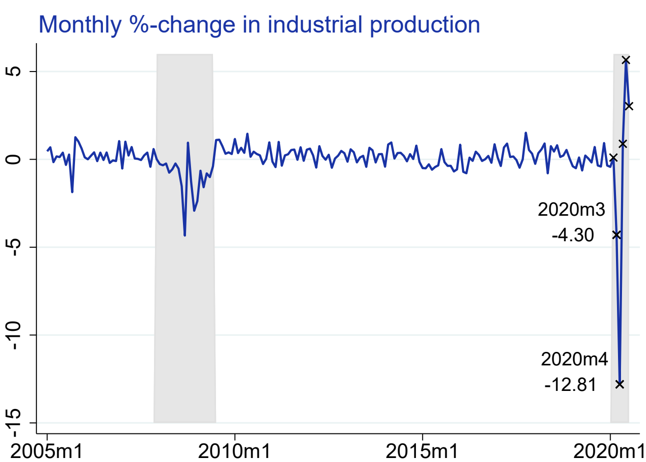
1 Introduction

The Covid-19 pandemic caused sharp contractions in real economic activity for most sectors and economies. The rapid decline in US industrial production during March and April 2020 dwarfs even the Great Recession (Figure 1). The economic effects of Covid-19 can be attributed to a number of different channels. These include the direct health effects, the effects of high uncertainty, the effects of mandated lockdowns, financial effects, and the effects of disruptions in trade. Understanding the role of these different channels is important for an effective policy response. For example, lockdowns can severely disrupt supply chains, which can transmit the initial shock across sectors and countries. If production is suppressed because of disrupted supply chains, a fiscal intervention that aims to stimulate demand may be ineffective. Conversely, providing liquidity or flexible furlough arrangements may be a more effective policy response to facilitate a quick recovery when the supply chain disruption dissipate.[1]

Figure 1: Industrial production in the US



Notes: The time series is the monthly percentage change in industrial production (seasonally adjusted), based on the Federal Reserve G.17 release. Recent months starting from February 2020 are highlighted by an x. The growth rates for March and April are printed into the plot. Gray-shaded areas indicate NBER recession periods.

[1]An early discussion of the implications for policy of the Covid-19 crisis is provided by Baldwin and di Mauro (2020). By now an externsive literature studies the policy implications of Covid-19. On optimal lockdown policy, see, e.g., Alvarez et al. (2020), Eichenbaum et al. (2020), Krueger et al. (2020), and Glover et al. (2020), on the effects of fiscal policy, see, e.g., Bigio et al. (2020), Mitman and Rabinovich (2020), Auerbach et al. (2020), and Bayer et al. (2020), and on monetary policy, see, e.g., Caballero and Simsek (2020), Woodford (2020), and Fornaro and Wolf (2020).

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Despite the quickly growing empirical literature on the economic transmission of the Covid-19 crisis, our paper is the first to provide empirical evidence on the effects of international supply chain disruptions caused by Covid-19.[2] Our empirical results suggest significant albeit relatively short-lived effects of Covid-19 supply chain disruptions. The evidence is not only important for the design of effective macroeconomic stabilization policy, it also relates to questions on the nature of the business cycle. For example, the Great Moderation is often associated to lower volatility in inventory investment, see McConnell and Perez-Quiros (2000), which can be linked to innovations in inventory management (just-in-time), see Kahn et al. (2002). While lean supply chains save inventory holding costs and raise productivity in normal times, recessions that are associated with supply chain disruptions can have much more severe effects. Indeed, during the Covid-19 crisis, supply chain disruptions and how to design more resilient supply chains have received a lot attention from the management literature, business consultancies, and the media.[3]

In this paper, we provide empirical evidence on the effects of international supply chain disruptions on real economic activity and prices during the Covid-19 crisis on a monthly basis. Our empirical strategy exploits variation in the share of imported intermediate goods across sectors before Covid-19.[4] The simple idea is that sectors that are more dependent on imported inputs should also be more affected by international supply chain disruptions. We are particularly interested in the economic transmission of the Covid-19 crisis in China, accompanied by rapid and widespread lockdowns, on the US economy. We show that sectors in the US with high exposure to Chinese imports contracted significantly and robustly more than other sectors. In particular during March and April 2020, highly exposed sectors suffered larger declines in production, employment, imports, and exports. Moreover, input and output prices moved up relative to other sectors, suggesting that real activity declines in sectors with a high China exposure were not particularly driven by a slump in demand. Quantitatively, cross-sectoral differences in China exposures account for about 9% of cross-sectoral differences in industrial production changes during March and April 2020 and about 7% for March alone. These differential effects appear to be short-lived and become insignificant by July 2020.

[2]For example, Chetty et al. (2020) documents that lower spending of high-income individuals transmitted to job losses for low-income individuals. Bachas et al. (2020) use bank account data to document a large increase in liquid asset savings across the income distribution. Balleer et al. (2020) use firm-level price data to disentangle demand and supply effects, whereas Brinca et al. (2020) disentangle labor supply and demand effects of the Covid-19 crisis.

[3]See, for example, Choi et al. (2020), Schmalz (2020), and Donnan et al. (2020).

[4]Using sectoral data in our analysis has some important advantages compared to using firm-level data. We can use monthly data. The data is publicly available and the data is quickly available. For example, monthly sectoral industrial production is released two weeks after the end of the month.

While our analysis focuses on Covid-19 disruptions of US-China trade, we also consider a broader exposure to intermediate good imports, which includes all imports except from China. This substantially changes the effects on input and output prices. Sectors with a high broad exposure to imported inputs also suffer larger output declines, but their input and output prices fall relative to other sectors. This suggests that the broad import exposure is contaminated by differential demand effects across sectors.

To construct sector-specific exposure measures, we combine detailed 6-digit NAICS import data for 2019 from the US Census with benchmark 6-digit input-output (IO) tables for 2012 from the US Bureau of Economic Analysis (BEA). We aggregate this data to compute exposure measures for 88 manufacturing and related industries, which we can match to the level of sector detail available in the monthly industrial output and other data (approximately 4-digit NAICS level). For the China exposure, we construct the sector-specific value of intermediate goods imports from China and divide by the value of all intermediate goods used by that sector. The broad import exposure measure replaces the numerator by intermediate goods imports excluding Chinese imports. Our empirical approach is to study whether, and to what extent, sector-specific ex-ante exposures can account for ex-post outcomes during the Covid-19 crisis. This approach can be justified by a simple model that helps frame our empirical analysis. In the model, the share of establishments that use inputs imported from a specific country differs exogenously across sectors. We show that this model explains a monotonic relation between higher ex-ante exposures and larger ex-post output responses.

When the US-China trade deal was signed on January 15, 2020, it was seen as positive news for US sectors highly dependent on imports from China. Not long after, China responded to the emerging Covid-19 pandemic by imposing widespread lockdowns of entire regions and sectors during February and part of March 2020. In China, the lockdowns caused sharp contractions in production and exports, which eventually spilled over to the US. While February industrial production in the US shows no sign of contraction, for both March and April 2020 we find lower industrial production growth in sectors with higher China import exposures. The differences are statistically and economically significant. In March, we estimate that industrial production growth is 3.82 percentage points (p.p.) lower for every p.p. increase in the sectoral share of Chinese intermediate goods imports. The effects in April are even larger. Industrial production falls by 14.23 p.p. more than average in sectors with a 1 p.p. above-average China exposure. The fraction of the variance of industrial production growth that can be explained by different China exposures is about 9%.

A critical question is whether our exposure measure captures the strength of China supply-chain shocks across US sectors. Instead, our exposure measure might be high for industries that were also more affected through other channels during the Covid-19 recession,

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such as a slump in domestic demand, external demand (namely from China), or tighter financing conditions. We address this concern in two ways. First, we control for sector-specific cyclicality, for exports to China, and for external finance dependence, all before Covid-19. Including these controls, we still find a significant relation between a higher China exposure and a larger contraction in industrial production. Second, we estimate how higher China exposure relates to sectoral prices. We find that both input import prices and output prices increase by more for sectors with higher China exposure. This result makes it unlikely that changes in real activity in industries with high China exposure were mostly affected by lower domestic or external demand. Not only industries with a high China exposure had larger output declines, but also industries with larger share of broadly-defined imported intermediates. However, while the former exposure seems to mostly reflect supply chain disruptions, the broad exposure seems to mostly reflect weaker demand.

Our paper contributes to the rapidly growing literature on the economic effects of the Covid-19 crisis by providing empirical evidence on the effects of international supply chain disruptions caused by Covid-19. Closely related are a number of papers using quantitative theory to study the propagation of Covid-19 related shocks through input and output linkages. For example, Barrot et al. (2020) study the effects of social distancing on GDP, Baqaee and Farhi (2020) study the role of demand and supply shocks during the Covid-19 crisis, and Bonadio et al. (2020) study the international propagation of labor supply shocks. Most closely related is Gerschel et al. (2020), who simulate the effect of a productivity decrease in China on GDP outside China. GDP in the US responds similarly to France and Germany, whereas GDP in Japan and Korea responds much more, reflecting the higher exposure of these economies to inputs imported from China.

Our paper is further related to earlier work on supply chain disruptions including Barrot and Sauvagnat (2016) and Meier (2020) on natural disasters in the US and Carvalho et al. (2020) and Boehm et al. (2019) on the Fukushima disaster. The empirical strategy our paper uses is similar to Boehm et al. (2019), as well as Huang et al. (2018) and Amiti et al. (2020) who study the US-China Trade War. Our empirical finding that supply chain disruption are a significant aspect of the Covid-19 crisis aligns well with the findings in Hassan et al. (2020). Analyzing earnings calls by public listed firms in the first quarter of 2020, the authors document that firms' primary concerns relate to the collapse of demand, increased uncertainty, and disruption in supply chains. Interestingly, firms with prior pandemic experience (SARS or H1N1) are more resilient to the Covid-19 crisis.

The remainder of this paper is organized as follows. Section 2 presents a simple model to provide intuition and to guide the empirical analysis. Section 3 describes the data and Section 4 presents our empirical findings. Section 5 concludes and an Appendix follows.

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2 A simple model of supply chain disruptions

Consider a sector in country A that is populated by two types of establishments. Type 1 establishments produce goods y_t^1 using imported intermediate goods from country B, denoted m_t^1, and a range of other inputs, such as capital, labor, and other imported or domestic intermediate inputs, captured by a composite factor x_t^1. The production technology is of the CES type

$$y_t^1 = \left[\alpha (x_t^1)^\rho + (1-\alpha)(m_t^1)^\rho\right]^{\frac{1}{\rho}} = f(z_t^1) m_t^1, \quad z_t^1 = \frac{x_t^1}{m_t^1}, \quad \rho \in (-\infty, 1),$$

where $\sigma = 1/(1-\rho)$ is the substitution elasticity between x_t^1 and m_t^1 and z_t^1 is the ratio of the composite factor to country B intermediate inputs (factor input ratio). Type 2 establishments produce goods y_t^2 using a linear technology in x_t^2. Hence, they use the same inputs as type 1 establishments except imported intermediate goods from country B. Sectoral output is

$$y_t = \phi y_t^1 + (1-\phi) y_t^2, \tag{2.1}$$

where ϕ is the (sector-specific) share of type 1 establishments. Before the economy is hit by a supply-chain disruption shock, it is in steady state and type 1 establishments choose x^1 and m^1 to maximize period profits

$$\pi^1 = p(y^1) y^1 - p^x x^1 - p^m m^1, \tag{2.2}$$

where $p(y) = y^{\gamma-1}$ with $\gamma \in (0,1)$ is a downward-sloping isoelastic inverse demand function. Similarly, type 2 establishments choose x^2 to maximize $\pi^2 = p(y^2) y^2 - p^x x^2$. Since only type 1 establishments use m_t, we will henceforth omit the type index of m_t^1 and z_t^1.

In period t, the economy is hit by a supply chain disruption that lowers the supply of country B inputs by a fraction δ for all sectors in the economy: $m_t = (1-\delta)m$.[5] We consider the response of type 1 establishments before prices adjust. The supply of m_t becomes a binding constraint, which means type 1 establishment only re-optimize x_t^1 after the disruption. The first-order condition for x_t^1 after the supply chain disruption, implies that the factor input ratio z_t is adjusted according to (see Appendix A for details)

$$\frac{d \log z_t}{d \log m_t} = -\frac{1-\gamma}{(1-\rho)-(\gamma-\rho)\epsilon} \geq 0, \quad \text{where} \quad \epsilon = \frac{z f'(z)}{f(z)} \geq 0. \tag{2.3}$$

[5]A supply chain disruption that is common across sectors should capture the disruptions caused by the widespread lockdowns in China during February and March 2020.

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The increase in z_t in response to a decrease in m_t gets smaller the lower the elasticity of substitution between the two inputs to production. In the Leontieff case ($\rho \to -\infty$), if m_t falls by $\delta\%$, it is optimal to lower x_t^1 by $\delta\%$ as well, and hence z_t remains unchanged. The effect on output y_t^1 depends on the direct effect of lower m_t and a (partially) offsetting indirect effect of z_t,

$$d\log y_t^1 = \underbrace{d\log m_t}_{\text{direct effect}<0} + \underbrace{\frac{-(1-\gamma)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} d\log m_t}_{\text{indirect effect}\geq 0}. \tag{2.4}$$

The response of sectoral output to the supply chain disruption is

$$d\log y_t = \frac{\phi y^1}{\phi y^1 + (1-\phi)y^2} \frac{(1-\rho)-(1-\rho)\epsilon}{(1-\rho)-(\gamma-\rho)\epsilon} d\log m_t. \tag{2.5}$$

If $\gamma \to 1$ or $\rho \to -\infty$, the response of sectoral output only depends on the output share of type 1 establishments.

Our empirical strategy is to identify cross-sector differences in effects of supply chain disruptions through cross-sector differences in the share of intermediate goods imported from country B. In the model, import exposure to country B is

$$e^B = \frac{p^m m}{p^x(x^1+x^2)+p^m m}, \tag{2.6}$$

and e^B monotonically increases in ϕ. Simultaneously, the sector-specific output response to a supply-chain disruption monotonically increases in ϕ, the share of establishments that produce using imports from country B. Hence, sectors with a higher import exposure also respond more to a common supply chain disruption. This provides justification to our empirical strategy.

Finally, we discuss the robustness of these results. First, if we fix ϕ but let α vary across sectors, we obtain similar results as long as inputs in type 1 production are somewhat substitutable ($\rho > -\infty$). The sector with a lower α has a higher expenditure share e^B for m. At the same time, a lower α implies a lower elasticity ϵ, which results in a larger output response to the supply chain disruption. Second, our analysis has conveniently maintained fixed input prices. If prices for the same inputs are common across sectors, the specific response of prices to the shock does not qualitatively change our result that in sectors with higher exposure to imported intermediate goods output should fall by relatively more.

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3 Data

3.1 Outputs, inputs, and prices

We consider a host of sector-level outcomes including measures of output, inputs, and prices. Industrial production (IP) is our primary outcome. IP is a monthly index computed for 4-digit NAICS manufacturing sectors by the Federal Reserve Board, and is constructed from an extensive range of data. For about 50% of industries, the index is based on observed physical quantities. For example, for NAICS sector 3361 (Motor vehicle) IP is based on the number of types of automobiles produced together with their list prices obtained from Ward's Communications, a publisher focused on the automotive industry, and car producers Chrysler and General Motors.[6] For the remaining 50% of industries, the Federal Reserve Board combines production-worker hours from the Bureau of Labor Statistics (BLS) and Fed data on electric power use with product prices from the BLS and spot markets to construct an industry-specific index of IP. The indices are regularly benchmarked against the Census and the Survey of Manufactures.

Panel (a) of Figure 2 shows the evolution of the median monthly IP growth together with the 25th and 75th percentiles of IP growth. The median evolves similarly to aggregate IP growth in Figure 1 during the Covid-19 recession. What stands out is the large heterogeneity across sectors. While even industries at the 25th percentile of the IP growth distribution shrank by more than 5% in April 2020, industries at the 75th percentile shrunk by more than 20%. IP and other growth rates in this paper are symmetric growth rates of the form

$$\frac{x_t - x_{t-h}}{\frac{1}{2}\left(x_t + x_{t-h}\right)},$$

where t is a monthly time index and x_t an outcome (e.g., IP). We have monthly growth rates for $h = 1$ and yearly growth rates for $h = 12$. At least since Davis and Haltiwanger (1990) these growth rates have been widely used to study establishment-level employment growth. Symmetric growth rates lie in the closed interval $[-2, 2]$ and avoid extreme statistical outliers when some outcome drops close to zero. This concern is specifically prevalent during the sharp contractions of the Covid-19 recession.[7] However, our results are robust to using standard growth rates.

We further use sector-specific employment, imports, exports, import prices and output prices. We obtain employment from the Current Employment Statistics maintained by the

[6] More details on the data sources for the construction of the industrial production index can be found here: https://www.federalreserve.gov/releases/g17/SandDesc/sdtab1.pdf

[7] For example, the (ordinary) growth rate of IP in sector 3361 (Motor Vehicle Manufacturing) is below -97% in April 2020 compared to March, and then above +1,000% between April and May.

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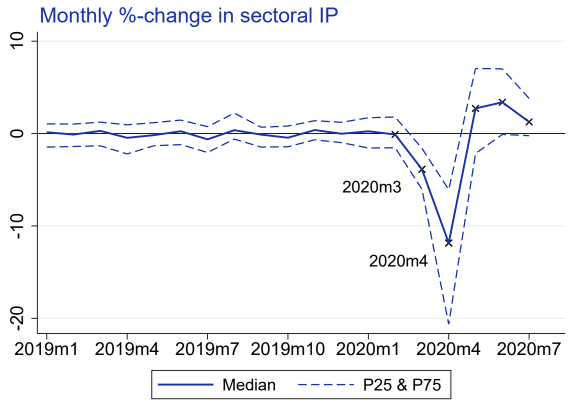
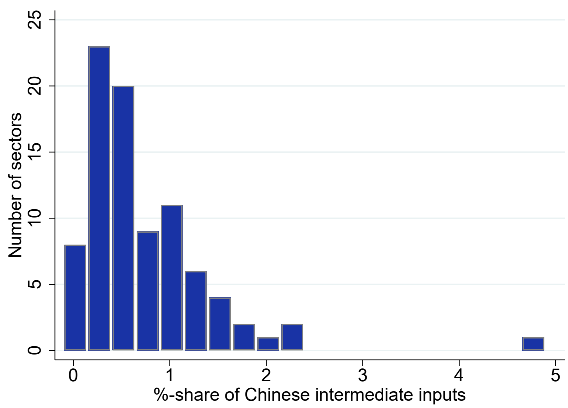
Figure 2: Heterogeneity across sectors

(a) Distribution of industrial production growth across sectors



(b) Distribution of Chinese exposure across sectors



BLS. Sector-specific imports and exports are from the International Trade Data maintained by the Census. Import prices are based on the International Price Index files from the BLS. Output prices are based on the sector-specific producer price index maintained by the BLS. In addition, we construct a number of control variables. We consider a measure of sectoral external finance dependence following the approach in Rajan and Zingales (1998), but using data between 2010 and 2019. We use sector-specific exports to China based on the

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International Trade Data. Finally, we consider sectoral cyclicality, which we compute as the correlation between sectoral annual IP growth and annual (aggregate) GDP growth, based on data before the Covid-19 crisis.

3.2 China exposure

We compute the sector-specific China exposure as the value of imported intermediate goods from China relative to the value of all intermediate goods used in production. However, sector-specific intermediate good imports from China are not directly measured by trade statistics. Instead, we observe imports from China in 2019 at the level of 6-digit NAICS commodities from the International Trade Data. In addition, we have the value of 6-digit NAICS commodity imports (from all countries) used by 6-digit NAICS sectors from the import matrix of the 2012 Input-Output tables. To construct sector-specific intermediate good imports from China, we adopt a proportionality assumption, as described in Johnson and Noguera (2012), and as as similarly applied to construct the World Input Output Database, see Timmer et al. (2015). In practice, we proceed in three steps to compute sector-specific intermediate good imports from China. First, we compute the share of 6-digit NAICS commodities that is imported from China relative to all imports of the same commodity. Second, we multiply the value of a 6-digit sector's 6-digit commodity imports (from all countries) with the China import share of the 6-digit commodity. This yields an estimate of the value of imports from China of 6-digit commodities in 6-digit sectors, which is exact under the proportionality assumption. Third, we aggregate to the 4-digit NAICS level. We obtain the value of all intermediate goods used in production from the input-output table. Our (baseline) China exposure is the ratio of intermediate goods imported from China divided by all intermediate goods.

Matching sector-specific China exposures to outcomes, we obtain a sample of 88 distinct manufacturing and related industries. In the Appendix, Table 7 lists all industries. Panel (b) of Figure 2 shows the variation in China exposures across these industries. We observe large differences in the share of intermediates imported from China ranging from less than 0.25% to more than 2%. Throughout the empirical analysis, we discard sector 3342 (Communications Equipment Manufacturing), which is the single outlier in the distribution of China exposures with a value close to 5%, see panel (b). While these fractions are relatively small, in theory a disruption in the supply of Chinese inputs can lead to as much as a complete halt of production in the US. The magnitude of the effect critically depends on how easily inputs can be substituted (as implied by the simple model in the preceding section).

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4 Empirical evidence

In this section, we provide empirical evidence suggesting that supply chain disruptions are a significant economic driver of the Covid-19 crisis.

4.1 Empirical strategy

Our empirical strategy exploits differences in the sector-specific exposure to intermediated goods imported from some country or region, say B. Let i index a sector and t a monthly time period. Our main regression model is

$$y_{it} = \alpha_t + \beta_t e_i^B + \Gamma_t Z_{it} + u_{it}, \quad u_{it} \sim (0, \sigma_t^2) \tag{4.1}$$

where y_{it} is a sector-time specific outcome (e.g., IP growth of steel manufacturing in March 2020), and Z_{it} is a vector of sector-time specific controls. Using the notation of Section 2, we denote by e_i^{B} the import exposure to country/region B, which we compute based on pre-Covid-19 data.

Most of our empirical analysis focuses on China exposures ($B = \text{China}$). If the exposure e_i^{China} is orthogonal to channels other than supply chain disruptions that explain differential outcomes across sectors, then β_t will capture the causal effect of supply chain disruptions. Similar strategies have been employed by Boehm et al. (2019) in the context of the 2011 Tohoku Earthquake, and in Huang et al. (2018) and Amiti et al. (2020) in the context of the US-China Trade War.

We next study whether industrial production fell by relatively more in sectors with higher China exposure. This naturally raises endogeneity concerns, which we address in Section 4.3. In particular, we address the concern that β_t may capture differential demand effects, by studying the differential effect not only on (output and input) quantities bot also on (output and input) prices.

4.2 Industrial production and China exposure

We first estimate the β_t coefficients using a regression (4.1) of China exposure (e_i^{China}) on IP growth (y_{it}) without controls (no Z_{it}). Figure 3 shows the estimated β_t coefficients over time. The coefficients for March, April, and May 2020 stand out both in significance and magnitude compared to the coefficients estimated over the preceding three years.

In fact, before the Covid-19 crisis, the β_t coefficients are consistently close to zero and statistically indistinguishable from zero. This may appear surprising against the backdrop of the US-China trade war during these years. We propose two explanations. First, the

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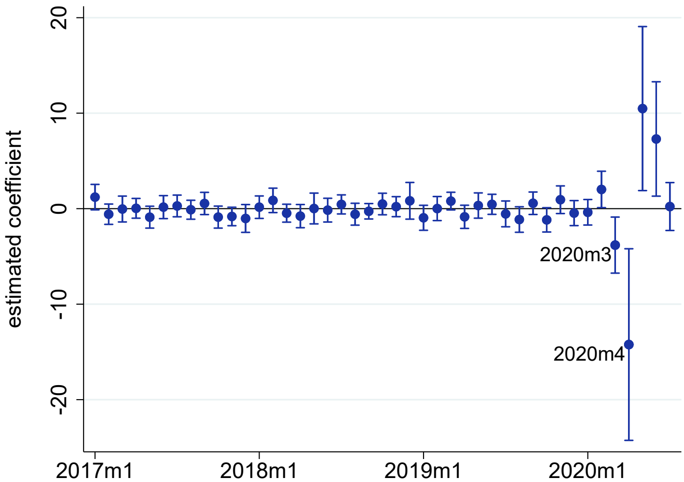
Figure 3: Coefficient β_t in a regression of IP on China exposure



Notes: Markers indicate the estimated coefficients β_t in a regression of monthly IP growth in period t on China exposures according to (4.1). Vertical lines indicate 95% confidence intervals.

tariffs imposed during the trade war often targeted specific sectors, e.g., washing machines as analyzed in Flaaen et al. (2020). Our exposure measure is unlikely to pick up these effects. Second, while tariffs change the costs of imported inputs they do no prohibit goods from being produced and transported across borders. In the short-run, higher tariffs have plausibly weaker effects on production than lockdowns.

Another interesting observation is that despite Covid-19 lockdowns in China around February 2020, the February 2020 β_t coefficient is is non-negative. Two explanations can plausibly account for this time delay. First, US producers hold some inventory of imports from China. Second, cargo transportation time from a supplier in China to a US producer takes time.[8] In fact, the point estimate in February 2020 is even significantly positive, which possibly reflects the US-China trade deal signed in January 2020.

The main take-away from Figure 3 are the large β_t coefficients in March and April 2020. The estimates are of economically relevant magnitudes. March 2020 industrial production growth is 3.82% lower in sectors with a 1% higher China exposure, and 14.23% lower in April 2020, see the first columns of panel (a) and (b) of Table 1. To understand how much variation in IP growth can be explained by variation in China exposures, note that $\sigma(e_i^{\text{china}}) = 0.51\%$.

[8]Cargo ships travel 12 days from China to US West Coast and 22 days to US East Coast, see `https://www.langsamreisen.de/en` which offers freighter travel.

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Table 1: Industrial Production and China exposure

(a) IP growth in March 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	-3.816	-3.740	-4.083	-2.875
	(1.467)	(1.451)	(1.870)	(1.831)
Observations	87	87	87	87
R^2	0.074	0.072	0.053	0.028

(b) IP growth in April 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	-14.23	-14.15	-16.25	-15.04
	(5.016)	(5.012)	(5.669)	(5.582)
Observations	87	87	87	87
R^2	0.086	0.086	0.088	0.079

Note: Based on regression (4.1). Standard errors in parentheses. The point estimates in the first column of panels (a) and (b) are identical to the March and April 2020 coefficients in Figure 3.

The standard deviation of IP growth in March 2020 is $\sigma(y_{i,2020\text{m}3}) = 7.20\%$ and in April 2020 $\sigma(y_{i,2020\text{m}4}) = 24.79\%$. Hence, 7.4% of the cross-sectoral variance in March 2020 IP growth can be associated to different China exposures, and 8.6% of the April 2020 IP growth variance. To gauge the combined March and April effect of China exposure on industrial production, we use the year-over-year IP growth in April 2020 as outcome variable, see third column of panel (b) in Table 1. We conclude that 8.8% of the variance in industrial production during the Covid-19 crisis can be attributed to different China exposures. If we instead use IP growth from February 2020 to April 2020 as left-hand-side variable, we find that 9.0% of the cross-sectoral variation in IP growth can be attributed to variation in China exposures.

Starting from May 2020, the β_t coefficients turns positive and significant. The growth of IP between April and May 2020, and between May and June, are substantially larger in more exposed sectors. While the reversal in May appears to be only a partial one compared to the large negative coefficients in March and April, by June we are closer to full reversal. In Section 4.4, we provide a more detailed discussion of the reversal starting in May. In what follows, we will first focus on March and April 2020.

A potential concern is that our estimate may be biased by the presence of cross-sector differences in IP trend growth before the Covid-19 crisis. To address this concern, we consider three alternative growth rate specification. First, the month-over-month growth

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rate detrended by subtracting the average month-over-month growth rate in the two year until February 2020. Second, the year-over-year monthly growth rate. Third, the year-over-year monthly growth rate detrended by its average over the two years until February 2020. Columns 2–4 of Table 1 show the estimated March and April β_t coefficients for the three alternative specifications. Overall, the coefficients are of similar magnitude and of similar statistical significance. In addition, variation in China accounts for a similar fraction of variation in IP growth as in the baseline.

4.3 Demand vs. supply

A question of critical importance is whether our exposure measure indeed captures the relative strength of supply shocks. A concern is that our exposure measure might be high for industries that were also more affected through other channels during the Covid-19 recession, such as a slump in domestic demand, external demand (namely from China), or tighter financing conditions. We address this concern in two ways. First, we control for sector-specific cyclicality, exports to China, and external finance dependence, all computed with data before the Covid-19 crisis. Table 2 shows the March and April β_t coefficients when including these controls. We still find a significant relation between a higher China exposure and a larger contraction in industrial production. Importantly, the magnitudes of the estimated coefficients β_t change by relatively little.

Second, we estimate how higher China exposure relates to sectoral prices. If sectors with higher China exposure contracted more than other sectors mainly because they faced a larger reduction in demand, then we would expect sector-specific prices to fall. Conversely, if sectors with high China exposure are indeed more affected by international supply chain disruptions, then both their import prices and their output prices should increase relative to other sector with lower China exposure. Table 3 shows that both import (IPI) and output (PPI) prices increase by more in sectors with higher China exposure. The differences are statistically significant at the 5% level for import prices and at the 10% level for output prices. This result makes it unlikely that changes in real activity in industries with high China exposure were mostly affected by lower domestic demand. To be clear, this does not rule out that differences in China exposure capture some differential demand effects across sectors. It merely suggests that the supply chain disruption is the dominant channel picked up by differences in exposure.

Comparing observed price changes across sectors may be misleading if sectors differ in the fraction of (item-level) prices being adjusted. In fact, average price adjustment frequencies differ a lot across sectors, see, e.g., Nakamura and Steinsson (2008) and Pasten et al. (forth-

Table 2: Industrial Production with additional controls

(a) IP growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-3.816	-3.548	-4.408	-3.389	-3.768
	(1.467)	(1.429)	(1.395)	(1.517)	(1.418)
Ext. Finance Dependence		-1.262			-1.258
		(0.512)			(0.486)
Exports to China			0.152		0.141
			(0.0447)		(0.0441)
Business cycle correlation				-3.544	-2.754
				(3.244)	(3.034)
Observations	87	87	87	87	87
R^2	0.074	0.136	0.185	0.087	0.250

(b) IP growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-14.23	-13.96	-15.25	-11.84	-12.52
	(5.016)	(5.046)	(5.008)	(5.124)	(5.207)
Ext. Finance Dependence		-1.294			-1.528
		(1.807)			(1.784)
Exports to China			0.262		0.213
			(0.160)		(0.162)
Business cycle correlation				-19.83	-18.41
				(10.96)	(11.14)
Observations	87	87	87	87	87
R^2	0.086	0.092	0.115	0.121	0.148

Note: Based on regression (4.1). Standard errors in parentheses.

coming). To address this concern, we compute adjusted output price growth (PPI*) by taking the ratio of PPI growth over the average price adjustment frequency documented in Pasten et al. (forthcoming). Using PPI* as outcome, we still find larger output price increases for sector more exposed to China. The April 2020 coefficient (in column 5) remains statistically significant at the 10% level, while the March 2020 coefficient is insignificant. One problem with this correction for price rigidity is that it rests on the assumption that the average price adjustment frequency is informative about the price adjustment frequency in March

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Table 3: Other outcomes

(a) Yearly growth rates in March 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-4.083	-0.379	4.991	2.590	7.120	-9.181	-5.612
	(1.870)	(0.795)	(2.005)	(1.609)	(4.533)	(3.854)	(2.543)
Observations	87	87	87	87	87	83	83
R^2	0.053	0.003	0.068	0.030	0.028	0.065	0.057

(b) Yearly growth rates in April 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-16.25	-6.215	9.075	4.887	12.03	-12.73	-21.08
	(5.669)	(2.470)	(2.976)	(2.667)	(6.223)	(7.153)	(6.343)
Observations	87	87	87	87	87	83	83
R^2	0.088	0.069	0.099	0.038	0.042	0.038	0.120

Note: Based on regression (4.1). Standard errors in parentheses. IP: industrial production growth, EMP: employment growth, IPI: import price index growth, PPI: purchaser price index growth, PPI*: PPI growth divided by price adjustment frequency, IMP: import growth, EXP: export growth.

and April 2020. Given the magnitude of the disruption caused by Covid-19, this may be a strong assumption. Table 3 further shows that more exposed sectors reduce their workforce (EMP) by relatively more, especially in April, they import (IMP) less, and export (EXP) less. This draws an overall consistent picture that more exposed sectors were contracting more during the Covid-19 crisis. In the Appendix, Tables 8–13 show that the March and April β_t estimates for employment growth, import and export growth, output and input growth are broadly robust to controling for sectoral external finance dependence, exports to China, and cyclicality.

4.4 Exposure to non-Chinese inputs

We next consider a broad sector-specific import exposure that includes all intermediate goods imports except imports from China. Figure 4 in the Appendix shows the histogram of ex-China import exposures across sectors. We then re-estimate regression (4.1) using ex-China exposure and present the β_t estimates in Table 4. We find that IP contracted significantly more in sectors with higher broad import exposure. However, the responses of employment and exports is insignificant and with positive point estimates in March 2020. In contrast, for sectors with higher China exposure, employment and exports fell more (Table 3). The fact that the output responses are less consistent suggests that the broad import exposure

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Table 4: Outcomes for non-China exposure

(a) Growth rates in March 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
Non-China exposure	-0.897	0.00554	-0.446	-0.689	-2.455	-0.430	0.163
	(0.280)	(0.0370)	(0.401)	(0.309)	(0.854)	(0.776)	(0.510)
Observations	87	87	87	87	87	83	83
R^2	0.108	0.000	0.014	0.055	0.089	0.004	0.001

(b) Growth rates in April 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
Non-China exposure	-2.394	-0.311	-1.175	-1.394	-4.235	-2.362	-0.830
	(0.988)	(0.442)	(0.597)	(0.507)	(1.149)	(1.397)	(1.315)
Observations	87	87	87	87	87	83	83
R^2	0.065	0.006	0.044	0.082	0.138	0.034	0.005

Note: Based on regression (4.1). Standard errors in parentheses. See notes of Table 3 for a resolution of the first row acronyms.

does not equally well capture differential exposure to international supply chain disruptions as the China exposure. More importantly, import and output prices in sectors with higher broad import exposure do not increase by more, but rather by less. This in turn suggests that the non-China import exposure is high in sectors that are more severely hit by demand slumps. Overall, these results caution against interpreting the ex-China β_t coefficients in the context of supply chain disruptions.

4.5 Persistence

We next look beyond April and March 2020 to study the persistence of China-specific supply chain disruptions on US production. Table 5 shows the β_t estimates for May, June, and July 2020, and the four alternative specifications of IP growth. The first two columns of panel (a) show that industrial production increased by more for more exposed sectors relative to April 2020. However, the last two columns of Table 5 show that relative to the preceding year, industries with higher China exposure still produce relatively less. Taken together the May estimates indicate that the effects of China-specific supply chain disruptions only partially dissipated in May 2020. For June and July 2020 the point estimates suggest that some effect persists, however, the IP growth differences across industries associated with China exposure become statistically insignificant. A similar picture emerges when estimating the May–July 2020 β_t coefficients for other outcomes, inputs, and prices, see Table 14 in the Appendix.

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Table 5: Industrial Production and China exposure during May–July 2020

(a) IP growth in May 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	10.48	10.55	-9.189	-7.991
	(4.294)	(4.293)	(4.409)	(4.344)
Observations	86	86	86	86
R^2	0.066	0.067	0.049	0.039

(b) IP growth in June 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	7.298	7.367	-2.830	-1.631
	(2.994)	(2.999)	(3.019)	(2.956)
Observations	86	86	86	86
R^2	0.066	0.067	0.010	0.004

(b) IP growth in July 2020

	Monthly	Monthly/Detr.	Yearly	Yearly/Detr.
China exposure	0.222	0.290	-2.075	-0.876
	(1.254)	(1.248)	(2.915)	(2.844)
Observations	86	86	86	86
R^2	0.000	0.001	0.006	0.001

Note: Based on regression (4.1). Standard errors in parentheses. The point estimates in the first columns are identical to the corresponding coefficients in Figure 3. We have one observation less for May–July 2020 because the data for sector 3211 (Sawmills and wood preservation) has not been released.

Essentially, supply chain disruption occurred around February 2020 in China, attained their peak effect on US production at the end of April, and seems to have dissipated by July. The relatively short-lived effects of the Covid-19 supply chain disruptions contrasts with Barrot and Sauvagnat (2016). Using regional natural disasters in the US, the authors find that the peak effect on sales of a supplier being hit by a disaster is about one year after the disaster. Clearly, the Covid-19 recession is quite different from the severe natural disasters in their sample. For example, while a storm or a flooding may destroy productive capacity and infrastructure, the Covid-19 lockdowns left productive capacity and infrastructure broadly unaffected. Hence it is at least plausible that production can resume relatively more quickly after Covid-19 lockdowns when compared to natural disasters.

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4.6 Alternative China exposures

Our baseline China exposure builds on trade flows of 6-digit commodities and assigns them to industries using the import matrix of the input-output table and applying a proportionality assumption. A potential problem with this approach is that some 6-digit commodities are used for multiple end-uses. Some 6-digit commodities may contain a mixture of intermediate goods, capital goods, and consumption goods. This is arguably not a large problem because we start from narrowly-defined 6-digit commodities, for which the scope of mixed end-use may be limited. To address the potential issue nonetheless, we categorize the 6-digit commodities using either the end-use classification from the BEA or the BEC. We then discard 6-digit commodities not classified as intermediate inputs and proceed with the remaining commodities to construct sector-specific China exposures. It turns out that we underestimate aggregate intermediate good imports in this way. Using the BEA or BEC classification, only 37% or 45% of imports are respectively considered intermediate inputs versus 55% in the import matrix. Our empirical results, however, are robust to using the alternative exposure measures.

In Table 6, the first rows of panel (a) and (b) repeat the baseline April and March β_t estimates whereas the last two rows show the β_t for the alternative China exposures based on the BEA and BEC classificiations, respectively. The results are re-assuring in the sense that the results are not dramatically different. If anything, our baseline approach seems to underestimate the role of China exposure. In particular for the BEA-based classification, the R^2 is substantially larger, which suggests that China-specific supply chain disruptions

Table 6: Exposure to intermediate good imports

	(1)	(2)	(3)	(4)	(5)	(6)
China exposure	-3.816			-14.23		
	(1.467)			(5.016)		
– BEA intermediates		-9.588			-35.70	
		(2.282)			(7.719)	
– BEC intermediates			-5.364			-17.66
			(1.962)			(6.780)
Observations	87	87	87	87	87	87
R^2	0.074	0.172	0.081	0.086	0.201	0.074

Note: Based on regression (4.1). Standard errors in parentheses. Columns (1)–(3) are based on March 2020 IP growth, columns (4)–(6) are based on April 2020 IP growth. The first row, China exposure, is based on all sector-specific imports from China. The second (third) row is based on constructing sector-specific imports of intermediate goods from China based on BEA (UNSTATS BEC) classification of goods into end-use categories.

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explain closer to 20% if the cross-sectoral variation in IP growth during March and April 2020.

5 Conclusion

In this paper, we study the role of international supply chain disruptions during the Covid-19 crisis. We show that US sectors with a high exposure to imports from China, significantly and substantially contracted more during March and April 2020 compared to less exposed sectors. Highly exposed sectors produce less, fire more workers, export and import less, and their import and output prices increase by more. Our results suggest that differential exposure to China-specific supply chain disruptions explain about 9% of the cross-sectoral differences in industrial production growth during March and April 2020. The effects appear to be relatively short-lived and become insignificant by July 2020.

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Appendix A

We consider the problem of type 1 establishments and drop index 1 for convenience. Before the shock, the input choices are denoted by x, m, and $z = \frac{x}{m}$. After the shock, they are denoted by x_t, m_t, and $z_t = \frac{x_t}{m_t}$. While the supply chain disruption constrains the choice of m_t to $m_t = (1-\delta)m$, the input x_t is chosen optimally before and after the shock. The first-order conditions for x/x_t expressed in terms of z/z_t and m/m_t are given by

$$\alpha\gamma m^{\gamma-1} f(z)^{\gamma-\rho} z^{\rho-1} = p^x, \tag{A.1}$$

$$\alpha\gamma m_t^{\gamma-1} f(z_t)^{\gamma-\rho} z_t^{\rho-1} = p^x. \tag{A.2}$$

We combining the two first-order conditions to obtain

$$f(z_t)^{\gamma-\rho} z_t^{\rho-1} = (1-\delta)^{1-\gamma} f(z)^{\gamma-\rho} z^{\rho-1}. \tag{A.3}$$

Taking a first-order Taylor expansion w.r.t. z_t and δ at $\delta = 0$ and hence $z_t = z$ yields

$$\left[-(1-\rho) + (\gamma-\rho)\epsilon\right] \frac{dz_t}{z} = -(1-\gamma) d\delta, \tag{A.4}$$

where $\epsilon = \frac{zf'(z)}{f(z)}$. Using $d\log z_t = \frac{dz_t}{z}$ and $d\log m_t \approx -d\delta$, we obtain

$$\frac{d\log z_t}{d\log m_t} = -\frac{1-\gamma}{(1-\rho)-(\gamma-\rho)\epsilon}. \tag{A.5}$$

Appendix B

Table 7: List of all sectors

NAICS	description	NAICS	description
1133	Logging	3273	Cement and concrete product
211	Oil and gas extraction	3274	Lime and gypsum product
2121	Coal mining	3279	Other nonmetallic mineral product
2122	Metal ore mining	3311,2	Iron and Steel Manufacturing
2123	Nonmetallic mineral mining	3313	Alumina and aluminum production
213	Support activities for mining	3314	Nonferrous metal production
2211	Electric power generation	3315	Foundries
2212	Natural gas distribution	3321	Forging and stamping
3111	Animal food	3322	Cutlery and handtool

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3112	Grain and oilseed milling	3323	Architectural and structural metals
3113	Sugar and confectionery product	3324	Boiler, Tank, Shipping Container
3114	Fruit and vegetable preserving	3325	Hardware
3115	Dairy product	3326	Spring and wire product
3116	Animal slaughtering and processing	3327	Machine shops; turned product; screw
3117	Seafood product preparation	3328	Coating, engraving, heat treating
3118	Bakeries and tortilla	3329	Other fabricated metal product
3119	Other food	3331	Agriculture, construction, mining
3121	Beverage	3332	Industrial machinery
3122	Tobacco	3333,9	Commercial and Service Industry
3131	Fiber, yarn, and thread mills	3334	Ventilation, heating, AC, refrigeration
3132	Fabric mills	3335	Metalworking machinery
3133	Textile, fabric finishing, fabric coating	3336	Engine, turbine, power transmission
3141	Textile furnishings mills	3341	Computer and peripheral equipment
3149	Other textile product mills	3342	Communications equipment
315	Apparel	3343	Audio and video equipment
316	Leather and allied product	3344	Semiconductor, electronic component
3211	Sawmills and wood preservation	3345	Navigational, measuring
3212	Veneer, plywood, engineered wood	3346	Magnetic and Optical Media
3219	Other wood product	3351	Electric lighting equipment
3221	Pulp, paper, and paperboard mills	3352	Household appliance
3222	Converted paper product	3353	Electrical equipment
323	Printing, related support activities	3359	Other electrical equipment
324	Petroleum and coal products	3361	Motor vehicle
3251	Basic chemical	3362	Motor vehicle body and trailer
3252	Resin, synthetic rubber and fibe	3363	Motor vehicle parts
3253	Pesticide, fertilizer	3364	Aerospace product and parts
3254	Pharmaceutical and medicine	3365	Railroad rolling stock
3255	Paint, coating, and adhesive	3366	Ship and boat building
3256	Soap, cleaning, toilet preparation	3369	Other transportation equipment
3259	Other Chemical Product	3371	Household and institutional furniture
3261	Plastics product	3372-9	Office Furniture Manufacturing
3262	Rubber product	3391	Medical equipment and supplies
3271	Clay product and refractory	3399	Other Miscellaneous Mfg
3272	Glass and glass product	5111	Newspaper, periodical, book

Note: Some sector descriptions are shortened.

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Figure 4: Heterogeneity across sectors

Distribution of (total) import exposure across sectors

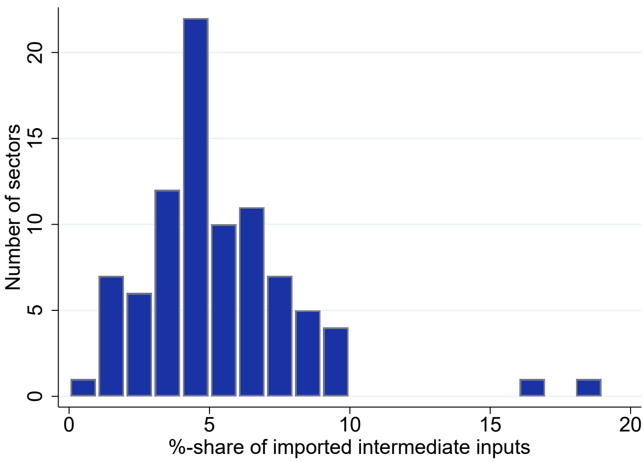

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Table 8: Employment (EMP) with additional controls

(a) Employment growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-0.227	-0.253	-0.243	-0.262	-0.328
	(0.189)	(0.187)	(0.191)	(0.196)	(0.197)
Ext. Finance Dependence		0.119			0.129
		(0.0670)			(0.0676)
Exports to China			0.00407		0.00547
			(0.00612)		(0.00613)
Business cycle correlation				0.288	0.432
				(0.419)	(0.422)
Observations	87	87	87	87	87
R^2	0.017	0.053	0.022	0.022	0.070

(b) Emploment growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-5.732	-5.682	-6.292	-4.169	-4.653
	(2.192)	(2.211)	(2.169)	(2.185)	(2.214)
Ext. Finance Dependence		-0.236			-0.396
		(0.792)			(0.758)
Exports to China			0.143		0.114
			(0.0695)		(0.0688)
Business cycle correlation				-12.95	-11.92
				(4.673)	(4.735)
Observations	87	87	87	87	87
R^2	0.074	0.075	0.119	0.152	0.183

Note: Based on regression (4.1). Standard errors in parentheses.

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Table 9: Import prices (IPI) with additional controls

(a) Import price growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	4.991	4.943	4.645	4.208	3.522
	(2.005)	(2.021)	(2.010)	(2.061)	(2.089)
Ext. Finance Dependence		0.223			0.394
		(0.724)			(0.716)
Exports to China			0.0885		0.109
			(0.0644)		(0.0649)
Business cycle correlation				6.480	7.954
				(4.407)	(4.468)
Observations	87	87	87	87	87
R^2	0.068	0.069	0.088	0.091	0.124

(b) Import price growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	9.075	9.125	8.573	8.058	7.258
	(2.976)	(3.002)	(2.986)	(3.069)	(3.120)
Ext. Finance Dependence		-0.236			-0.0125
		(1.075)			(1.069)
Exports to China			0.128		0.153
			(0.0957)		(0.0969)
Business cycle correlation				8.421	10.13
				(6.563)	(6.675)
Observations	87	87	87	87	87
R^2	0.099	0.099	0.118	0.116	0.142

Note: Based on regression (4.1). Standard errors in parentheses.

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Table 10: Output prices (PPI) with additional controls

(a) Output price growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	2.590	2.694	2.417	1.822	1.611
	(1.609)	(1.616)	(1.624)	(1.643)	(1.678)
Ext. Finance Dependence		-0.491			-0.356
		(0.579)			(0.575)
Exports to China			0.0443		0.0596
			(0.0521)		(0.0521)
Business cycle correlation				6.355	6.799
				(3.515)	(3.590)
Observations	87	87	87	87	87
R^2	0.030	0.038	0.038	0.066	0.086

(b) Output price growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	4.887	5.059	4.693	3.712	3.508
	(2.667)	(2.680)	(2.699)	(2.733)	(2.800)
Ext. Finance Dependence		-0.805			-0.610
		(0.960)			(0.959)
Exports to China			0.0498		0.0724
			(0.0865)		(0.0870)
Business cycle correlation				9.732	10.16
				(5.844)	(5.991)
Observations	87	87	87	87	87
R^2	0.038	0.046	0.042	0.069	0.082

Note: Based on regression (4.1). Standard errors in parentheses.

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Table 11: Output prices adjusted by price rigidity (PPI*) with additional controls

(a) Adjusted output price growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	7.120	7.782	5.590	5.845	4.447
	(4.533)	(4.474)	(4.398)	(4.689)	(4.507)
Ext. Finance Dependence		-3.112			-2.739
		(1.602)			(1.544)
Exports to China			0.392		0.416
			(0.141)		(0.140)
Business cycle correlation				10.56	13.50
				(10.03)	(9.641)
Observations	87	87	87	87	87
R^2	0.028	0.070	0.110	0.041	0.168

(b) Adjusted output price growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	12.03	12.71	10.75	10.19	9.104
	(6.223)	(6.201)	(6.211)	(6.433)	(6.442)
Ext. Finance Dependence		-3.208			-2.789
		(2.221)			(2.207)
Exports to China			0.327		0.361
			(0.199)		(0.200)
Business cycle correlation				15.19	17.48
				(13.76)	(13.78)
Observations	87	87	87	87	87
R^2	0.042	0.065	0.072	0.056	0.111

Note: Based on regression (4.1). Standard errors in parentheses.

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Table 12: Imports (IMP) with additional controls

(a) Import growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-9.181	-9.279	-9.639	-8.137	-8.807
	(3.854)	(3.890)	(3.865)	(3.962)	(4.052)
Ext. Finance Dependence		0.407			0.343
		(1.370)			(1.376)
Exports to China			0.142		0.123
			(0.122)		(0.125)
Business cycle correlation				-9.489	-7.743
				(8.550)	(8.786)
Observations	83	83	83	83	83
R^2	0.065	0.067	0.081	0.080	0.091

(b) Import growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-12.73	-13.01	-13.54	-12.68	-14.26
	(7.153)	(7.215)	(7.181)	(7.410)	(7.557)
Ext. Finance Dependence		1.130			1.259
		(2.542)			(2.565)
Exports to China			0.249		0.261
			(0.227)		(0.233)
Business cycle correlation				-0.536	3.461
				(15.99)	(16.39)
Observations	83	83	83	83	83
R^2	0.038	0.040	0.052	0.038	0.055

Note: Based on regression (4.1). Standard errors in parentheses.

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Table 13: Exports (EXP) with additional controls

(a) Export growth in March 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-5.612	-6.014	-5.598	-4.834	-5.226
	(2.543)	(2.513)	(2.572)	(2.608)	(2.631)
Ext. Finance Dependence		1.671			1.580
		(0.885)			(0.893)
Exports to China			-0.00426		-0.0170
			(0.0811)		(0.0812)
Business cycle correlation				-7.073	-6.463
				(5.630)	(5.706)
Observations	83	83	83	83	83
R^2	0.057	0.097	0.057	0.075	0.112

(b) Export growth in April 2020

	(1)	(2)	(3)	(4)	(5)
China exposure	-21.08	-22.25	-21.79	-17.11	-19.16
	(6.343)	(6.213)	(6.367)	(6.299)	(6.287)
Ext. Finance Dependence		4.904			4.531
		(2.189)			(2.134)
Exports to China			0.222		0.151
			(0.201)		(0.194)
Business cycle correlation				-36.04	-31.74
				(13.60)	(13.63)
Observations	83	83	83	83	83
R^2	0.120	0.172	0.133	0.191	0.240

Note: Based on regression (4.1). Standard errors in parentheses.

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Table 14: Other outcomes

(a) Yearly growth rates in May 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-9.189	-4.047	8.107	3.537	8.961	-18.59	-14.12
	(4.409)	(2.303)	(2.786)	(2.186)	(5.906)	(8.392)	(6.948)
Observations	86	86	86	86	86	82	82
R^2	0.049	0.035	0.092	0.030	0.027	0.058	0.049

(b) Yearly growth rates in June 2020

	IP	EMP	IPI	PPI	PPI*	IMP	EXP
China exposure	-2.830	-1.351	5.155	2.810	9.261	-10.07	-2.419
	(3.019)	(1.485)	(1.887)	(1.333)	(4.577)	(6.730)	(4.716)
Observations	86	86	86	86	86	82	82
R^2	0.010	0.010	0.082	0.050	0.046	0.027	0.003

Note: Based on regression (4.1). Standard errors in parentheses. IP: industrial production growth, EMP: employment growth, IPI: import price index growth, PPI: purchaser price index growth, PPI*: PPI growth divided by price adjustment frequency, IMP: import growth, EXP: export growth.

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Epidemics, poverty, and social cohesion: Lessons from the past and possible scenarios for COVID-19[1]

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Since COVID-19 broke out, there has been renewed interest in understanding the economic and social dynamics of historical and more recent epidemics and pandemics, from the plagues of Antiquity to modern-day outbreaks like Ebola. These events can have significant impacts on the interplay between poverty and social cohesion, i.e. how different groups in society interact and cooperate to survive and prosper. To that effect, this survey paper provides an overview of how social responses to past epidemics and pandemics were determined by the epidemiological and non-epidemiological characteristics of these outbreaks, with a particular focus on the scapegoating and persecution of minority groups, including migrants. We discuss existing theories as well as historical and quantitative studies, and highlight the cases where epidemics and pandemics may lead to milder or more severe forms of scapegoating. Finally, we conclude with a summary of priorities for future research on epidemics, pandemics and social cohesion and discuss the possible effects and policy implications of COVID-19.

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1. Introduction

Epidemics – disease outbreaks that infect a large share of individuals in a community – and *pandemics* – epidemics that are spread over a wide geographic area, such as over multiple countries – have drastic impacts on economic and social setups.[1] Social cohesion and its interplay with poverty and inequality during these crisis events is determined by how different groups in society coordinate and interact with each other to ensure collective survival and prosperity during and after these disaster events.

Widespread reports in media sources over the first six months of the COVID-19 crisis provide suggestive evidence that various minority groups, including migrant communities and religious groups, have been scapegoated for the spread of the disease and its pursuant health and economic impacts. Worldwide, such scapegoating has already given rise to cases of medicalized prejudice and discrimination, and cases of both individual and collective acts of targeted violence.

Since COVID-19 broke out, there has also been renewed interest in understanding the social effects of epidemics and pandemics, such as the plagues of Ancient Greece and Ancient Rome, the Black Death of 1347-1352, syphilis from the late 15th century to the 19th century, cholera, smallpox and yellow fever in the 19th century, the Third Plague Pandemic of 1894-1901 and the 1918 Influenza, and more recent outbreaks such as HIV and Ebola. While the literature has described how some of these events have given rise to social unrest and violence, most studies focus on one event at a time and do not provide a systematic overview of the scapegoating-epidemic relationship and its determinants.

In particular, why did some epidemics and pandemics lead to scapegoating while others did not? Why did scapegoating take a "milder" form in some cases (e.g., medicalized prejudice) or a more "severe" form in other cases (e.g., mass murders)? Did the probability of scapegoating, and its severity, depend on the characteristics of the epidemic itself – how mysterious and deadly it was, who died more (e.g., children or adults? the poor?), etc. – and/or the economic, social and political context in which it took place? And how did the flow of information (and misinformation) during these crises impact social conflict? Lastly, what was the role of policies in place before and after these events, and what lessons can be drawn to inform the policies that developing countries could adopt today to manage the social impacts of COVID-19?

This survey paper sheds light on these questions by discussing existing theories as well as historical and quantitative studies. The available evidence suggests that epidemics and pandemics may be more likely to lead to social conflict: (i) when they are highly lethal; (ii) when they have distressing symptoms; (iii) when mortality rates are disproportionately higher for young children than for working-

[1] Neither the U.S. Centers for Disease Control and Prevention nor the World Health Organization specify how many countries or how many people need to be affected in order for a disease to be declared a pandemic. Nonetheless, we will refer to the word "pandemic" when characterizing an epidemic striking an entire country or multiple countries instead of individual localities.

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age adults or the elderly, due to the behavioral response it triggers from parents and society; (iv) at "intermediary" levels of knowledge of the mechanisms by which the epidemic transmits, i.e. when the epidemic is neither attributed to supernatural causes nor yet fully understood by the medical community, authorities, and populations; (v) when intergroup tensions were already rife; and (vi) when authorities encourage, or allow, scapegoating or implement heavy-handed policies that lead to distrust within the population.

Finally, we identify questions that should be addressed by future research, with regards to both past epidemics and pandemics as well as COVID-19.[2]

2. Theoretical Literature on Economic and Non-Economic Shocks and Social Cohesion

2.1 General Theories of Social Conflict

When multiple groups defined on the basis of identity exist in a society, they compete and coordinate to determine the allocation of resources between their members. The political power of groups in influencing the collective bargaining process is determined by their population size as well as the distribution of economic resources between and within groups. Large shocks modify the "social equilibrium" attained in a given society and may increase, or decrease, the likelihood of social conflict.

In particular, the literature has shown how inter-group conflict can be driven by "grievances" - when people engage in conflict over issues of identity - or "greed" - when engaging in conflict is motivated by a desire to improve one's economic situation (Collier and Hoeffler, 1998, 2004; Kanbur, 2007). Grievances can be exploited to obtain gains by violent means (Ray and Esteban, 2017). Economic inequality between groups also leads to conflict if it causes grievances and/or incentivizes a relatively poor group to engage in conflict (Kanbur 2007; Blattman and Miguel, 2010).

Negative shocks raise the likelihood of conflict, because poverty makes it easier for groups prone to engaging in conflict to recruit members and the capacity of the state to counter conflict is weakened (Miguel et al, 2004; Bazzi and Blattman, 2014). At the same time, negative shocks reduce the size of the cake to fight over (Dal Bo and Dal Bo, 2011; Esteban and Ray, 2017). Inequality then fuels or decreases grievances depending upon the power balance between groups (Esteban and Ray, 2017).

While the literature has focused on civil war, there is also a broader literature on social conflict, which Ray and Esteban (2017) defines as "within-country unrest, ranging from peaceful demonstrations,

[2] One advantage of turning to history to understand the effects of COVID-19 on developing economies today is that the economies of Antiquity or the Medieval economies that this review focuses on had similar income levels as countries classified as "low-income" by the World Bank today (Bolt and van Zanden, 2014). In addition, the income level of Western countries in the first half of the 19th century when cholera, smallpox, and yellow fever outbreaks were frequent, as well as the world's average income level when the 1918 Influenza broke out, were similar to the most developed low-income countries today. Finally, South Africa was a lower-middle income country when HIV spread rapidly and Ebola outbreaks have affected low-income countries.

processions, and strikes to violent riots and civil war". Within this literature, the general focus has been on the respective roles of ethno-linguistic fractionalization - when there are many groups in society - (Collier and Hoeffler, 1998, 2004) and polarization - when there are deep cleavages along large group lines - (Esteban and Ray, 1994, 2011a; Montalvo and Reynal-Querol 2005; Esteban et al, 2012).

Conflict is more likely to take place along ethnic lines than along class lines, because: (i) Ethnicity is not easily disguisable; (ii) Conflict requires both economic resources and conflict labor (i.e. individuals who accept to be paid little to fight), which can both be found within a same ethnic group but usually not within the same class (Esteban and Ray, 2008); (iii) Ethnicity proxies for income if ethnic groups are professionally specialized (Esteban and Ray, 2011b); and (iv) Ethnicity is "a strategic basis for coalitions that seek a larger share of economic or political power" (Ray and Esteban, 2017). Strategic ethnic conflict allows "winners" to share the spoils of conflict among fewer individuals.[3] In contrast, revolutions imply that the spoils of conflict are shared among a broader set of individuals (the poor).

2.2 The Scapegoat Theory of Intergroup Conflict

In the wake of the Holocaust, a literature arose in political science, psychology, and sociology investigating the importance of scapegoating as a cause of violence (Doob et al, 1939; Hovland and Sears, 1940; Girard, 1978; Allport, 1979; Staub, 1992; Poppe, 2001; Glick, 2002, 2005, 2009). According to this theory, members of a majority experiencing prolonged negative experiences settle on a specific target to blame for their grievances. By blaming a minority group, members of a majority group experience emotional relief. Lack of control is now no longer the fault of the individual, but the fault of the minority. In addition, some members of the majority group may have strong pre-existing biases before the epidemic. The crisis provides the cover and a rationale for furthering these agendas. Epidemics can thus serve as a coordination mechanism for majority members with strong anti-minority views and as a persuasion mechanism for majority members who do not have such views. Pre-existing concentration of political power with the majority group can magnify this effect.[4]

2.3 Immigration and Public Attitudes Toward Immigrants

Providing a survey of the literature on the effects of immigration on public attitudes toward immigrants, Hainmueller and Hopkins (2014) explain that migrants could be blamed because of the competition over economic resources between migrants and natives or because they are seen as a threat to their safety (for example, because of crime) and national identity (for example, their culture or religion is

[3] Hoff and Walsh (2017) summarize the evidence on how such strategies can be cognitively internalized as behavioral responses and give rise to discriminatory behaviors and exclusionary practices.
[4] Groups can be scapegoated based on varying definitions of identity (race, religion, gender, sexual orientation, nation of origin, or disease status). The salience of different identities depends on the pre-existing political context.

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viewed as too “different”).[5] In the scapegoating literature, the targeting of certain groups arises as a coping strategy, giving rise to minorities being (wrongly) blamed for the negative experiences of the majority group. In contrast, the migration literature points to cases where migration indeed negatively impacts the economic situation of selected groups of natives. However, “blaming” the outgroup in these cases may be unwarranted if economic differences arise due to prevailing policies and other factors related to migrant-selection and inequality in the host region – such as trade and technology.

2.4 Epidemics, Mortality, Incomes, Life Satisfaction, and Scapegoating

Epidemics affect incomes and satisfaction with life. First, people could have relatives or friends that die or are affected. Second, due to the number of deaths or the policies implemented to contain the disease (for example, lockdowns), both demand and supply, and thus production, initially collapse, causing incomes to fall (Barro et al., 2020). In the longer run, net effects are more ambiguous as epidemics could have more positive or negative effects. First, survivors often obtain the property of the deceased. Second, if population decreases and the stock of housing and infrastructure is “durable” (Glaeser and Gyourko, 2005), housing prices and congestion decrease (Jedwab and Vollrath, 2019). Third, the epidemic may cause a labor scarcity effect, which leads to wage increases (Young, 2005). In addition, inequality could be significantly reduced if the price of labor (wages) dramatically increases relative to the value of capital and land (Scheidel, 2018; Alfani, 2020). These effects then depend on how many people die, and who dies, in particular working-age adults or dependents (Bloom and Canning, 2006; Weil, 2010). At the same time, during the epidemic, private and public investments in physical and human capital contract in reaction to the large uncertainty that accompanies such events (Baker et al 2020). Companies delay their purchase of equipment. Schools may be closed and lower incomes affect nutritional intakes and health inputs (Almond, 2006; Beach, Ferrie and Saavedra, 2018). Finally, an epidemic could directly or indirectly (via income) affect fertility (Boucekkine et al., 2009; Boberg-Fazlic et al. 2017), and thus future population and economic growth (Galor, 2011), as well as institutions (Evans, 1988), which would also impact economic development (Acemoglu et al., 2019).[6]

In the short-run, the negative effects on life satisfaction raise the probability of scapegoating. In the longer run, a few epidemics have led to improvements in living standards, thus reducing the same probability. The literature shows how some epidemics have resulted in the scapegoating of minorities (Nelkin and Gilman, 1988; Eamon, 1998; Craddock, 2004; Edelstein et al., 2014; Lin et al., 2015).

[5] Other studies on the effects of migration on attitudes include Mayda (2006), Facchini and Mayda (2009), Card et al. (2012), Becker and Fetzer (2017), Dustmann et al. (2019), and Tabellini (2019).
[6] The epidemic could produce growth-enhancing institutional change, for example by fostering nation-building if the epidemic reinforces national identities over ethnic or religious identities –, state-building – if the epidemic leads to reforms that improve state capacity –, and pro-poor policy agendas – if containing, and mitigating the economic impact of, the epidemic cannot be done without policies targeting the poorest segments of society. On the negative side, nationalistic, authoritarian and rent-seeking governments could use the epidemic to adopt more protectionist policies and further their control of society and the economy.

Unskilled migrants are often scapegoated during an epidemic due to the "competition over resources" and "threat to safety" effects. Regarding the second effect, unskilled migrants are often blamed for causing the spread of the disease across locations. However, skilled migrants, businesspersons and tourists might be even more likely to contribute to this spread. Yet, such groups are almost never directly blamed, which implies that other factors than migrant status *per se* may contribute to the scapegoating. In particular, unskilled migrants, being poorer, may have weaker immune systems, are more likely to live in crowded conditions, and have to work in sectors where infection rates are high. They also often need to work despite government-imposed lockdown policies. Unskilled migrant populations may thus show significantly higher infection rates than the rest of the population. In addition, migrants, if undocumented and/or denied access to healthcare, may see their communities act as reservoirs for the disease, thus validating the "threat" argument. Finally, unskilled and skilled migrants may come from different countries and backgrounds and have distinct preferences (e.g., religious preferences), and unskilled migrants might be seen as physically and culturally "different".

2.5 Epidemics and Mechanisms Other than Scapegoating

The scapegoating effect could be offset, or even dominated, by three other possibly important effects.

There could first be a "come together" effect if the stress of disaster brings people together. Stress leads to a sense of vulnerability, which leads to greater empathy and generosity (Taylor et al., 2000; Converse et al., 2012). The majority group could see that the minority is also affected and realize they cannot be blamed for the epidemic. In addition, large population losses could make the majority group value having people around, even if these belong to the minority group. The psychological literature also explains that acute stress (e.g., coming from "one-time" life-threatening shocks such as epidemics and natural disasters) leads to more demand for social bonding, because humans feel vulnerable and stress is reduced by interacting with other humans (von Dawans et al., 2012; Sapolsky, 2017, 2018).

Chronic stress (e.g., coming from repeated exposure to stress over a long period of time, for example due to chronic poverty), on the other hand, could lead to lower demand for social bonding (Sapolsky, 2017, 2018) and lower empathy (Martin et al, 2015; Starcke et al., 2011; Youssef et al., 2012). Chronic stress also "provokes [displacement] aggression for the simple reason that aggression reduces stress" (Sapolsky, 2018). Since stress limits a human's ability to restrain impulses (Hackman et al., 2010; Sheridan et al., 2012), it can result in acts of aggression (Sapolsky, 2018). If the epidemic or its economic effects prolong, stress becomes chronic and "displacement aggression" more likely to occur.

Second, if a large number of individuals die during an epidemic, survivors may experience a sustained improvement in their standards of living, which could limit occurrences of scapegoating.

Third, there could be an economic complementarity effect if minority groups, including migrants, provide specialized skills that help a society eliminate an epidemic. Similarly, minority groups could provide skills that could help an economy be resilient during a epidemic, or recover after it.

2.6 Epidemics and Social Capital

Social capital "refers to the norms and networks that enable people to act collectively" and trust and reciprocity are some of its important features (Woolcock and Narayan, 2000). While social capital promotes economic development (see Algan and Cahuc (2014) for a survey), the role of social capital can also be destructive (Woolcock and Narayan, 2000; Mansuri and Rao, 2004). Members of a close-knit community may isolate themselves from economic opportunities outside the community and strong intracommunity ties may come at the expense of intercommunity networks. The literature thus distinguishes "bonding" (intracommunity) and "bridging" (intercommunity) social capital.

During an epidemic, bonding social capital could help individuals weather the negative life satisfaction effects from increased mortality and economic decline. At the same time, if bridging social capital is weak, in other words if there is mistrust between communities and/or with regard to government action (thus weakening it), bonding social capital might contribute to reinforcing intergroup conflict, for example by more easily inciting community members to participate into occurrences of scapegoating against other communities. If governments fail in their policy response to the epidemic, this may negatively impact trust and communities may turn inward to rely on their social networks to weather the shock. However, if bridging social capital is strong and there is confidence in the government's response, then an epidemic can instead foster sentiments of compassion beyond one's community.

Unfortunately, there is little research on the theoretical relationship between epidemics, social capital and social conflict, one exception being Aassve et al (2020) who show that the 1918 Influenza lowered social trust. In particular, they find reductions in social trust for the descendants of people who migrated to the U.S. from countries more heavily hit by the epidemic. More generally, during an epidemic, bonding social capital could help individuals weather the negative life satisfaction effects from increased mortality and economic decline. At the same time, if bridging social capital is weak, in other words if there is mistrust between communities and/or with regard to government action (thus weakening it), bonding social capital might contribute to reinforcing intergroup conflict, for example by more easily inciting community members to participate into occurrences of scapegoating against other communities. If governments fail in their policy response to the epidemic, this may negatively impact trust and communities may turn inward to rely on their social networks to weather the shock, with possibly negative consequences for long-run development. However, if bridging social capital is strong and there is confidence in the government's epidemic response, then an epidemic can instead foster sentiments of compassion beyond one's community, and thus expand generalized social capital.

3. Past and More Recent Epidemics, Poverty and Scapegoating

3.1 Epidemiological and Non-Epidemiological Characteristics

The mortality rate of a disease depends on its contagiousness - measured by the *basic reproduction number* (R0) - and deadliness - measured by the *infection fatality rate* (IFR), or *case fatality rate* (CFR) if only diagnosed cases are considered. Contagiousness is reduced as previously infected individuals acquire immunity and policies such as social distancing and contact tracing are implemented and changes in behavior such as wearing masks and washing hands are induced. The reproduction number after accounting for these factors is referred to as the *effective reproduction number*. Likewise, deadliness decreases as medical technology and health infrastructure adapt. Mortality rates can then vary by age or gender or preexisting health or economic conditions. Next, there are various modes of transmission. Epidemics can be water- or insect-borne infectious diseases or can spread through respiratory droplets, sex, or body fluids. As a result, mortality rates could be higher in more developed and connected areas, or in overcrowded poor areas. Finally, epidemics can have symptoms that are particularly visible (i.e., cannot be easily hidden by clothes), novel, and distressing to the eyes.

Non-epidemiological characteristics that may matter are: (i) How economically impactful the disease is; (ii) The economic context in which the epidemic takes places. For example, was the economy thriving or declining, do most people live close to the subsistence level, etc.; (iii) The social context in which the epidemic takes places. For example, are there already some tensions along racial, religious, gender, class, or origin lines; and (iv) The political context in which the epidemic takes place. For example, is the state democratic, benevolent and inclusive, or autocratic, extractive and exclusive, etc.

The following section discusses the scapegoating effects of selected epidemics and pandemics. Note that the characteristics of each epidemic are reported in Table 1.

3.2 The Plagues of Antiquity: How "Natural" Causes Did Not Lead to Scapegoating

Ancient Greece and Ancient Rome were often afflicted by epidemics, including the Plague of Athens (430-427 BC), the Antonine Plague (165-180 AD), Plague of Cyprian (249-262 AD), and the Justinian Plague (541-542 AD). The consensus is that the Antonine Plague was smallpox, the Plague of Cyprian was possibly smallpox or Ebola, and the Justinian Plague was the bubonic plague (Littman, 2009).

During the Plague of Athens, possibly 25 percent of the population of Athens died. At that time, Athens was fighting the Peloponnesian War against Sparta. The plague was overall attributed to natural and economic conditions, in particular a very wet winter and overcrowding (Cohn, 2018).[7] Cohn (2018)

[7] The Plague of Athens was possibly typhus, given the symptoms described by Thucydides and the fact that typhus (spread by lice) was common during times of war and deprivation, and in crowded and unhygienic military and refugee camps in particular. According to WHO (2020a), the CFR is up to 40% in the absence of specific treatment.

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then describes how no minority group was blamed during the plague, and this despite the fact that migrants had higher mortality rates than natives. For example, Samuel Cohn cites the first century BC historian Diodorus Siculus who explained that mortality was high in Athens because many migrants had moved to its "cramped quarters" where they were breathing "polluted air". As such, migrants were seen as the victims of the "polluted air" that caused epidemics, not the instigators.

The Antonine Plague possibly killed as much as 25 percent of the Roman Empire's population (Duncan-Jones, 1994). The contemporary chronicler Galen documents how skin eruption was a particular symptom of the plague, which explains why it was most likely smallpox, whose CFR is about 30 percent in its major form (WHO, 2020b). The fatality rate for infants was particularly high (Barquet and Domingo, 1997). Smallpox was transmitted by breathing the droplets of an infected person coughing, sneezing, or talking, through contact with infected body fluids or contaminated objects. Despite the fact that the disease was particularly lethal and distressing to the eyes (infected individuals had pustules all over their body and face), no major persecutions were recorded by contemporary chroniclers (Cohn, 2018), and this despite the fact that the Roman emperor Marcus Aurelius Antoninus could have blamed it on Christians (who were persecuted then) or foreigners. With the plague, the Roman Army was devastated. In addition, due to extreme labor shortages, wages suddenly increased. The Roman state and elite needed soldiers and laborers. This could explain why authorities became more charitable and tolerant during the period. Marcus Aurelius' "strategy for maintaining stability during the plague was not to blame any social group or foreigners" (Cohn, 2018). State subsidies were granted to help the poor bury their dead and slaves and foreigners were hired as soldiers.

The Plague of Cyprian was either smallpox or Ebola and mortality was particularly high (Harper, 2017). Chroniclers around that time attributed the plague to natural causes, specifically "corrupted air" (see Harper 2017, Cohn 2018). Until the 19th century, and especially in Antiquity, the dominant theory of why infectious diseases existed was the miasma theory according to which diseases were caused by poisonous vapors, or "bad air" (Last, 2007).[8] Poisonous vapors were then thought to come from rotting organic matter (e.g., corpses that were neither buried or cremated) in rivers and overcrowded areas with poor hygienic conditions, while extreme winters or summers made the "bad air" worse. The same was said of military sieges because of the inability to bury the dead.

Finally, the Plague of Justinian (541-542) killed 25-50 percent of the population of the Mediterranean basin. The bubonic plague was a particularly lethal and frightening disease. CFRs in the pre-modern era were 50-60 percent (Benedictow, 2005, 2010). Symptoms were gruesome and included the formation

[8] *Miasma* means bad air in Greek and bad air is *malaria* in Italian.

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of large buboes as well as necrosis of fingers, toes, the nose, and lips. Major episodes of bubonic plague were caused by the bacterium *Yersinia pestis* which was transmitted by the fleas of the black rat.

Crops went unharvested and herds untended, food was exhausted, and urban economic activities collapsed (Little, 2008). In the medium run, wages increased, which reduced inequality (Scheidel, 2018). Authorities initially tried to prevent any improvement in the bargaining power of workers (Little, 2008). At the same time, Justinian “stepped in, sending the military to assist civilians and to distribute money to them” and “gave from his own purse to ensure that piles of the plague dead would be buried” (Cohn, 2018). Foreigners were invited to settle in what were then the border provinces of the Empire, for example Lombards – a Germanic people – in present-day Lombardy, and Arabs in Roman Syria (Little, 2008). As such, because the bubonic plague was explained by “bad air” (Cohn, 2018), the elite did not blame particular groups. If anything, acute labor shortages implied that migrants and the poor needed to be better integrated. Thus, tolerance prevailed over scapegoating.

3.3 The Black Death and the Mass Persecution of Jews

The Black Death (1347-1352) killed 40 percent of the population of Europe but England, France, Italy and Spain lost 50-60 percent of their populations in just one or two years (Benedictow, 2005, 2010). Indeed, the medical profession and authorities did not understand the role of black rat fleas in spreading the disease. Medical knowledge was rudimentary. Prevention measures were non-existent: the practice of quarantine was not employed until 1377, 25 years after the Black Death (Gensini et al, 2004). Its symptoms were frightening – large black buboes would form all over the body and extremities would turn black - and its CFR was very high, at 70 percent. Death rates were then surprisingly similar across groups. Christakos et al. (2005) writes that the Black Death, was “massive and indiscriminate, making no exception to factors such as personal hygiene, health, age, sex, or social class.”

Initially, European economies were severely affected (see Campbell (2016) and Jedwab et al. (2020a,b) for a summary of the effects of the Black Death). In rural areas, harvests went uncollected (Robbins, 1928), and food prices increased (Munro, 2003). In cities, trade was disrupted, causing an “urban crisis” (Nicholas, 1999; Hohenberg, 2004). However, due to labor shortages, nominal wages increased (Routt, 2018). Real wages, however, rose only gradually, once the inflationary pressures induced by trade and supply chain disruptions subsided. In addition, authorities tried to limit wage demands (Routt, 2013).

Following the plague numerous states and localities encouraged migration by giving immigrants citizenship rights, tax exemptions, housing, etc. (Byrne, 2012). In urban areas, the wealthy needed servants and sectors needed craftsmen. In rural areas, landowners needed tenants. As a result, “the first few years after the epidemic witnessed especially high migration rates” (Poos, 1991). More generally, the plague contributed to the weakening of serfdom in Western Europe (Bailey, 2014).

During the pandemic itself, the plague was initially attributed to the "vengeance of God" or the "conjunction of certain stars and planets" that caused "bad air" (Horrox, 1994). However, the plague was eventually attributed to the poisoning of wells by Jews, which led to mass expulsions and murders.

In the Medieval era, Jews were non-citizens of the cities where they lived. As such, city authorities could ask them to leave anytime. Jews were then particularly represented among doctors, and were thus blamed for spreading the plague (Cohn, 2007). In 1348, Jews were tortured in Switzerland and forced to admit to poisoning wells which, in turn, started the rumor that Jews had caused the disease.

Scapegoating Effect. Why were Jews blamed? It was the apocalyptic scale of the plague that made individuals who already suspected Jews of conspiring against Christians blame them for causing the plague (Moore, 1987). In addition, people resented the fact that Jews were specialized in moneylending and charged high interest rates (given the lack of financial competition). Jews also worked as tax collectors, and people resented the high taxes they were paying to city authorities. Finally, many doctors in Medieval times were Jewish, giving rise to suspicions regarding their knowledge of poisons.

This suggests that the probability of persecuting the Jews was likely to increase with plague virulence. Studies point to the plague as a direct cause of unprecedented scapegoating of Jewish communities (Cohn, 2007; Voigtlander and Voth, 2012). In Germany, Austria, and other Central European countries, mass persecution against 235 Jewish communities were recorded during the pandemic (Cohn 2018).

Complementarity Effect. In aggregate, the scapegoating effect dominated the unifying incentives, and complementarities effects. Yet, locally, Jedwab et al. (2019) find strong evidence for the complementarities effect, in that higher-mortality cities persecuted their Jewish community *less*, not more.[9] Jews played a vital role in relatively high-skilled trades such as money-lending and trade, and the economic value they generated was clearly recognized at the time (Chazan, 2010). This protective effect was especially likely given that many cities relied on special taxes paid by Jews (Johnson and Koyama, 2019). Many cities took extra steps to protect their Jewish quarters against mob violence, for example Regensburg in Germany which was able to reach new heights of prosperity by offering asylum to rich Jewish refugees in the aftermath of the Plague (Wasserman, 2007). Similar motivations explain why leaders in Strasbourg, Basel, and Freiburg agreed that the Jews should be protected from popular demands for persecution (Rowan, 1984). Consistent with this, Jedwab et al. (2019) find stronger protective effects in cities where Jews were moneylenders and important merchants.

Jedwab et al. (2019) find that Jews were also more likely to be persecuted in towns where people were inclined to believe antisemitic canards as measured by past antisemitic actions. Starting with the First Crusade (1096), persecutions were increasingly perpetrated against Jews. From the 12th century

[9] They use data for 124 European cities with Jews present in 1347 and for which they know Black Death mortality.

onwards Jews were accused of ritually murdering Christian children. They find that the protective effect of high mortality was attenuated for towns closer to where such accusations were made. The protective effect was also weaker in cities first infected during Christmastide and Easter — when Christians blamed Jews for the death of Jesus — and stronger for Advent and Lent — when Christians were doing penance. In these cities, antisemitism thus outweighed economic considerations.

Finally, standards of living did not increase right away with the Black Death, so the labor scarcity effect was not important to explain these patterns. There is also not much evidence for a "come together" effect, as the only motivation city officials mentioned then was the economic future of their city.

Thus, these results suggest that epidemics can lead to biases against minorities manifesting themselves as persecutions, with conspiracy theories one of several mechanisms through which scapegoating spreads. However, when minority and majority groups engage in economically complementary activities, then these relationships may be a powerful way to reduce inter-group conflict.

3.4 Plague Recurrences and Accusations of Plague Spreading

Subsequent outbreaks of bubonic plague reoccurred for a few centuries following the Black Death. These plague recurrences were caused either by local plague reservoirs or the repeated reintroduction of the bacteria from Asia (Schmid et al., 2015). In general, only a few cities at a time were affected, and mortality was much lower than in the initial pandemic (Aberth, 2010). In addition, when such recurrences occurred, the poor were disproportionately affected (Alfani and Bonetti, 2019, Alfani, 2020).[10] Such recurrences eventually disappeared in Europe, but the plague struck Asia at the turn of the 20th century as will be discussed below. Indeed, European black (*Rattus Rattus*) rats were through natural selection replaced by brown (*Rattus Norvegicus*) rats in the 18th century.

Cohn (2018) argues that subsequent plague outbreaks did not lead to scapegoating, but more compassion instead. First of all, plague epidemics led to peace movements and the constitution of organizations that provided for the poor. Bornstein (1993) describes how the religious movement "The Bianchi" that emerged in Florence in 1399 called for peace between warring Italian cities and convinced many to give up arms and also help the poor. Second, when plague recurrences did cause accusations of "plague spreading", it was later in the 16th and 17th centuries, and Jews or the poor were not systematically targeted.[11] If anything, accusations of plague spreading increasingly focused on non-Jewish members of the community, in particular people who financially benefited from plague outbreaks lasting longer, such as workers who removed corpses during plague events or the members

[10] Alfani and Bonetti (2019) writes "The historical literature […] seems to have clearly established that, in contrast to the Black Death and other early plague waves, the disease acquired a social character from the fifteenth century, striking the poor preferentially." As the disease mutated, and mortality decreased, pre-existing conditions became more determining.

[11] Cohn (2018) describes how Jews were sometimes accused to be "plague spreaders" but few occurrences of plague-spreading related persecutions have been recorded. Thus, accusations almost never led to acts of organized violence.

of city health boards and physicians (who were not generally Jews anymore). In particular, it was often alleged that plague spreaders were purposely greasing doors and doorknobs with poison or directly sprinkling poison in the streets (Davies, 2016). Such conspiracies often led to the arrest and execution of "plague greasers", but victimization in these cases was limited to a few selected individuals being targeted by conspiracies and trials, rather than whole ethnic or class groups (Cohn, 2018).

However, Alfani (2020) explains that the "socially-selective character of epidemic mortality does not depend purely on environmental factors […] or biological factors, but it is also determined by institutions and human agency." One could thus argue that authorities and elites, through prejudice, ignorance and bad policy more generally, passively contributed to the exterminating effects that plague recurrences and other epidemics exhibiting patterns of selective mortality had on poor populations (see Alfani, 2020 for a recent survey of the literature on epidemics and inequality in mortality).

3.5 Syphilis and the Scapegoating of Foreigners, Migrants and Sex Workers?

Syphilis spread in Europe after the discovery of the Americas in 1492. The first recorded syphilis epidemic took place in Naples after it was invaded by French troops in 1494-1495, and it thus became known as the "French disease". Syphilis is transmitted by sexual contact with the infectious lesions of another person. Infected individuals initially develop skin ulcerations and a rash. Eventually, they experience non-cancerous growths and neurological or heart problems (Kent and Romanelli, 2008). If untreated, it has a mortality rate between 8 and 58 percent (Ibid). However, since few people ended up infected, overall mortality rates were usually low. Lastly, because it was sexually transmitted, it was associated with prostitution and more likely to be found in cities (Craddock, 2004). In addition, invading armies and migrants were often spreaders of syphilis. As such, it is not surprising that syphilis was seen as a disease of foreigners. It was "the Neapolitan disease outside Naples, the French disease outside France, the Polish disease in Germany, the German disease in Poland [...]" (Cohn, 2012).

Were foreigners, migrants or sex workers more likely to be scapegoated as a result? Cohn (2018) explains that people saw the disease as "God's punishment of sin", since it was associated with sexual activities that were frowned upon by the Church, but also because stars and planets were misaligned.[12] Consequently, infected individuals were either not responsible or they were responsible because they had sinned. Second, Cohn (2018) argues that naming is not blaming. Even if syphilis was often called the French disease, it did not lead to the persecution of French individuals (or migrants in general). Third, while authorities often criticized the existence of houses of prostitution, syphilis epidemics did not lead to the persecution of sex workers. Fourth, if anything, the persecution of female sex workers began only after the first effective treatment for syphilis was discovered in 1909. Indeed, once a

[12] Syphilis means "swine love" in Greek (Tannenbaum, 1918), reflecting its association with sexual promiscuity.

treatment became available, women who still had syphilis came to be seen as "guilty" (Cohn, 2018). During both World Wars, health boards in the U.S. incarcerated thousands of infected female sex workers (Brandt, 1987). Today, however, infection rates have been considerably reduced.

3.6 The Cholera Pandemics and the Cholera Riots of the 19th Century

While cholera was prevalent in India before the 18th century, it began to spread to North America and European cities from 1826 (Clemens et al., 2017). It then became a global pandemic, with each outbreak killing several hundred thousand people. Indeed, cholera had a very high CFR of 50 percent in the 19th century. At the time, cholera disproportionately killed children and the poor (Ali et al., 2012; Clemens et al., 2017). It is a water-borne infectious disease, meaning it is transmitted through the fecal-oral route of contaminated water. Cholera epidemics have become much less lethal in the 20th century, thanks to improved sanitation and improved access to clean water (Cutler and Miller, 2005). Understanding and controlling cholera outbreaks became particularly important in the fast-growing, and thus congested and poorly infrastructure-endowed, cities of 19th century Industrial Europe and North America. For example, Chicago lost one-twentieth of its population in 1854 during the third cholera pandemic (Ashraf et al., 2016). Finally, the symptoms of cholera are particularly frightening, such as violent diarrhea and vomiting of a clear fluid that looks like "rice water" and also because the skin turns bluish-gray due to extreme loss of fluids (cholera was called "blue death").

After the second cholera pandemic of 1826-1837, doctors and authorities believed the disease came from people living in poor environments. For example, when the third cholera pandemic spread in the U.S. in 1849, it was believed that the disease was brought from Europe by Irish immigrants that came as a result of the potato famine of 1845-1849 (Rosenberg, 1987). The prevalent "miasma theory" of the times ascribed the source of cholera to bad airs (in this case, coming from poor overcrowded areas). However, in the 1850s, the germ theory of disease became more established (Mokyr and Stein, 1996). In 1857, a discovery by the London physician John Snow changed the way people thought about water and the propagation of disease. Using observational statistics and a "Ghost Map", he traced the deaths from the cholera epidemic that swept London in 1854 to a sewage-contaminated water pump used to supply household water. In this way, John Snow demonstrated that cholera epidemics were due to water sources being contaminated with human waste, not because of foul air (Ambrus et al., 2020). Some years later, in 1883, during the fifth cholera pandemic, Robert Koch isolated the cholera bacillus firmly establishing the link between bacterial contamination of water and cholera outbreaks.

Few other infectious diseases such as cholera "triggered violence even after their agents and mechanisms of transmission had become well known" (Cohn, 2012). Indeed, violent "cholera riots" took place in many cities of various industrializing nations throughout the 19th century (Cohn, 2012, 2017). Cholera disproportionately killed the urban poor, especially children, and life in 19th century

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industrial cities was dominated by a constant, and already violent, class struggle between the bourgeoisie and the proletariat. In addition, measures to contain cholera outbreaks (quarantines, checkpoints, etc.) also disproportionately affected the economic livelihoods of the urban poor who, in European cities, were usually migrants from rural areas. In U.S. cities, many of the urban poor were recent immigrants, and cholera was thus not surprisingly called the 'Strangers' Disease (Cohn, 2012). Overall, it is likely that the cholera outbreaks added fuel to a smoldering social fire.

Violent cholera riots took place in British towns in 1831-1832, especially as the population believed "elites with physicians as their agents had invented the disease to cull populations of the poor" (Cohn, 2018). Indeed, just thirty years before, Thomas Malthus wrote his infamous book *An Essay on the Principle of Population* in which he criticized the working class's tendency to reproduce rapidly. Throughout the early 19th century, British politics was dominated by Malthus' ideas such as the question of whether poverty relief created a vicious cycle by encouraging the poor to be idle and reproduce instead of working. This led to the Poor Law Amendment Act of 1834 according to which poverty relief would only be given in workhouses. In addition, the population believed doctors and hospitals were scheming to exterminate their patients so as to sell their bodies to anatomical schools. In 1828, just three years before the riots took place, two individuals were charged with murdering sixteen people in order to supply a doctor with bodies for his anatomy lectures. As Cohn (2018) explains, the "trial filled British newspapers, and remained alive in the minds of the poor when cholera reached Britain." Likewise, authorities buried cholera victims rapidly, and in separate cemeteries (cholera pits), which infuriated populations because victims were not given a decent burial (Cohn, 2018). Riots broke out in industrializing cities with high shares of impoverished migrants. Doctors, hospitals and their equipment were violently attacked. Patients in such hospitals were "liberated".

Violent cholera riots also took place in Russian cities when the second pandemic reached them in 1830-1831. 100,000 members of the lower classes died and "rumors that the aristocracy and upper classes were responsible for the plague set off insurrections" (Bosin, 2009). "The rumor that doctors poisoned the wells sparked a wave of bloody riots throughout Russia, with large crowds sacking affluent households, smashing quarantines, and killing medical personnel." Insurgents destroyed ambulance carriages, sacked hospitals and murdered doctors. Cholera riots re-occurred frequently after that in Russia. In 1892, the tsarist regime had to send the army to regain control of cities (Friedgut, 1987).

Finally, cholera riots also occurred in China in 1892. In the 19th century and after a series of military defeats, the Qing Dynasty had to grant territorial concessions to various colonial powers. In these mostly urban concessions, Chinese individuals were treated as second-class citizens. Unsurprisingly, most of the cholera riots that took place that year targeted Westerners, who were accused of poisoning wells (Cohn, 2018). Mobs attacked Western neighborhoods and murdered Western residents.

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Cholera led to similarly violent riots in other countries throughout the 19th century, because the context was similar. Cohn (2017) argues that “the content and character of the conspiracy theories, divisions by social class, and the targets of rioters’ wrath were uncannily similar.” Cohn (2017) also explains that rumors were more likely to spread and revolts be violent “where elites continued to belittle the supposed ‘superstitions’ of villagers, minorities, and the poor, violated their burial customs and religious beliefs, and imposed stringent anti-cholera regulations even after most of them had been proven to be ineffectual. Moreover, ruling elites in these places addressed popular resistance with military force and brutal repression.” Cholera riots continued even after the mode of transmission of cholera was identified, because of the establishment’s reluctance to cater to the needs of the poor and due to widespread distrust in the motives of the government. Over time, cholera riots changed from being against government controls to being in favor of such controls (Cohn, 2018). For example, in Italy in 1884, people “protested against authorities’ laxity in handling the cholera outbreak.”

3.7 Smallpox Outbreaks and Social Violence in the 19th Century

Smallpox particularly impacted North American cities in the 18th and 19th centuries. Smallpox was very lethal, especially for children, could be transmitted in various ways (droplets, body fluids, objects), and exhibited distressing symptoms (pustules all over the body and face).

Much like cholera, smallpox caused class conflict, but this time the poor and diseased victims were scapegoated (Cohn, 2018). Indeed, the major difference between cholera and smallpox is that inoculation for smallpox was adopted as a practice as early as the 18th century and a vaccine was developed by the British physician Edward Jenner in 1796 (Wolfe and Sharp, 2002). Smallpox victims were disproportionately found among the poor and less educated and were seen by the elite as “guilty” for their infection. Since smallpox epidemics forced governments to adopt economically harmful quarantine measures, property owners, merchants, and local authorities were the ones targeting the poor and diseased victims. Cohn (2018) lists many cases of “vigilante violence and brutal neglect of smallpox victims by neighbors, along with collective violence from gangs of ten to riots of thousands.”

For example, various communities were scapegoated during the 1881 smallpox epidemic, especially individuals of Chinese origin as it was wrongly believed that smallpox came from China. Why this group in particular? Following the Burlingame Treaty of 1868, Chinese migration to the U.S. was encouraged. However, natives saw Chinese immigrants as an economic and cultural threat. Anti-Chinese sentiment grew, and the Page Act of 1875 prohibited the entry of Chinese women whereas the Chinese Exclusion Act of 1882 prohibited all immigration of Chinese laborers. Chinese immigrants were then forced to live in ghettos, “Chinatowns”. Because such areas were overcrowded, they may indeed have exhibited higher smallpox rates. Eventually, all migrant communities came to be seen as hotspots for smallpox outbreaks, no matter whether migrants came from abroad or were internal

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migrants. Cohn (2018) describes how smallpox outbreaks were also blamed on "immigrant trains" in California, in other words, trains that brought in migrants from the East.

Likewise, smallpox hospitals and victims were targeted by violent mobs. For example, the New York Marine Hospital in Staten Island was the largest quarantine facility in the U.S. in the 1850s, 40 years prior to the construction of the Ellis Island immigration station. Because residents believed the facility was responsible for local smallpox outbreaks, which then harmed property values, it was attacked by a mob, one doctor was shot, and 32 buildings were burned (Stephenson, 2004). Next, in Montreal in 1885, English papers blamed smallpox outbreaks on French-Canadians because of their 'filthy customs' and 'ignorance of vaccination' (cited in Cohn, 2018). Eventually, compulsory vaccination in French areas sparked riots against "health authorities, the police, mayor, and eventually, the military".

3.8 Yellow Fever Outbreaks in the U.S. Deep South in the 19th Century

Yellow fever is a virus that is spread by the bite of an infected *A. aegypti* mosquito. The role of mosquitoes as a carrier of the disease was not understood until the late 19th century. The first vaccine against yellow fever was developed in 1937. Before that time, yellow fever had relatively high case fatality rates (between 7.5 and 50 percent), and was seen as a dangerous infectious disease (Tomori, 2004; Oldstone, 2012). Originating from Africa, it spread to the rest of the world with the slave trade and colonization. Yellow fever epidemics were particularly frequent in the Americas, including in the South of the U.S. where it killed 100,000-150,000 people during the 19th century (Patterson, 1992). In 1793, yellow fever killed 9 percent of the population of Philadelphia, then the U.S. capital (Miller, 2005). New Orleans was also repeatedly plagued by the disease. In Memphis in 1878, 70 percent of whites who remained in the city once a yellow fever epidemic broke out perished (Cohn, 2018). Yellow fever disproportionately kills older adults in more urban areas (Humphreys, 1999; Blake and Garcia-Blanco, 2014).[13] It is accompanied by severe fever, jaundice (the skin and whites of the eyes turn yellow), bleeding through the mouth, nose and the eyes, and the vomiting of blood.

Cohn (2018) documents how the yellow fever epidemic of 1793 in Philadelphia did not lead to social violence. In particular, African Americans, who possessed greater immunity to it because their African ancestors had historically been more exposed to it (Blake and Garcia-Blanco, 2014), were not blamed. Likewise, when yellow fever hit New Orleans in 1853, poor Irish immigrants who were greatly affected were not blamed. African Americans were again not blamed (Carrigan, 1961).

Cholera and yellow fever are both lethal, killed the urban poor, were mysterious for most of the 19th century, and had frightening symptoms. Why did yellow fever not lead to riots? One possibility is that

[13] Uncovered water installations in informal urban areas and repeated floodings due to poor drainage provide breeding grounds for mosquitoes. Rural areas close to bayous as in the U.S. South could also be severely affected.

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cholera disproportionately killed children whereas yellow fever killed older adults. Another possibility that could explain why African Americans were not blamed is because they were particularly "needed" due to their immunocapital. Many were slaves in plantations (Olivarius, 2016). In cities, sick White residents needed African Americans to help them with domestic tasks and businesses.

3.9 The Third Plague Pandemic of 1894-1901 and Revolts Against Colonial Powers

The Third Plague Pandemic of 1894-1901 was a milder form of bubonic plague than the Black Death, as it killed between 30 and 60 percent of infected and untreated individuals (WHO, 2020c). In most cases, infected individuals had only one bubo found in the groin.

In India, where it killed 1 million people, the plague led to violent riots in 1896-1898, but mostly as a result of heavy-handed and inefficient policies adopted by British colonial authorities that strongly, and wrongly, believed in extreme sanitarianism. Severe quarantine controls were imposed, infected individuals were taken to segregation camps and their houses and belongings burned without compensation, slum areas were destroyed, religious temples and cemeteries were closed, and male doctors forcibly examined women against the will of their communities (Cohn, 2018). In addition to the coercive anti-plague policies by the colonial state, the policies also had a pronounced class bias in the urban context. This was borne out of the belief that the urban poor, and not the "respectable class" of Indians, were the vectors of disease spread in cities. Hundreds of huts were set on fire or razed to the ground in the poor neighborhoods of Bombay (Kidambi, 2004). There were first peaceful protests organized against what people saw as abusive policies by colonial authorities. However, as the protesters' pleas for more respectful control measures were ignored, riots emerged in large Indian cities. Medical workers and British officers and hospitals and government buildings were attacked.

Interestingly, protests against colonial policies did not lead to a backlash against Western medicine (Cohn, 2018). The bacterium for the plague, *Y. Pestis*, and its mode of transmission via the bites of rat fleas, were discovered in 1894. The Indian press was aware of these discoveries and asked British authorities to be more "scientific" in their control policies. Another interesting fact is that the plague unified Hindus and Muslims, as they joined mass protests against colonial authorities.[14]

3.10 The 1918 Influenza

The 1918 Influenza (1918-1920) killed about 2.1 percent of the world's population (Barro et al, 2020). It was transmitted by breathing in droplets from an infected person coughing, sneezing, or talking. Its CFR was then at least 2.5 percent (Taubenberger and Morens, 2006). The 1918 influenza killed the

[14] Plague riots occurred in China in 1893-1894. Chinese residents complained about the overzealousness of plague regulations adopted by colonial authorities in the concessions (Cohn, 2018). Plague outbreaks also led to conspiracy theories according to which Western colonial powers and their agents (e.g., missionaries) were poisoning wells to get rid of Chinese residents.

"very young, those around age 30, and the elderly" (Almond, 2006b; Beach et al., 2020) – thus exhibiting a W-shape – and the poor (Mills, 1986; Mamelund, 2006, 2018). Comparing mortality rates across locations, the higher infection rates in more connected, and thus generally wealthier, areas were compensated by higher infection fatality rates in less developed regions with poorer health infrastructure, generating a negative relationship between mortality and economic development (Barro et al., 2020; Beach et al., 2020). Finally, its symptoms are not particularly frightening to the eyes.

By the time of the 1918 Influenza, the germ theory of disease was already established. "Public health officials and many members of the public understood the importance of hand washing and covering the mouth and nose to reduce transmission of tuberculosis, a lesson that translated readily to influenza [and] schools had been closed and public gatherings had been limited before" (Beach et al., 2020). At the same time, the medical ability to respond to the 1918 Influenza was limited by a lack of knowledge about the virus, limited health care capacity, and the fact that antibiotics and vaccines did not exist yet (Jester et al., 2019; Beach et al., 2020). Non-pharmaceutical interventions – school closures, quarantines, and bans on public assemblies – were implemented (Markel et al., 2007; Jones, 2010), but often in a haphazard way and for a limited period of time (Clay et al., 2018; Barro, 2020).

Barro et al. (2020) show how countries that experienced higher mortality rates saw their economy collapse. They find some evidence for recovery, but the estimated effects are not significant. In the US, the pandemic killed 0.5-0.8 percent of the population and led to a historic downturn in the economy (Beach et al., 2020). However, the pandemic only led to a brief V-shaped recession (Velde, 2020).

The 1918 Influenza was historically called the 'Spanish flu' because of its believed origin in Spain. However, naming is not necessarily blaming. The 1918 Influenza led to few cases of scapegoating. Collier (1996), Crosby (2003), and Cohn (2018) describe how, in the face of collapsing public services, the 1918 Influenza led to compassion and self-sacrifice by both individuals and entire communities.

According to Cohn (2012), the fact that the 1918 Influenza "provoked no major riots or religious and sectarian hatred is more remarkable still" given the fact that "the pandemic exploded in the midst of war frenzy and heightened nationalistic hatreds". Anti-migrant sentiment was also particularly rife in the US, as politicians and the public criticized shifts in immigrants' origins from Northern and Western Europe to Southern and Eastern Europe as well as Mexico and Asia (Jaret, 1999). Actually, the 1918 Influenza brought native and migrant communities together, as shown for the US by Kraut (2010).[15]

3.11 The Global Spread of HIV Since the 1980s

[15] Kraut (2010) writes: "Because this influenza struck individuals of all groups and classes […], no single immigrant group was blamed" and the epidemic did "not appear to have triggered a wave of medicalized prejudice". In particular, "foreign-born physicians, ethnic community leaders, and the foreign language press were important mediators between public health officials and immigrants. They labored to diminish fears of the native-born that newcomers might be responsible for the epidemic".

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HIV is spread sexually and its CFR without antiretroviral therapy (ART) is about 80-90 percent ten years after the infection. In the 2000s, about 25 percent of pregnant South Africa women had HIV, and the share of infected individuals who had access to ART was below 20 percent for most of the decade (South Africa, 2011). As a result, a significant share of South Africa's population died of HIV post-2000. HIV is dominantly a trade-related and urban disease (Oster, 2012; Djemai, 2018), and within urban areas poorer residents have higher prevalence rates (CDC, 2016).

Since HIV disproportionately kills sexually active (i.e., working-age) adults, Weil (2010) explains how HIV impacts growth by increasing dependency ratios and Young (2005) describes how HIV has a negative impact on the human capital accumulation of orphaned children. At the same time, if individuals are less willing to engage in unprotected sexual activity, or if labor scarcity increases the value of a woman's time, increased HIV prevalence could lower fertility, which could permanently increase incomes per capita. Young (2005b) simulates the impact of the AIDS epidemic on living standards in South Africa and finds that the positive fertility effect dominates the negative human capital effect, meaning that per capita incomes increase on average (for survivors only).[16]

The spread of AIDS in the 1980s led to the scapegoating of groups in which the disease was said to be more prevalent. HIV was initially called the "4H disease" by officials of the U.S. Center for Disease Control, because the disease seemed to disproportionately affect heroin users, homosexuals, hemophiliacs, and Haitians (Gilman, 1987). In Africa in the 2000s when the disease was still relatively unknown, there were many cases of targeted violence where infected individuals would be murdered (Iliffe 2005; Cohn, 2018). Persons living with HIV still suffer from discrimination today. Chin (2013), dos Santos et al. (2014) and Durevall and Lindskog (2015) all find that HIV increases intimate partner violence in Africa. Likewise, because homosexuality is associated with HIV, LGBT people are often discriminated against (Badgett, 2014). Yet, HIV did not lead to "riots and collective acts of physical violence" (Cohn, 2012). Of course, the stigmatization of people with AIDS is unacceptable. Denialism and stigmatization also increase the likelihood that infected individuals do not get tested and do not seek medical care, which helps spread the disease (Gersovitz, 2011).[17]

3.11 The African Ebola Outbreaks of the 2010s

10,000 people died during the 2014-2016 Ebola Outbreak in West Africa (or 0.04 percent of the total population of the three affected countries: Guinea, Liberia and Sierra Leone) and 2,500 people have died so far since the Kivu Ebola Epidemic broke out in 2018 (0.003 percent of the population of the

[16] Bloom and Mahal (1997) and Fortson (2011) find similar results. It might be that the negative individual, household, and firm level effects estimated in the literature are compensated by positive effects at the sector or national level (Mahal, 2004).
[17] In the 1990s in Apartheid South Africa and in other African countries and Haiti, rumors claimed that the white had created the disease to convince Africans or Haitians to have sex less often, and thus fewer kids (Cohn, 2018).

Democratic Republic of the Congo). Ebola is a threatening disease due to its high CFR (50 percent) and the fact that it can spread through any body fluids, whether saliva, mucus, feces, sweat, tears, urine or semen (WHO, 2020d). While Ebola outbreaks start in rural areas, the fact that it spreads through body fluids makes it dangerous for cities (Zinszer et al., 2017; Levy and Odoi, 2018). Thus, slum areas with worse sanitation facilities, "poor health infrastructure, lack of health education, and inadequate government-enforced quarantine", and where migrants live, act as Ebola hotspots (Snyder et al., 2014). Young children are the most likely to die, and adults tend to die more than older children (WHO Ebola Response Team, 2015). Symptoms include severe diarrhea, vomiting, and hemorrhaging.

The economic impact of Ebola was important for the affected economies (Huber et al., 2018). Food production decreased (de la Fuente et al., 2020), and there was a significant decline in foreign direct investment, tourism, and trade. Urban sectors were particularly affected as a result of the strict lockdown measures adopted by authorities (Bowles et al, 2016).

Ebola outbreaks have led to localized but nonetheless violent attacks against health and government officials and Ebola clinics (The Washington Post, 2015, 2019). Health and government workers were murdered by protesters, as in Womey in Guinea in September 2014. In other cases, health and government workers were attacked for spraying disinfectants, for example at a market in Nzerekore, a Guinean mining town with a high share of migrants (The New Yorker, 2014). The lack of communication by authorities and the fact that many local young people already felt excluded from economic opportunities led many of them to violently protest about such operations. In addition, Ebola victims were rapidly buried by authorities without taking into account cultural and religious considerations, which also incited protests (Manguvo and Mafuvadze, 2015). Consequently, international organizations have been pushing for "safe and dignified burials" (Tiffany et al, 2017).

Distrust in the government, the health sector, and foreign aid agencies already existed prior to the outbreaks. Instead of engaging communities and building trust, economically harmful containment efforts were imposed with a top-down approach, which led to a backlash against the authorities (Cohn and Kutalek, 2016). Thus, rumors spread that government agencies and international organizations planned the outbreak and that the organs of the dead were harvested and sold (Hayden, 2019).

4. Summary of the Possible Determinants of the Scapegoating-Epidemic Relationship

4.1 How Often Did Epidemics lead to Scapegoating?

The Black Death of 1347-1352 led to the mass persecution of Jews, and the Cholera, smallpox, and plague riots of the 19th century and the Ebola outbreaks of the 20th century led to murderous attacks against health and governments officials, which is referred to as the *violent scapegoating scenario* here. When other outbreaks – plague recurrences after the Black Death, syphilis, the 1918 Influenza and HIV

- led to scapegoating, they did not necessarily cause social violence, which is referred to as the *mild scapegoating scenario* here. More typically, minority groups were blamed for disease outbreaks, which led to cases of medicalized prejudice, discrimination, and individual cases of targeted violence. Finally, the plagues of Antiquity and the yellow fever outbreaks of the 18th and 19th centuries did not particularly lead to scapegoating social violence, which is referred to as the *non-scapegoating scenario* here.

Based on Table 1, nine out of the fourteen major epidemics discussed in this paper, i.e. slightly more than two thirds, led to scapegoating. Among these, about half of them were cases of violent scapegoating and the other half consisted of cases of mild scapegoating. Among the cases of violent scapegoating, only the Black Death led to mass murders. In the three other cases, violent riots took place. However, the number of victims was small, as riots focused on properties.

There are also many cases in which epidemics led to greater compassion and increased social cohesion. It could be that the scapegoating effect was not as strong as expected, possibly because there was less polarization to start with, and/or that the come together effect highlighted by Cohn (2018) and the labor scarcity and complementarities effects highlighted by Jedwab et al (2019) were stronger than expected.

To answer the first question on whether epidemics on average cause social violence, one would need (much) better data on all events that ever took place, including their mortality rate, as well as data on all occurrences of social violence during and after an outbreak. As argued by Cohn (2012), there is a selection bias due to the fact that the literature and the media focus on the most extreme examples of minority persecution during epidemic times instead of studying *all* epidemics.

4.2 How Did the Scapegoating-Epidemic Relationship Change Over Time?

In the absence of better data on epidemics, this paper studies the broad patterns highlighted by Table 1. First of all, the plagues of Antiquity did not cause scapegoating. They all have in common that contemporaries explained them by natural causes, in particular the fact that the cities of Ancient Greece and Ancient Rome had "bad air" (i.e., toxic foul smell) due to the combination of external causes (extreme changes in the weather) and internal causes (overcrowding and military sieges).

Most violent cases of scapegoating took place between the 14th and 19th centuries (included), which were times of political and economic changes and thus uncertainty (which frequent epidemics also contributed to). They were also times of great social upheaval. The Black Death was the most violent pandemic of all. However, it was followed by two much milder cases of scapegoating. Indeed, subsequent plague recurrences until the 17th century and syphilis from the 15th to the 19th centuries led to cases of medicalized prejudice, discrimination, and/or individual cases of targeted violence, but not collective violence. Epidemics that emerged in the 19th century - cholera, smallpox and the plague - led

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to violent riots. Yellow fever, which was important in the 18th and 19th centuries and was often as lethal and frightening as these other three epidemics, did not lead to scapegoating or violence.

Finally, with the exception of Ebola in the 21st century, epidemics and pandemics have since then led to "milder" cases of scapegoating and social violence, including COVID-19 as will be seen below.

Based on this analysis, it appears that the scapegoating-epidemic relationship followed an inverted-U shape over time. In particular, conspiracy theories played a particularly important role in the epidemics of the 14th-19th centuries. Other factors, for example whether governments were non-benevolent and adopted heavy-handed and counterproductive disease control policies, mattered as well. Finally, the relationship weakened in the modern era because societies became more inclusive and governments more benevolent and their disease control policies more established in science.

4.3 Aggregate Mortality and Scapegoating and Social Violence

With the exception of the Black Death, the deadliest epidemics did not lead to scapegoating (e.g., the plagues of Antiquity), or only to the "mild" scapegoating scenario (HIV). One possibility is that high-mortality epidemics dramatically increase the need for social bonding (Section 2.5). In addition, epidemics that kill a lot of people raise wages due to the labor scarcity effect. Lastly, labor shortages make the labor supply, and thus presence, of minority groups particularly valuable. This is all the more true if minority groups provide specialized economic services that can help with recovery.

During the plagues of Antiquity, some evidence can be found for both the social bonding and labor scarcity effects. The Black Death may be the exception that confirms the rule. It had the highest overall mortality rate of all epidemics and it led to the mass persecution of Jews. However, wages did not increase right away because of serfdom in rural areas and wage controls in cities. In addition, cities that experienced higher mortality rates persecuted their Jewish community less, not more. In this case, labor scarcity and economic complementarities were the determining factors, not social bonding. Yellow fever outbreaks were not as deadly as bubonic plague outbreaks but they were at times particularly deadly for some U.S. cities. However, yellow fever outbreaks did not lead to violent riots like cholera or smallpox outbreaks did. Slavery and segregation were at the time ubiquitous in the U.S. and African Americans were affected much less than White Americans. Yet, they were not overtly scapegoated, perhaps because their immunocapital made them particularly valuable for the slave-based economy. Finally, as HIV spread in South Africa, it might have not been so harmful to the economy.

However, low-mortality epidemics did not necessarily cause scapegoating, as evidenced by the 1918 Influenza. Yet, the negative economic impact of the Influenza seems to have been very temporary. The end of World War I also helped in improving living standards, and thus relieving collective stress.

4.4 Emotional Responses to Frightening Diseases and Scapegoating and Social Violence

Humans are not always rational and may more emotionally react to diseases with perceived high CFRs and visibly distressing symptoms. Most outbreaks listed in Table 1 had high CFRs above 30 percent, the only exception being the 1918 Influenza, which did not particularly lead to scapegoating and social violence. It is thus difficult to infer any correlation between CFRs and scapegoating.

However, some of the most violent epidemics were caused by diseases with distressing symptoms that were hard to conceal. The Black Death caused large black buboes all over the body and blackened the extremities. Cholera was frightening, with people having "rice water" coming out of their body and their skin turning blue. Smallpox caused disgust, with pustules and scabs all over the body and face. Ebola also shows frightening symptoms, as blood comes out of all openings in the body (mouth, nose, eyes, ears, etc.). In the cases of the Black Death, cholera, and Ebola, there have also been conspiracy theories that specific groups were using poison to eliminate other groups. At the same time, the Justinian Plague was a bubonic plague like the Black Death, and yellow fever was also seen as a terrifying disease as skin turned yellow and people were vomiting blood. Yet, these two epidemics did not lead to scapegoating. However, other more important factors may have mattered in these cases.

4.5 Selective Mortality, Scapegoating and Social Violence

Most epidemics disproportionately hit cities, possibly because population density and connectedness were important factors of contagion. However, it could be that rural mortality was not well-recorded.

Next, based on Table 1, epidemics appear to have disproportionately killed the poor, especially the urban poor. First of all, the urban poor are more likely to live in overcrowded and unsanitary areas. Second, the poor may have weaker immunity and other comorbidities, making them more likely to die for a given infection risk. Now, are scapegoating and social violence more likely to occur when the "poor", rather than the "rich", disproportionately die? The poor live close to the subsistence level so epidemics may particularly increase stress levels for these populations. Second, high levels of inequality may feed feelings of "relative deprivation", which may erupt in epidemic times. Third, the poor are more likely to die when an epidemic hits, which reinforces feelings of "relative deprivation". Fourth, governments may adopt heavy-handed disease control policies that may disproportionately harm the poor. If these policies are not implemented with the support of important actors in the poor's communities, or if they are not meant to reduce mortality in poorer areas but protect richer areas against contagion from poorer areas, they will be seen as exclusionary. The poor also experience higher levels of chronic stress, an important determinant of displacement aggression. If the poor do not have a voice, there is a higher risk that epidemics lead the poor to riot against the government (or aggress minority groups if the government is too powerful, as was the case with the Black Death). Fifth, the poor are more numerous than the rich. As such, they are capable of forming mobs, and mobs can become violent.

As with the cholera, plague and Ebola riots, such protests turned violent because the authorities implemented policies that were economically harmful and caused mistrust. In the cases of cholera and Ebola, there were conspiracy theories that richer segments of the society used the epidemic and the apparatus of the government and the medical system to eliminate the poor.

Lastly, evidence suggests that epidemics that kill children more are the most socially dangerous. If diseases kill working-age adults, this contributes to labor scarcity and wages increasing. If working-age adults are sick, they may also be less able to commit persecutions. Likewise, diseases that kill the elderly reduce dependency ratios. Epidemics that kill children also lower dependency ratios. However, one could argue that working-age adults become more emotional, and angrier, when they lose their children, because it seems less "natural" than losing older relatives.[18] Cholera, smallpox, and Ebola disproportionately kill children and they all led to violent forms of scapegoating. Syphilis, HIV, and yellow fever kill working-age adults more and did not lead to as violent forms of scapegoating.

4.6 Knowledge of the Disease and Scapegoating and Social Violence

Until the late 19th century, the dominant theory for why epidemics happened was the miasma theory according to which "bad air" due to the weather, the misalignment of planets or unsanitary overcrowding caused people to be sick. As such, specific groups were less likely to be blamed.

While killings by poison took place in Antiquity, poison became a major form of killing in the Medieval and Renaissance periods (Wexler, 2017), as the Islamic Golden Age (8th-14th centuries) contributed to major advances in pharmacology (Hadzovic, 1997). Apothecary shops were open throughout the Middle East and Europe. While such shops sold remedies, they also sold poison. It is thus not surprising that epidemics became increasingly associated with accusations of poisoning. To some extent, this explanation was more scientific than the naturalistic explanations that prevailed during Antiquity.

When the germ theory of disease became more established, some epidemics still led to scapegoating, especially against diseased victims. In the case of the smallpox epidemics of the 19th century, a vaccine already existed in 1796. Victims were blamed because they were viewed as "guilty", either because of their ignorance or their lack of consideration for the rest of society. Likewise, it is only when a treatment became available for syphilis in 1910 that women who still had syphilis came to be seen as "guilty".

Finally, as the determinants of epidemics became more widely understood, as is evidenced by the 1918 Influenza and HIV, persecution probability has decreased. Ebola outbreaks have occurred in some of

[18] The value of statistical life measures how much people are willing to pay to avoid their own death or the death of other people. Such values are higher for children (Zelizer, 1994, Andersson and Treich, 2011, Balmford et al, 2019) because "parents are usually more concerned about the mortality and morbidity risks of their children than for themselves" (Leung and Guria, 2006).

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the poorest places on earth, where lack of access to education and unbiased information is quantitatively important and distrust in authorities widespread and entrenched.

4.7 Social and Political Contexts and Scapegoating and Social Violence

Contexts where rife intergroup tensions already exist are more likely to see occurrences of scapegoating, as was the case during the Black Death (where non-Jews resented the presence of Jews), Europe's Cholera riots (when the poor resented the disdain with which the elite treated them), Asia's Cholera and plague riots (when natives resented the disdain with which colonial officers treated them), South Africa's HIV epidemic (when Black South Africans resented the disdain with which White officers treated them during the Apartheid), and Africa's Ebola outbreaks (when the poor resented the disdain with which the elite treated them). Yet, there are examples of epidemics that united communities despite pre-existing tensions, for example before America's yellow fever outbreaks (when there was widespread discrimination against African Americans), India's plague epidemic (between Hindus and Muslims) and the 1918 Influenza (between natives and migrants in the US).

More generally, more autocratic actions by not-necessarily benevolent governments may have contributed to social violence during epidemic times. During the Black Death, city leaders turned a blind eye to the persecution of Jews, or even organized them. Cholera, smallpox, the plague, and Ebola led to riots because of the distrust populations had toward authorities, especially when authorities excluded local communities from the decisions that were made and actions that were implemented.

5. Epidemic, Poverty, and Social Cohesion: Possible Scenarios for COVID-19

5.1 How COVID-19 Differs from Past and More Recent Epidemics

COVID-19, much like the 1918 Influenza, spreads from inhaling respiratory droplets of infected individuals who are in close contact, and causes mostly an infection in the lungs. A preliminary study (Sanche et al., 2020) indicates a high reproduction number (R0) of up to 5.7 – meaning that one infected person potentially infects 5.7 people, which is higher than 1.4-2.8 for the 1918 Influenza (Coburn et al., 2009). COVID-19 has a high R0 because of its long incubation period. Available estimates suggest a CFR of 5 percent and an infection fatality rate (IFR) of 0.1-0.5 percent.[19] This low IFR hides important differences across age, gender and income groups, as the elderly, males and individuals with pre-existing conditions and low access to health care have significantly higher IFRs.[20] Governments have adopted measures to both reduce the effective reproduction number (R) and avoid overcrowding their

[19] Source: https://www.cebm.net/covid-19/global-covid-19-case-fatality-rates/.

[20] Even if IFRs are higher for the elderly, a high share of the deaths could come from younger adults in developing countries (The Washington Post, 2020a), because population density is high in poorer areas, health systems are fragile, and people must keep working to survive (The Washington Post, 2020a). Likewise, while COVID is seen as an urban disease, it could become more lethal in rural areas, where the population is older, and access to health infrastructure limited (The Washington Post, 2020b).

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health system.[21] Thanks to these measures, COVID has killed only 0.01 percent of the world's population as of September 2020, so much less than other epidemics. Finally, its symptoms are not as distressing as other epidemics and the fact that COVID-19 is due to a virus is well-understood.

5.2 Economic Consequences of COVID-19

The economic crisis that the world is currently experiencing is similar to what happened during the 1918 Influenza. Since aggregate mortality is low, the labor scarcity effect observed as a result of the plagues of Antiquity or the Black Death is unlikely to be realized. Instead, the economy of developing countries could remain particularly disrupted for some time, thus contributing to increased stress levels. However, the 1918 Influenza led to a quick V-shaped recovery. After the COVID-19 crisis ends, developing countries could experience a V-shaped or W-shaped recovery, and some of them could remain permanently affected, as happened after the Ebola outbreak of 2014-2016. More generally, it is difficult to predict which scenario will prevail just six months into the crisis (World Bank, 2020).

5.3 Consequences of COVID-19 for Social Cohesion

Six months into the COVID-19 crisis, available evidence suggests that the *mild scapegoating scenario* is more likely overall. In some contexts where tensions were already rife, however, there is a risk that the mild scapegoating scenario turns into the *violent scapegoating scenario*.

People of Asian descent. Reports suggest increased discrimination against people of Asian descent, for example in the U.S. (New York Times, 2020a, The Washington Post, 2020c). Cases of anti-Asian racism have also been observed in the rest of the world (Human Rights Watch, 2020), in particular "people of Asian descent around the world have been subjected to attacks and beatings, violent bullying, threats, racist abuse, and discrimination that appear linked to the pandemic."

Religious Groups. The majoritarian bias of societies has increased hate and discrimination against religious minorities (Human Rights Watch, 2020). In South Asia, faith-based discrimination against Muslims has increased in India (where they represent about 14 percent of the population), Sri Lanka (10 percent) and Myanmar (4 percent). In India, a large religious gathering organized by a Muslim religious group emerged as a super-spreader and major source of COVID-19 infections across India. The ensuing outrage calling for action against the organizers of the gathering, however, took a communal turn and the episode led to discrimination against Indian Muslims. There have also been riots during which gangs of young Hindu men attacked Muslim communities (The Guardian, 2020a).[22] Likewise, in Sri Lanka, Muslim religious practices were singled out as "super spreader events", Muslim

[21] See https://en.wikipedia.org/wiki/COVID-19 pandemic for the latest "quantitative" information on COVID-19.

[22] In addition, Muslim businesses have been boycotted, Muslims are sometimes prevented from using public toilets and collecting food provisions from ration shops, and localities have set up blockades to bar Muslims from entering (The Guardian, 2020a).

shops have been boycotted, and cremations were made compulsory for all COVID-19 victims, which goes against the Islamic tradition of burying the dead (Al Jazeera, 2020a). Shia pilgrims returning from Iran have been found to be a source of the spread of the virus in Pakistan (Badshah et al 2020), a Sunni-majority country in which the minority sect has often been the victim of discriminatory behavior.

People of African origin. In various Chinese cities, people of African origin have been forcibly tested for the coronavirus and ordered to self-isolate in designated hotels (Human Rights Watch, 2020). In other Chinese cities, African residents were evicted by landlords, and hotels, shops, and restaurants have refused to serve African customers (The Guardian, 2020b).

Migrants. Migrants have been regularly blamed for being "super-spreaders", and either directly targeted or purposely excluded from COVID-19 policy responses. In India, migrant workers have been doused in disinfectant by authorities (Al Jazeera, 2020b). Communities of Rohingya migrants have been targeted by police raids in Malaysia (Reuters, 2020). In the Gulf states, low-income migrants from South Asia and South-East Asia have been fired and are excluded from emergency financial protections (Al Jazeera, 2020c; The Guardian, 2020c). The same situation is occurring with South Asian and South-East Asian migrants in Singapore (The Guardian, 2020d) and central Asian migrants in Russia (ABC News, 2020). Because migrants have to work to survive, and travel significant distances to find work, they are more likely to become infected and are at a higher risk of being carriers of infection when they return (Ahsan et al. 2020; Khanna et al. 2020). Using phone surveys in Bangladesh, Ahsan et al. (2020) find that human mobility is critical to the geographic spread of COVID-19 and that communities where a migrant returned in the 2 weeks prior were 242% more likely to report COVID-19 symptoms. The finding raises concerns that returning migrants could face increasing stigma (Kumar et al. 2020).

Doctors. Health workers have been discriminated against in the U.S. (The Washington Post, 2020c) and attacked, or evicted from their homes, in India, Ivory Coast, Mexico, Pakistan and the Philippines (BBC, 2020; McKay et al, 2020; New York Times, 2020b). Likewise, various governments have blamed the World Health Organization for the spread of the disease (New York Time, 2020c).

Government Officials. There have also been anti-lockdown protests calling for violent actions against specific government officials (Los Angeles Times, 2020; The Washington Post, 2020d). Studies suggest that provision of misinformation on mass media has been used as a political weapon to dismiss government calls for measures designed to contain the epidemic (Bursztyn et al. 2020)

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Foreign Nations. Other countries (and international companies) have been blamed for creating the virus or intentionally not doing enough to control it (Nature, 2020; The Atlantic, 2020). Bartoš et al. (2020) provide evidence that COVID-19 fuels hostility against foreigners.[23]

5.4 Parallels with Past and More Recent Epidemics

Because COVID-19 is not that deadly overall, it is similar to the 1918 Influenza or the African Ebola outbreaks of the 2010s. These epidemics led to medicalized prejudice, discrimination, and individual cases of targeted violence, as well as a few violent and murderous riots in the case of Ebola. Social violence has not reached the levels seen during the Cholera riots or the Black Death. Why is that?

It appears that: (i) COVID-19 is not that deadly and its symptoms are not as suspicious as the ones observed for some epidemics; (ii) Mortality rates are higher for the elderly, not children. Mortality is higher for the poor but government members and celebrities have been affected too (Boris Johnson, Prince Charles, Amitabh Bachchan, Tom Hanks, etc.). Such cases have been widely publicized, weakening conspiracy theories that the virus was created to eradicate the poor; (iii) With a few exceptions, the causes of COVID-19 are widely understood; (iv) Intergroup tensions are not as rife as they were historically, especially in the past when wars were frequent and international migration levels higher. Conversely, where prevailing religious or communal cleavages are high, COVID-19 has ignited riots. Likewise, among richer countries, COVID-19 has led to more cases of blame, conspiracy theories and violent anti-lockdown protests in the US, where interethnic tensions were already high, conspiracy theories already in vogue, and distrust in the government more entrenched before the pandemic; and (v) With a few exceptions, governments have not encouraged scapegoating. Governments have implemented more pro-poor agendas during the COVID-19 crisis than the governments of the 19th century and before did. While governments have imposed harsh lockdowns, they have communicated the purpose and engaged with local communities in a way that past governments did not.

5.5 Policy lessons from Past and More Recent Epidemics

First, governments stand to gain from ensuring that the poor, migrants, and minorities are systematically included in their medical and economic responses to COVID-19. The COVID crisis is an exceptional situation, so helping particularly vulnerable communities is a human imperative. In addition, by excluding them, there is a risk that socially excluded communities act as COVID-19 hotspots. This risk is amplified by the fact that the poor and migrants often reside in slums and lack access to health, hygiene, water, and sanitation infrastructure that is critical to containing the spread of diseases. Indeed, when health externalities are large, as is the case when trying to lower COVID's

[23] Using a controlled experiment with a nationally representative sample in the Czech Republic, they find that exogenously elevating salience of COVID-19 related thoughts magnifies hostility against people living in the E.U., U.S. and especially Asia, with no effects on behavior towards domestic out-groups, including minorities and migrants.

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effective reproduction number below 1, government programs are economically justified in subsidizing the livelihoods and health care of the poor and migrants. The spread of COVID-19 related myths and conspiracy theories, often conflated with other political objectives, militates against these policies.

Second, governments have to become more transparent and efficient in their responses to COVID-19. As of now, COVID-19 cannot be controlled without harsh measures. If governments do not have a clear plan that openly considers the important trade-offs between saving lives directly and letting poverty increase, lives will be lost and the economy durably impacted. If populations do not trust governments because they squandered the opportunities they had to control the spread of the disease and help mitigate its impact on the economy, disease control policies will be more and more difficult to impose in the future, and recovery will take longer. As distrust in governments grow and states become more fragile, risks that various groups exploit the situation to scapegoat other groups increase.

Lastly, stigmatization constrain migrants' ability to assimilate (United Nations, 2020). Exclusionary policies where local communities are purposely excluded or unintendedly omitted from decision and action processes can also have counter-productive economic effects, if it contributes to inefficiency in the disease control policies it adopts, if it causes distrust in the government, or if it spurs conflict between groups. More importantly, governments must abstain from encouraging actions that promote stigma or discrimination. Discrimination is likely to rise if susceptibility to the virus is associated with specific groups – such as the poor, migrants and minorities –, for example due to underlying differences in access to hygiene infrastructure. More directly, governments must ensure that the rule of law is enforced, and that national action plans against discrimination are adopted and applied if they exist.

6. Conclusion

In the past 20 years there have been many studies of the effects of epidemics on social cohesion. These studies can help inform the policy debate on the effects of, and best responses, to COVID-19, especially for developing countries. The available evidence reviewed in this paper suggests that epidemics be more likely to lead to social conflict: (i) when they are highly lethal; (ii) when they have distressing symptoms; (iii) when mortality rates are disproportionately higher for young children than for working-age adults or the elderly, due to the behavioral response it triggers from parents and society; (iv) at "intermediary" levels of knowledge of the mechanisms by which the epidemic transmits, i.e. when the epidemic is neither attributed to supernatural causes nor yet fully understood by the medical community, authorities, and populations; (v) when intergroup tensions were already rife; and (vi) when authorities encourage, or allow, scapegoating or implement heavy-handed policies that lead to distrust within the population. Six months into the COVID-19 crisis, available evidence suggests that the pandemic led to scapegoating, but not necessarily social violence. In some contexts where tensions were already rife, however, there is a risk that scapegoating could lead to social violence.

There is plenty of scope for future research, whether on the social effects of COVID-19 or on the social effects of historical epidemics. For example, recent epidemics have featured either low rates of contagion (e.g. Ebola) or relatively low fatality rates (e.g. COVID-19). But what if an epidemic that is both highly contagious and has a high fatality rate was to spread? For example, given its high fatality rate (50 percent), an uncontrolled Ebola pandemic could have dramatic effects (UNECA, 2015; Gates, 2018). This shows the continued importance of studying past epidemics, in order to better understand the mechanisms by which epidemics with different characteristics can impact social cohesion.

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TABLE 1: EPIDEMIOLOGICAL CHARACTERISTICS OF HISTORICAL AND MORE RECENT EPIDEMICS AND SCAPEGOATING

Epidemic	Location, Period	Disease	Mode of Transmission	Distressing Symptoms	CFR (%)	Mortality (%)	By Area	By Age	By Class	Explanation	Scapegoating Scenario
Antiquity											
1. Plague of Athens	City of Athens, 430-427 BC	Typhus?	Lice?	Rash all over the body	Up to 40	25	Cities	Adults?	All?	Naturalistic (bad air)	Non-
2. Antonine Plague	Roman Empire, 165-180 AD	Smallpox?	Droplets, body fluids?	Pustules all over the body	30-95	Up to 25?	All?	Children and adults?	All?	Naturalistic (bad air)	Non-
3. Plague of Cyprian	Roman Empire, 249-260 AD	Smallpox or Ebola?	Droplets, body fluids?	Pustules all over the body?	30-95 or 50?	?	All?	Children and adults?	All?	Naturalistic (bad air)	Non-
4. Justinian Plague	Roman Empire, 541-542 AD	Bubonic plague	Rat fleas	Buboes, necrosis of extremities	50-60	25-50	All?	All?	All?	Naturalistic (bad air)	Non-
Pre-Industrial Period											
5. Black Death	Western Europe mostly, 1347-1352	Bubonic plague	Black rat flea bites	Buboes, necrosis of extremities	70	40	All	All	All	Naturalistic (bad air) or water-poisoning conspiracy	(Very) Violent
6. Plague Recurrences	Western Europe mostly, 14th-17th	Bubonic plague	Black rat flea bites	Buboes, necrosis of extremities	Lower	Lower than 40	Cities	All?	The poor	Naturalistic (bad air)	Mild
7. Syphilis	All of Europe, 15th-19th	Syphilis	Sexual	Lesions, localized rashes	8-58	Low	Cities	Adults	All?	Punishment for sins	Mild

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Epidemic	Location, Period	Disease	Mode of Transmission	Distressing Symptoms	CFR (%)	Mortality (%)	By Area	By Age	By Class	Explanation	Scapegoating Scenario
Industrial Era											
8. Cholera Pandemics	Global, mostly 19th Century	Cholera	Water (fecal-oral route)	Violent diarrhea / vomit, blue skin	50	High	Cities	Children	The poor	Naturalistic (bad air) or water-poisoning conspiracy	Violent
9. Smallpox Outbreaks	Global, mostly 19th Century	Smallpox	Droplets, body fluids	Pustules all over the body	30-95	Up to 25?	All?	Children	The poor	No inoculation / no access to vaccine	Violent
10. Yellow Fever Outbreaks	Global, mostly 18th-19th Century	Yellow Fever	Mosquito bites	Jaundice, vomitting blood	7.5-50	High	All?	Older adults	All?	Poor hygiene	Non-
11. Third Plague Pandemic	Global, mostly 1894-1901	Bubonic plague	Rat flea bites	One bubo, some necrosis	30-60	Low	Cities	All?	All?	Poor hygiene first, then rats	Violent
12. 1918 Influenza	Global, mostly 1918-1920	Influenza	Droplets	_	> 2.5	2.1	Cities	W shape	The poor	Influenza	Mild
Recent Pandemics											
13. HIV Crisis	Southern Africa, Global, 1980s-	HIV	Sexual	Rash, Kaposi's sarcoma	80-90	High	Cities	Adults	The poor	HIV	Mild
14. Ebola Outbreaks	West & Central Africa, 2010s-	Ebola	Body fluids	Vomitting blood	50	Low	Cities	Children, older adults	The poor	Ebola	Violent
15. COVID-19	Global, 2019-	Influenza	Droplets	_	5	0.006	Cities	Older adults	The poor	COVID-19	Depends

Forecasting the impact of the COVID-19 shock on the Mexican economy[1]

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We forecast the short-term evolution of the Mexican economy after the COVID-19 shock. We take into account the fact that there is no similar shock observed in contemporaneous data. We combine an econometric procedure with a basic SIR model of the pandemic. To make the forecasts we first calculate an estimate of the shocks that hit the economy starting in March 2020. We then produce several forecasts in which we make variations on two dimensions: introducing a path for the pandemic or not, and if we do, we consider three scenarios. The introduction of paths of the pandemic in which new cases fall has a positive effect on the economy. The main results are the following. First, the shocks that hit the economy starting in March 2020 have the potential to produce a slow recovery of economic activity. In a forecast not conditioned on any path for the pandemic, the annual growth rate of the economy recovers positive values in the second quarter of 2021. Second, in our baseline scenario that includes a pandemic path based on the SIR model, the recovery is faster, having positive growth rates in the first quarter of 2021. To maximize the benefits of a fall in new cases, policy makers should reduce persistent effects of the initial shock that hit the economy. Otherwise economic activity would tilt towards a longer recession.

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1 The views expressed in this paper are exclusively those of the author and do not necessarily reflect those of ITAM. Any errors are my responsibility.

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1 Introduction

The COVID-19 pandemic is proving to be a very difficult test for Latin American economies, and for Mexico in particular. At the time of writing the curve for new cases in Mexico probably reached its peak. The curve for new deaths shows a plateau at approximately 600 per day. The Institute for Health Metrics and Evaluation (IHME) at the University of Washington recently predicted 118,810 COVID-19 deaths by December 1, 2020.

At the same time there was a sudden and large impact on economic activity. The government implemented a social distancing program on March 23. The program included the suspension on non-essential activities. One of Mexico's main economic indicators, the Global Economic Activity Indicator (IGAE in Spanish), showed in March a decline of 1.3% with respect to to February (with the deseasonalized series provided by INEGI, Mexico's national statistical institute). Then in April the indicator displayed a fall of 17.3% relative to March. Comparing April 2020 to April 2019, the fall was 19.6%.

These events lead to crucial questions. How persistent will be the fall of economic activity? Will there be a quick rebound? Will the liquidity crisis, due to lower sales in many sectors, become a solvency crisis? Will the crisis generate very persistent negative effects?

The objective of this paper is to forecast the short-term evolution of the Mexican economy after the COVID-19 shock. To construct the forecast we combine the procedure in Primiceri and Tambalotti (2020) with a basic SIR model of the pandemic.

In contrast to Primiceri and Tambalotti (2020), who calculate a forecast for the U.S. economy with three non-model-based scenarios for the pandemic, we use a simple version of the SIR model of Kermack and McKendrick (1927) to produce a path of the pandemic. Afterwards, with this path in hand, we then feed into the econometric model alternative paths based on what the SIR model produced.

Primiceri and Tambalotti (2020) analyze how to solve the problem of producing forecasts given the novel characteristics of the COVID-19 shock. As we have seen recently, many economic variables have suffered changes starting in March 2020 and especially afterwards. The problem that we face as econometricians is to produce a forecast of the impact of COVID-19 based on contemporaneous data, which exclude COVID-19-type crises.[1] Below we will describe the assumptions made by Primiceri and Tambalotti (2020) to produce a forecast of the effect of the COVID-19 shock.

To make the forecasts we first calculate an estimate of the shocks that hit the economy starting in March 2020. We then produce four forecasts in which we make variations on two dimensions: introduce a path for the pandemic or not, and if we do, we consider three scenarios. The introduction of paths of the pandemic in which new cases fall has a positive effect on the economy.

The first result is that the shocks that hit the economy starting on March 2020 have the potential to produce a slow recovery of economic activity. In a forecast not conditioned on any path for the pandemic, the annual *growth rate* of the economy reaches positive values in the second quarter of 2021. This implies that the recovery of the economic activity *level* pre March 2020 would take even longer.

[1]Most of our time series start in the 1990s, and a few of them only in the 2000s.

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The second result is that, in our *baseline* scenario that includes a pandemic path based on the SIR model, the recovery is faster. In this case the annual growth rate takes positive values in the first quarter of 2021.

An additional result that permeates all forecasts is the slower recovery of investment. In all our forecasts the annual growth rate of investment lags the recovery of overall economic activity. From the point of view of aggregate demand components, our predicted recoveries are driven by consumption, not by investment. This prediction points to a negative impact on potential output and on long-term growth. The crisis then would have a negative long-term impact.

Finally, we want to highlight the increase in the volatility of the consumption growth rate. It falls as much as the overall economic growth rate, and tracks its recovery. The large variations in consumption growth over time would have a negative impact on welfare.

The rest of the paper is organized as follows. Section 2 presents a literature review of recent COVID-19 research documents making special emphasis in Mexico. Section 3 presents the data description for each of the variables used in the model. In Section 4 we present our baseline specification, along with the Primiceri and Tambalotti (2020) approach for dealing with the pandemic shock. We also present the simple SIR model used to obtain our scenarios. Section 5 presents the main results while Section 6 concludes.

2 Literature Review

Following the start of the COVID-19 pandemic, economists have contributed to understanding the nature of the shock, its transmission channels to the real and financial sectors, and possible measures to mitigate the severity of the observed contraction. There is a growing literature on the impact of COVID-19 on the Mexican economy.

First of all, in terms of methodology, there is a literature that analyzes econometric estimation and forecasting for the U.S. economy in the presence of COVID-19 shocks. As mentioned earlier, Primiceri and Tambalotti (2020) propose a set of assumptions to forecast the evolution of the U.S. following the outbreak of COVID-19. Lenza and Primiceri (2020) illustrate how to handle the sequence of extreme observations when estimating a vector autoregression, showing that the ad hoc strategy of dropping these observations may be acceptable for the purpose of parameter estimation. However, disregarding these recent data is inappropriate for forecasting the evolution of the economy because it underestimates uncertainty.

A set of papers uses econometric methods to measure the impact of COVID-19 on Mexico. This is the case of Jiménez Gómez et al. (2020) who, using cointegration, find that 205,863 jobs of permanent workers insured by the Mexican Social Security Institute (IMSS in Spanish) would be lost by each percentage point that Mexican GDP drops in 2020 as a consequence of the quarantine.[2] According to the authors, if GDP drops 8.2% in 2020, about 1.69 million of this kind of jobs would be lost. Compared to our work, these authors use data up to 2019. We estimate the model with data up to February 2020, and use data for March, April and May to measure the COVID-19 shock, analogously to Primiceri and Tambalotti (2020). ECLAC (2020) argues that the COVID-19 pandemic has hit Latin America and the Caribbean in a period of economic weakness and macroeconomic vulnerability. This work projected a contraction of

[2]IMSS is the public health institute that insures workers in the formal sector of the economy.

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6.5% of GDP in 2020 for Mexico. Sampi and Jooste (2020) use the Google Mobility Index to nowcast monthly industrial production growth rates in selected economies in Latin America and the Caribbean, including Mexico.

Another group of papers uses general equilibrium models (GE) to measure the effect of COVID-19. McKibbin and Fernando (27 April 2020) explore seven different scenarios of how COVID-19 might evolve in the coming year using a hybrid DSGE/CGE general equilibrium model. They produce results for 20 developed and developing countries, including Mexico. Bekkers et al. (2020) develop three scenarios for the impact of the COVID-19 pandemic: a V-shaped, a U-shaped and an L-shaped recovery scenario. These authors use a dynamic CGE model. They analyze a group of developed and developing countries, including Mexico. It is important to say that there are GE models, aimed at studying the case of the U.S., that model explicitly the dynamics of the SIR model. One such model is, for example, Eichenbaum et al. (2020) who extend the SIR model to study the interaction between economic decisions and epidemics.

Our contribution to this literature is twofold. First, to the best of our knowledge, we are the first ones to include explicitly, in a simple way, the implications of a SIR model of the evolution of the pandemic to forecast the behavior of economic activity in Mexico. Jiménez Gómez et al. (2020) do not include any assumption on the evolution of the pandemic. Nor do, according to our reading, Sampi and Jooste (2020). ECLAC (2020) does have an assumption on the re-opening of the economy, which would be a reflection of the behavior of the pandemic. Second, we analyze and forecast the impact of the pandemic at a basic level of sectoral disaggregation. We forecast the behavior of the components of the Global Economic Activity Indicator for primary, secondary and tertiary activities. We find heterogeneous effects across sectors, with the primary one reacting less than the others. We also forecast the behavior of employment in those three sectors, with similar results.

3 Data Description

We use monthly data to calculate annual percent growth rates of twelve variables that measure real economic activity: the Global Economic Activity Indicator (IGAE in Spanish), the Economic Activity Indicator for the Primary, Secondary and Tertiary Activities, the Private Consumption in the Domestic Market Monthly Indicator (IMCPMI in Spanish), the Gross Fixed Capital Formation Indicator (IMFBCF in Spanish), the Capital Formation Indicator for Machinery and Equipment, the Capital Formation Indicator for Construction, the total number of insured workers associated with permanent or temporary urban jobs registered by the Mexican Social Security Institute (IMSS in Spanish), and its decomposition into workers in the primary, secondary and tertiary sectors. The IGAE index closely tracks real GDP. The IMSS data is considered a measure of formal employment, in a country with a large, low-productivity, informal sector. From now on we will refer to these variables as, respectively, Global Economic Activity (GEA), Primary Sector, Secondary Sector, Tertiary Sector, Consumption, Investment, Machinery and Equipment, Construction, Total Employment, Employment: Primary Sector, Employment: Secondary Sector, and Employment: Tertiary Sector. Due to availability of IMSS data the sample covers the period January 2000 to May 2020. The IMSS series had a seasonal component and were filtered using X-12-ARIMA. The other variables were deseasonalized by the source, Mexico's National Statistical Institute (INEGI in Spanish).

The impact of COVID-19 is sudden and large. Figure 1a displays the evolution of GEA, and its components. Figure 1b plots the evolution of the annual percent variation of Consump-

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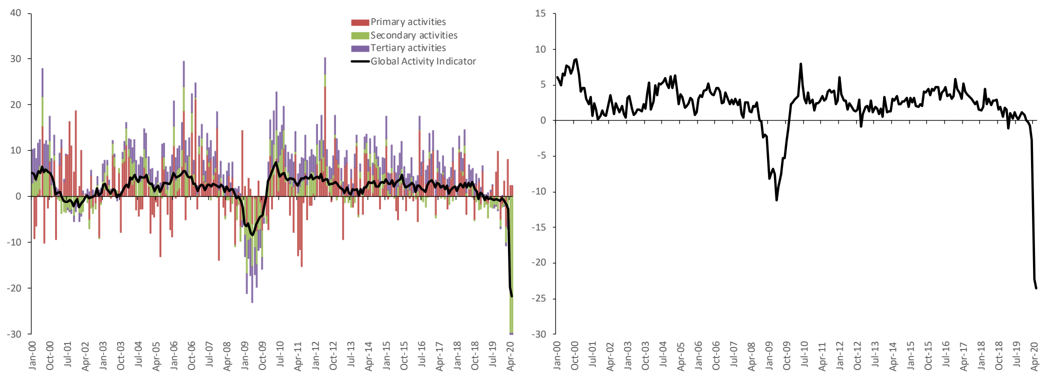
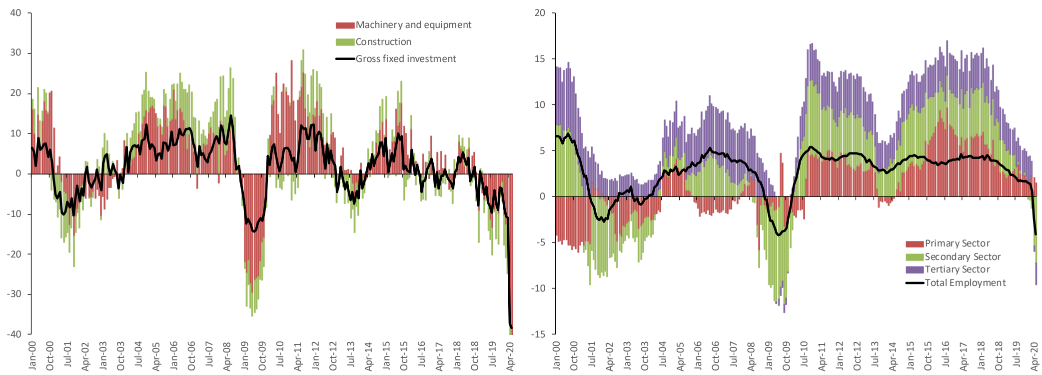
tion. Figure 2a displays the dynamics of the annual percent variation of Investment and its components. Finally, Figure 2b presents the annual percent variation of employment and its components.

FIGURE 1. ANNUAL % VARIATION



(A) Economic Activity, Global and Disaggregated (B) Consumption

FIGURE 2. ANNUAL % VARIATION



(A) Investment, and Disaggregated (B) Employment, Total and Disaggregated

Table 1 presents descriptive statistics using a pre COVID sample and the complete sample. We compute the statistics using the annual percent variation of all variables using as pre COVID sample January 2000 to February 2020. The post COVID sample uses the period January 2000 to May 2020. The COVID-19 shock generated a new minimum in the time series analyzed, it increased the variance of the time series, and reduced the average percent growth rates. Primary activities, both output and employment, are insensitive to crisis episodes such as the dot-com crisis in 2001, the 2008 financial crisis, and the novel COVID-19 crisis.

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Table 1: Descriptive statistics

Variable	Mean		Min		Std. Dev.	
	Pre COVID	Post COVID	Pre COVID	Post COVID	Pre COVID	Post COVID
Global Economic Activity	1.99	1.78	-8.29	-21.65	2.52	3.25
Primary Sector	2.15	2.17	-15.17	-15.17	6.27	6.24
Secondary Sector	0.86	0.59	-10.59	-29.69	3.10	4.15
Tertiary Sector	2.64	2.46	-8.13	-19.06	2.46	3.06
Consumption	2.41	2.19	-11.21	-23.53	2.71	3.55
Investment	1.82	1.45	-14.36	-38.41	6.24	7.20
Machinery and Equipment	4.18	3.72	-29.53	-43.76	10.44	11.23
Construction	0.71	0.39	-13.85	-36.29	5.72	6.54
Total Employment	2.81	2.75	-4.15	-4.15	2.35	2.40
Employment: Primary Sector	1.19	1.20	-6.04	-6.04	3.62	3.60
Employment: Secondary Sector	1.89	1.81	-10.00	-10.00	4.26	4.30
Employment: Tertiary Sector	3.60	3.55	-0.92	-2.35	1.47	1.54

Sources: Authors' calculations using information from INEGI and IMSS.

4 Bayesian VAR

To analyze the COVID-19 shock to the Mexican economy we use a Bayesian VAR. The econometric specification is

$$\mathbb{Y}_t = c + \sum_{p=1}^{P} A_p \mathbb{Y}_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma) \text{ and } t = 1, \ldots, T, \tag{1}$$

where $\mathbb{Y}_t$ is the (12×1) vector of endogenous variables that we listed above, c is a (12×1) vector of constants, and ε_t is a (12×1) vector of error terms following a multivariate normal distribution. As mentioned earlier we use annual percent growth rates of each variable. The estimation sample covers the period January 2000 to February 2020. The number of lags used is 12 months and we use the Minnesota prior. Our reference for the model is Dieppe et al. (2016).

As in Lenza and Primiceri (2020) we remove from the sample the observations of March, April and May 2020 to avoid explosive dynamics. Notice that by incorporating the last three observations, which are extreme values, we might turn into non-stationary some of the variables in the model. In fact, we confirmed that adding the information of March, April and May 2020 made each time series non-stationary. We also confirmed that the BVAR did not satisfy the stability condition after including those data points. We also compared the impulse-response functions between the sample up to February 2020, and the one ending in May 2020, finding explosive dynamics in the latter.

4.1 Modeling the COVID-19 shock

Primiceri and Tambalotti (2020) propose a set of assumptions, in the context of a Bayesian VAR, to estimate the effect that the COVID-19 pandemic would have on economic activity for the United States. We briefly describe their points here. The idea is to make a "synthetic" shock representing COVID-19 since there are no contemporaneous dynamics of macroeconomic fundamentals like the ones recently observed. The assumptions are: i) the COVID-19 shock is the main source of variation in macroeconomic variables in March-May 2020 (they used data only for March and April), ii) the shock will propagate in the following months through the economy like a combination of shocks previously observed in the history of macroeconomic variables, and iii) the propagation of the shock takes into account the diffusion path of the pandemic. In their paper, scenarios are generated regarding its evolution. Below we apply their procedure to Mexican data, using the codes they provided online. We add one element. We use a simple SIR model to predict a path for the pandemic. Based on this path, we construct scenarios for the pandemic, and produce forecasts.

Based on Primiceri and Tambalotti (2020) we describe the dynamics of an $(n \times 1)$ vector $\mathbb{Y}_t$ using the following two equations

$$\mathbb{Y}_t = G(L)\eta_t, \tag{2}$$
$$\eta_t = F(L)\varepsilon_t. \tag{3}$$

The first expression relates the evolution of $\mathbb{Y}_t$ to a vector of exogenous variables η_t and their lags, and the second expression states that η_t is a moving average of an $(n\times 1)$ vector of shocks, whose variance-covariance matrix is normalized to the identity matrix. $G(L)$ and $F(L)$ are lag polynomial matrices, of suitable dimensions and of potentially infinite order, that describe the endogenous and exogenous propagation of ε_t, respectively. The authors assume that $\mathbb{Y}_t$ and ε_t are of the same dimension so that matrices $G(L)$ and $F(L)$ imply a fundamental representation of $\mathbb{Y}_t$ as a moving average of ε_t.

Using both expressions we get the Wold representation of equation (1) in terms of past errors

$$\begin{aligned} \mathbb{Y}_t &= \Theta(L)G_0\varepsilon_t, \\ \Theta(L) &\equiv G(L)F(L)G_0^{-1}, \\ \Theta_0 &= I_n. \end{aligned}$$

To account for the effects of the pandemic the authors modify the previous expression to incorporate a virus shock ν_t such that

$$\mathbb{Y}_t = \Theta(L)G_0\varepsilon_t + \underbrace{\theta(L)r(L) \odot r_0\nu_t}_{\substack{\text{COVID-19} \\ \text{effect}}}, \tag{4}$$

where $\odot$ denotes the element-wise product of two vectors, $\theta(L) \equiv I_{n\times n} + \sum_{i=1}^{\infty} \theta_i L^i$ is an $(n\times n)$ lag polynomial matrix, $r(L) \equiv 1_{n\times 1} + \sum_{i=1}^{\infty} r_i L^i$ is an $(n \times 1)$ lag polynomial vector, r_0 is an $(n \times 1)$ vector, and ν_t is the COVID-19 shock. This shock is zero in all time periods except for the month in which COVID-19 started affecting the Mexican economy, March 2020.

In terms of symbols, assumption ii) is stated as $\Theta(L) = \theta(L)$. This is interpreted as, absent $r(L)$, the pandemic shock ν_t would propagate as shocks ε_t. Under the assumption that $\Theta(L) = \theta(L)$, the COVID-19 effect can be written as $G(L)F(L)G_0^{-1}r(L) \odot r_0\nu_t$. Let $f(L) \equiv F(L)G_0^{-1}r(L)$. $f(L)$ characterizes the propagation of $r_0\nu_t$. We expect that the size and duration of the contraction of economic activity will depend on the evolution of the pandemic. To incorporate this idea into the model, assumption iii) plays a crucial role. The main idea of the third assumption is to impose restrictions on the coefficients of vector $f(L)$ that characterize the evolution of the pandemic. Scenarios below will be specified in terms of paths for $f(L)$.

4.2 The SIR model and Scenarios for Mexico

To make three possible scenarios of the evolution of the virus in Mexico we use the *simplest* SIR model introduced by Kermack and McKendrick (1927). It consists of a differential equations

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system that characterizes the evolution of a pandemic by taking into account the number of susceptible people $S(t)$, the number of infected people $I(t)$, and the number of recovered people $R(t)$ for a given population of size $\bar{N} = S(t) + I(t) + R(t)$. The differential equations system is

$$\frac{dS(t)}{dt} = -\beta S(t)I(t), \tag{5}$$

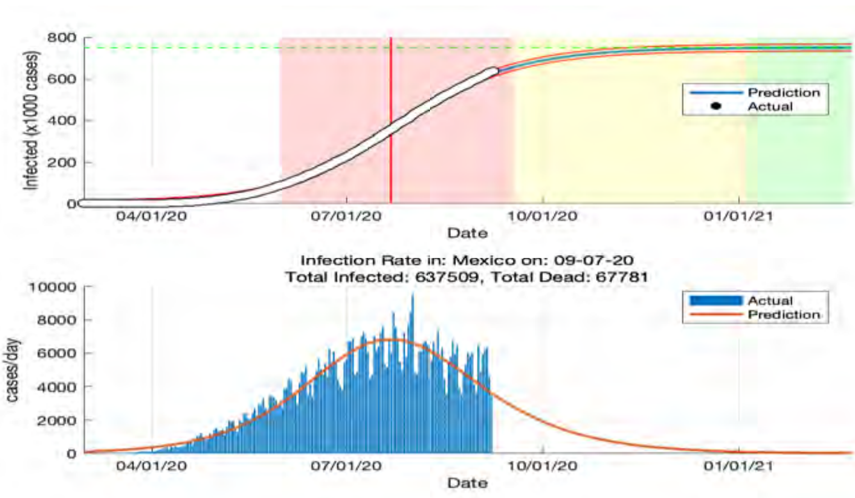
$$\frac{dI(t)}{dt} = \beta S(t)I(t) - \gamma I(t), \tag{6}$$

$$\frac{dR(t)}{dt} = \gamma I(t), \tag{7}$$

where β represents the transmission rate and γ is the recovery rate. We used the codes from McGee (2020) to compute the model-based prediction of the pandemic. Figure 3 presents the evolution of the virus for Mexico using $\beta = 16.8\%$ and $\gamma = 12.6\%$. As of August 9, 2020, the estimate is that new cases would have started falling in the second half of July 2020. The pandemic would end at the end of December 2020.

This clearly represents an optimistic prediction since the actual data, i.e. the blue bars in Figure 3, show a possible flattering of the curve for new cases only at the beginning of August 2020.

Figure 3. Evolution of pandemic in Mexico according to SIR model

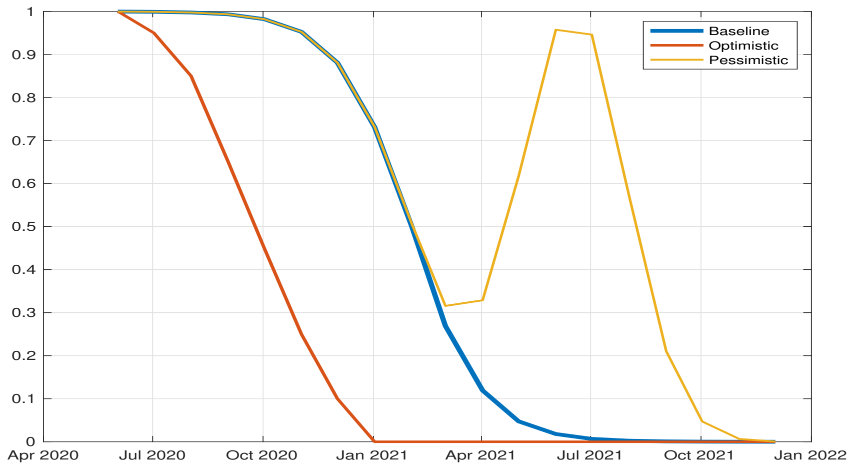


Given this prediction we define three possible scenarios of the evolution of the pandemic. As in Primiceri and Tambalotti (2020), the scenarios are specified in terms of $f(L)$. Figure 4 presents the evolution path of the pandemic in Mexico for each scenario. The date of the first point in each scenario is June 2020. Notice that the possible paths start at values close to 1. Afterwards they fall to zero. The interpretation is that the virus shocks disappear at changing speeds over time.

The paths for each scenario are:

- **Optimistic scenario:** this one is based on the prediction of the SIR model. The pandemic in Mexico began easing in mid-July 2020 and will end in January 2021, following

Figure 4. Pandemic evolution path for each scenario



the path

$$[f_2^{Mex}, f_3^{Mex}, f_4^{Mex}, f_5^{Mex}, f_6^{Mex}, f_7^{Mex}, f_8^{Mex}] = [1, 0.95, 0.85, 0.65, 0.45, 0.25, 0.10] f_1^{Mex}, \quad \text{with } f_j^{Mex} = 0_{(n\times 1)} \ \forall j \geq 9.$$

- **Baseline scenario:** in this scenario we take the prediction of the SIR model and shift it to the right, using a functional form for the evolution of f. This function is based on Primiceri and Tambalotti (2020). We are assuming that new cases will peak in August 2020 and that the pandemic in Mexico will end by July 2021, following the path

$$f_j^{Mex} = \frac{1}{1+\exp(j-9)} f_1^{Mex}, \ \forall j \geq 2.$$

- **Pessimistic scenario:** there is a second wave of the virus starting in April 2021, with a maximum on June 2021, and ending in December 2021, following the path (also based on Primiceri and Tambalotti (2020))

$$f_j^{Mex} = \left[\frac{1}{1+\exp(j-9)} f_1^{Mex} + \exp\left(-\frac{1}{4}(j-13.5)^2\right)\right] f_1^{Mex}, \ \forall j \geq 2.$$

This scenario is important as we are currently observing a second wave in Europe. In this particular scenario for Mexico the second wave of the pandemic rises sharply and also falls quickly. A smaller persistence in the second wave would be associated with a faster recovery of the economic activity. In the real world the initial negative shock on economic activity came from the lockdown. There is a lot of uncertainty on what response the government would undertake in case of a second wave. We interpret our assumption as a partial lockdown (or weaker compared to the first one).

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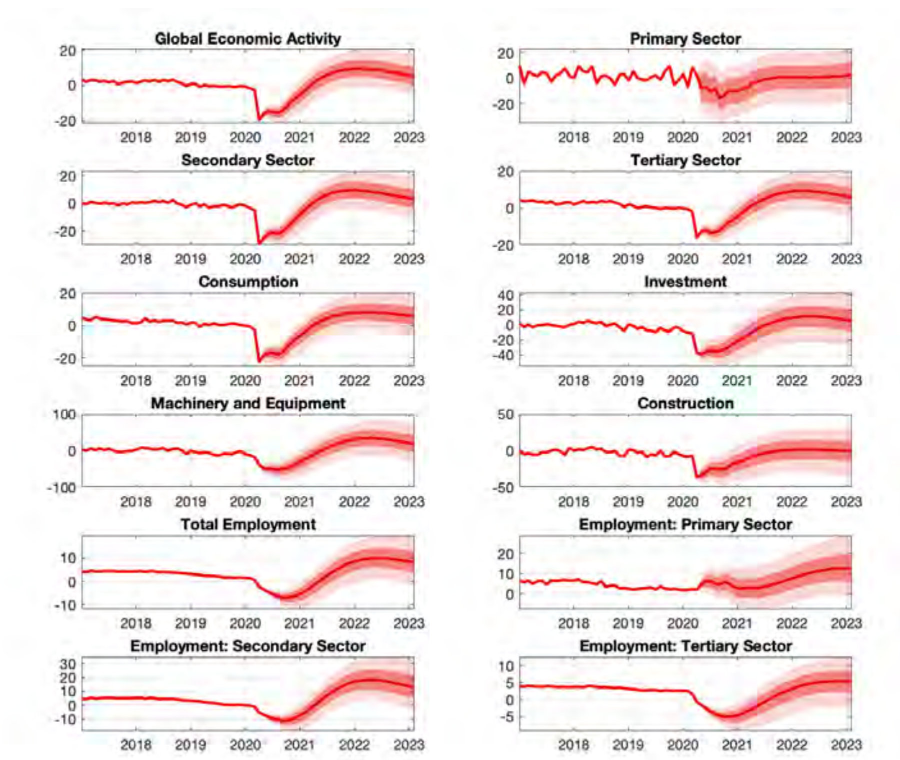
5 Results

We first compute an unconditional forecast finding that the negative impact on the economy would be persistent. This forecast excludes any path for the pandemic evolution. It simply uses the observed shocks for March, May and April 2020 recovered from the data, and parameter values estimated with data between January 2000 and February 2020. The forecast starts in June 2020. Results are shown in Figure 5.

Figure 5. Unconditional Forecast



Note: The unconditional forecast does not inlcude any evolution path of the pandemic shock. The solid red line represents the actual data until May 2020, and the posterior median of the predictive density afterwards. The shaded area correspond to the 68 and 95 percent posterior credibility regions, respectively.

In this forecast Global Economic Activity (GEA) shows positive annual growth rates until the second quarter of 2021, after falling approximately 20% in April 2020. This implies that it would take several more months for this important indicator, highly correlated with GDP, to reach the *level* it had in December 2019.

Another interesting result is that Investment starts to show positive annual growth rates until the second half of 2021, after falling 37.1% in April 2020. This prediction has negative implications for Mexico's potential output, i.e. for long-term growth.

An additional interesting result is related to Consumption, which shows positive annual growth

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rates until the second quarter of 2021, following closely the behavior of GEA. The 22.2% fall in April 2020, and the persistent fall in the consumption growth rate, would produce a large negative effect on welfare.

Regarding other variables, we start with the behavior of the Primary, Secondary and Tertiary Sectors. The COVID-19 shock had a large impact on the Secondary and Tertiary sectors, given that several industries, restaurants, entertainment and transportation (partially in that case) shut down. The Secondary Sector, contracting 29.7% in April 2021, suffered both because of the fall in economic activity in the U.S., as both economies are closely linked by trade agreements, and because of the shut-down in Mexico. The Tertiary Sector fell 15.9% in April 2020. Under this forecast, the Secondary and Tertiary sectors show positive growth rates until the second quarter of 2021. The Primary Sector, more volatile than the others before the COVID-19 Crisis, contracts in response to the shock. This contraction is smaller than in the other sectors on impact. Afterwards the Primary Sector displays positive growth rates in the first half of 2021.

In terms of the components of Investment, Machinery and Equipment has a larger fall than Construction. Both falls are very large in April 2020. Machinery and Equipment fell 38%. Construction fell 36.3%. Machinery and Equipment has a faster recovery, showing positive growth rates in the second quarter of 2021. Construction has positive growth rates only until the second half of 2021. The rates for this type of investment are only slightly above zero, suggesting a very weak recovery.

In terms of the unconditional forecast for Total Employment and its decomposition into Primary, Secondary and Tertiary sectors, we find heterogeneous results regarding the size and duration of the contraction. After several months of negative growth, Total Employment has positive rates in the second quarter of 2021. The Primary Sector does not show a contraction on impact, and it displays positive growth rates throughout the forecast.[3] On the other hand, employment in the Secondary and Tertiary Sectors shows larger falls on impact. Afterwards, the Secondary Sector shows positive growth rates in the first half of 2021. Employment in the Tertiary Sector displays a slower recovery, having positive growth rates until the second half of 2021.

The fact that the predicted recovery is slow is reminiscent of Primiceri and Tambalotti (2020). They argue that producing a forecast *excluding* a path for COVID-19, with fewer cases over time, would yield a Depression. The reason behind this fact is that shocks in the data are associated with hump-shaped dynamics that imply slow recoveries.

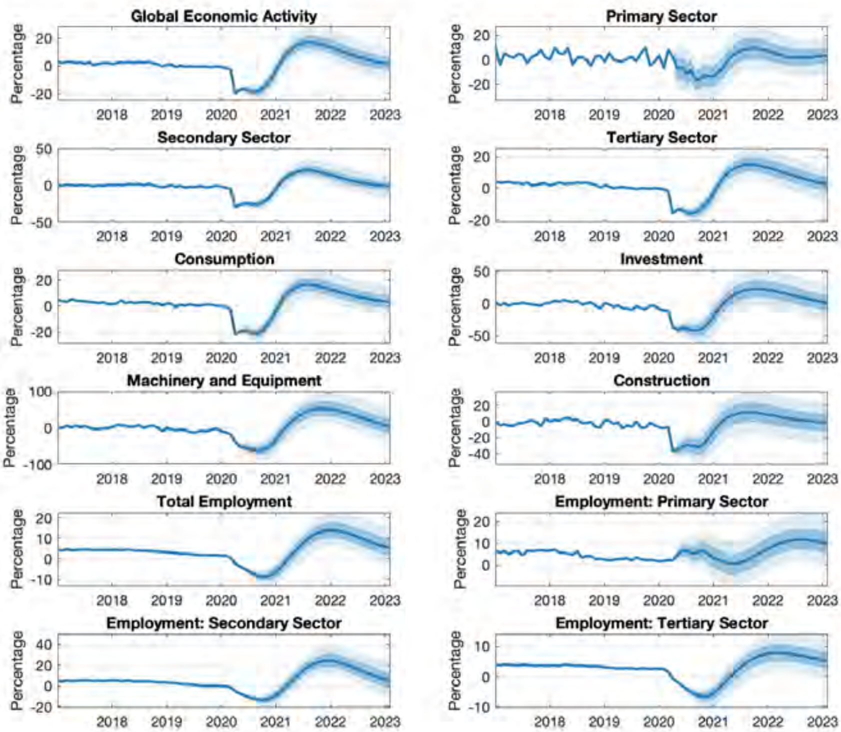
In contrast, our forecast that includes a baseline scenario for the pandemic produces a much faster recovery, because there is a positive effect on the economy coming from the fall in new cases (see Figure 6). More intuitively, it comes from a re-opening of the economy. GEA shows positive growth rates in the first quarter of 2021. These rates are bigger than those observed in the unconditional forecast. In spite of those bigger growth rates the forecast implies a recovery of December 2019 values at the end of 2021.[4]

Investment shows positive growth rates in the second quarter of 2021. But remarkably, the projected positive annual growth rates are smaller, in absolute terms, than those observed in

[3] In these data, employment in the primary sector is a small fraction of the total, approximately 3%.

[4] To obtain the levels we proceeded in two steps. First, we obtained the prediction in levels using the annual growth rates. Second, we used a simple exponential filter to smooth this forecast since we observed a pattern. It is common in forecasting to observe patterns when going from predicted growth rates to levels or when there are unknown trends. For example, see Holt (2004) and De Gooijer and Hyndman (2006).

Figure 6. Forecast for Baseline Scenario



Note: The COVID-19 shock follows the baseline path showed in Section 4. The solid blue line represents the actual data until May 2020, and the posterior median of the predictive density afterwards. The shaded area correspond to the 68 and 95 percent posterior credibility regions, respectively.

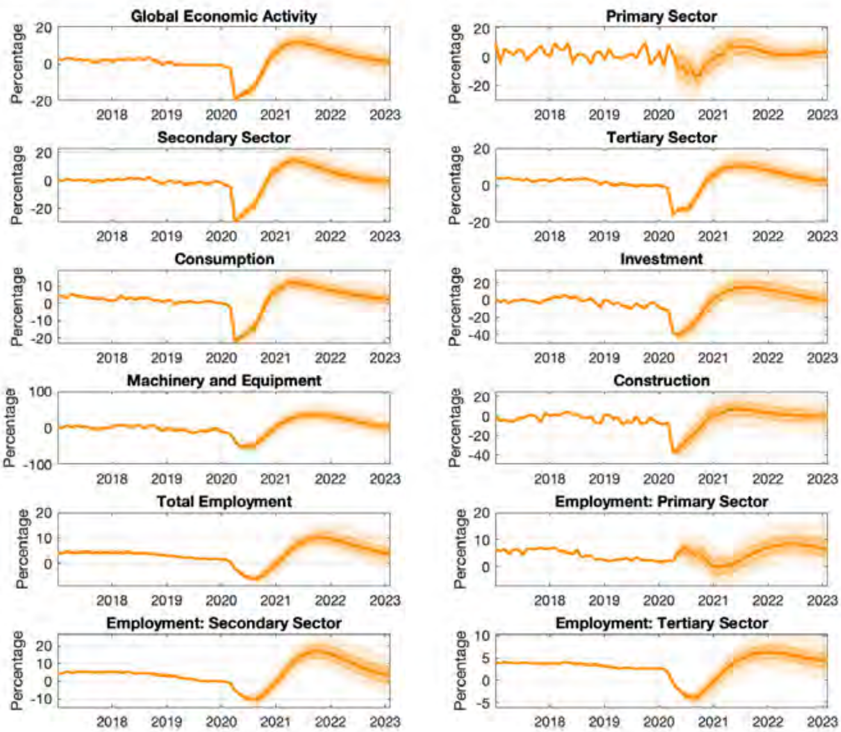
the contraction (although the positive rates last for longer in our horizon). This suggests that Investment will not recover its pre pandemic values in the short-term. In levels, the forecast for investment does not recover its December 2019 values at the end of our forecast horizon, which is February 2023. Therefore, even taking into account the positive effect of the decrease in new cases, the outlook for investment, potential output, and long-term growth remains very negative.

Consumption behaves in a similar way as GEA. It shows positive growth rates in the first quarter of 2021. In this baseline scenario for the pandemic, the implied welfare cost would be smaller than in the unconditional forecast.

In the case of total employment, we observe positive growth rates in the second quarter of 2021. As in the previous forecast, there is a heterogeneous behavior across sectors, with employment in the primary sector being affected much less. The other sectors show bigger contractions, and positive growth rates in the second quarter of 2021. The forecast implies a recovery of the December 2019 values in mid-2021.

The optimistic scenario (see Figure 7), in which the fall in new cases is faster, yields a faster

Figure 7. Forecast for Optimistic Scenario



Note: The COVID-19 shock follows the optimistic path showed in Section 4. The solid orange line represents the actual data until May 2020, and the posterior median of the predictive density afterwards. The shaded area correspond to the 68 and 95 percent posterior credibility regions, respectively.

recovery. It predicts that GEA will have positive growth rates in the last quarter of 2020. One remarkable result of this forecast is that Investment has positive growth rates in the first quarter of 2021. In the case of the Consumption, it behaves similarly to GEA. Total Employment has positive growth rates in the first quarter of 2021.

The pessimistic scenario (see Figure 8) produces a slower recovery compared to the baseline. In this scenario, which has a second wave of the pandemic that peaks in June 2021, Global Economic Activity has positive growth rates in the first quarter of 2021. These rates are smaller than in the baseline scenario. The second wave produces negative growth rates in the second quarter of 2021. Investment displays a very negative behavior, with negative growth rates until the second quarter of 2021. Consumption follows closely the behavior of GEA. In terms of welfare, this path for consumption would generate a fall, not only because of the contractions in 2020 and 2021, but also because of the extra volatility caused by the sequence contraction-recovery-contraction. Total employment has a long sequence of negative growth rates which ends in second quarter of 2021.

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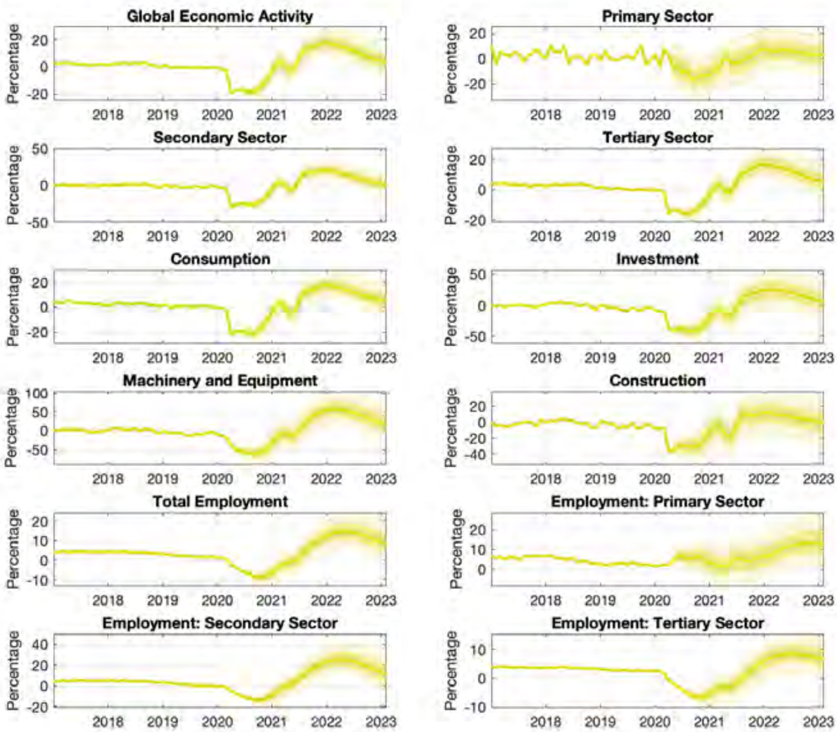
Figure 8. Forecast for Pessimistic Scenario



Note: The COVID-19 shock follows the pessimistic path showed in Section 4. The solid yellow line represents the actual data until May 2020, and the posterior median of the predictive density afterwards. The shaded area correspond to the 68 and 95 percent posterior credibility regions, respectively.

5.1 Robustness

We estimated the model with variables in levels, as opposed to annual growth rates. We then computed the annual growth rates implied in this alternative estimation. Focusing on the baseline scenario, and on GEA, we find the following. First, the two forecasts have similar values and dynamics in the second half of 2020. Second, they differ in the recovery period between February 2021 and February 2022. In particular, the prediction using the estimation with levels has higher rates between April 2021 and February 2022. Third, after the latter month the growth rates become similar again. Fourth, the correlation between the two forecasts is 95%. We prefer our main estimation with annual growth rates, as in the alternative, recovery rates during 2021 are asymmetrically large, i.e. higher in absolute value in the recovery than in the contraction, which we think is not plausible.

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6 Conclusions

We combined an econometric procedure with a SIR model to answer the question of how the Mexican economy would evolve after the COVID-19 shock. We looked at the prediction of the simplest SIR model regarding the path of the pandemic for June 2020 and afterwards. Then we generated three scenarios based on that path. These scenarios are an input into the econometric forecast.

One important lesson is that the shocks that hit the economy have the potential to produce a long lasting recession. The unconditional forecast, in which we did not include a path for the pandemic with a fall in new cases, has that prediction. In this case economic activity would display positive growth rates until the second quarter of 2021.

On the other hand, in the baseline path for the pandemic, the fall in new cases has a positive effect on the economy. This forecast, conditional on a pandemic path based on the SIR model, yields positive annual growth rates in the first quarter of 2021.

The outlook for investment looks particularly bleak. In all our scenarios this variable takes many quarters to have positive growth rates. Such a behavior would imply a reduction in potential output and a fall in long-term growth. In turn, that would have implications for the rest of the economy: a lower growth rate of consumption, and a trend towards having current account surpluses because of the fall of domestic spending.

The model predicts different speeds of recovery for consumption, depending on the experiment. The fastest recovery to positive growth rates is realized in the optimistic scenario, taking place in the last quarter of 2020. But even in this case the initial fall in consumption is large. Consumption growth takes several months to recover. Therefore the COVID-19 shock would imply a fall in welfare. A second wave would amplify this cost, as a second large fall in economic activity would increase the volatility of the consumption growth rate, reduce income, and eventually spending.

We conclude that the outlook for the Mexican economy looks negative. At the time of writing, new cases (the speed of the pandemic) seem to grow more slowly. But there is obviously uncertainty about the evolution of the pandemic. To maximize the benefit of a fall in new cases, i.e. the gradual re-opening of the economy, policy makers should try to reduce persistent effects of the initial shock. There is already evidence that the initial liquidity crisis (the fall in sales) has caused a solvency crisis, both for the largest firms, and for micro businesses. An additional effort could be made to reduce insolvency. Otherwise economic activity would tilt towards a longer recession.

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Risk communication during COVID-19: A descriptive study on familiarity with, adherence to and trust in the WHO preventive measures

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Background: *Risk communication is a key component of public health interventions during an outbreak. As the coronavirus pandemic unfolded in late 2019, the World Health Organization (WHO) was at the forefront in the development of risk communication strategies. The WHO introduced a range of activities with the purpose of enabling the public to avail verified and timely information on COVID-19 prevention behaviors. Given the various WHO activities to protect the public health during COVID-19, it is important to investigate the extent of familiarity and uptake of the WHO recommendations among the public so far during the pandemic.*

Methods: *To do this, we conducted a large-scale Pan-European survey covering around 7500 individuals that are representative of populations from seven European countries, collected online during April 2-April 15, 2020. We use descriptive statistics including proportions and correlations and graphical representations such as bar charts to analyze and display the data.*

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Results: *Our findings suggest that information from the WHO in the context of COVID-19 is well trusted and acted upon by the public. Overall familiarity and adherence were quite high in most countries. Adherence was higher for social distancing recommendations compared to hygiene measures. Familiarity and adherence were higher among older, female, and highly educated respondents. However, country level heterogeneities were observed in the level of trust in information from the WHO, with countries severely affected by the pandemic reporting lower levels of trust.*

Conclusion: *Our findings call for efforts from health authorities to get regular feedback from the public on their familiarity and compliance with recommendations for preventive measures at all stages of the pandemic, to further develop and adapt risk communication as the pandemic evolves.*

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INTRODUCTION

Risk communication is key to improving familiarity with and adherence to preventive measures, in normal times but also particularly during health emergencies. Failure to communicate the right message effectively can result in loss of trust, damage to the economy and loss of lives (1). For risk communication to be effective, risk messages have to be shared with the public in an openly and timely manner, so as to reduce the knowledge gap and to convince the public to adjust their behavior during a crisis (2). In addition to disseminating recommendations that are easy for the public to understand and comply with, trust in the source of the message is important for an effective risk communication (1, 3).

The World Health Organization (WHO) has been in the frontline in its operations to contain and mitigate the spread of the COVID-19 pandemic. The WHO is a key player in disseminating up to date information and recommendations on COVID-19 preventive behaviors to the public (4). With a physical presence in 149 countries, these recommendations are also adapted to national and local considerations, thereby setting the WHO protocol as a foundation for further containment strategies at various levels of government (5, 6).

As the coronavirus pandemic unfolded in late 2019, the WHO was quick to realize the need for a tailored risk communication strategy. The WHO Information Network for Epidemics (or EPI-WIN) was introduced when COVID-19 was declared a public emergency of international concern on 30th January 2020 (7). EPI-WIN provides customized information and guidance to specific target groups in addition to fighting the „infodemic" (7). For example, this involved increasing the public awareness on preventive measures against COVID-19 through easy to understand behavioral messages using infographics and videos on the WHO website. EPI-WIN also guides national governments in risk communication and community engagement according to the transmission scenario of each country with the purpose of developing, implementing, and monitoring a communication plan that can help protect the public health during the health crisis (8). Another such WHO and national government collaboration in risk communication is the Global Outbreak Alert and Response Network (GOARN), a network of

250 technical institutes across the globe that has been actively involved in co-creating and co-implementing risk communication messages so as to adapt to the local context (9).

Additionally, the WHO undertook a range of other innovative steps to improve risk communication during this pandemic. They teamed up with social media companies and Google to ensure that any search queries related to COVID-19 directs the user to the WHO pages (10). The WHO introduced an online training course on COVID-19 and collaborated with celebrities on the safe hands challenge to demonstrate hand hygiene on social media (11, 12). Given all the actions undertaken by the WHO to promote public awareness on COVID-19, it seems important to investigate the familiarity of the public with the WHO recommended preventive measures, whether familiarity translates into adherence to these measures, and the role of trust in the information in this relationship.

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METHODS

We use individual level data covering 7000 respondents representative of the adult population in seven European countries: Denmark, France, Germany, Italy, Portugal, the Netherlands, and the UK. The online survey was conducted during April 2-15, 2020 by the market research company Dynata. The questionnaire was initially developed in English by the authors of the study and was then translated and adapted to country specific context by native speakers. In each country, data was collected from 1000 respondents" representative of the national population in terms of region, age, gender, and education. Representativeness of the sample was achieved by using quotas for the demographic characteristics in each country based on the national census statistics. As part of a larger survey, respondents were asked about their familiarity with the preventive measures recommended by the WHO, their adherence to these measures, and their trust in the information from the WHO.

Summary statistics including percentages and Spearman"s rank correlations were used to analyze the data. The statistical significance for difference in proportions between groups was tested using Chi-squared test. Additionally, we use graphical representations and simple ranking for summarizing results. Statistical analyses were performed on STATA 15 (STATA Corp, College Station, TX, US).

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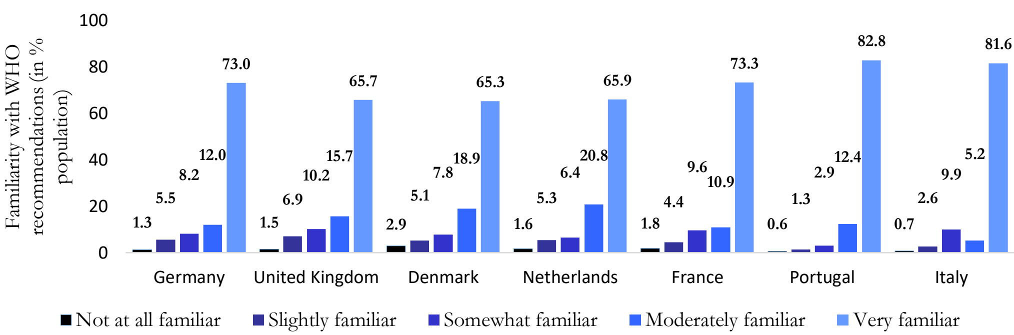
RESULTS

Familiarity with the WHO recommendations

In the wake of the COVID-19 crisis, the WHO put forward six basic preventive measures to help contain and mitigate the spread of coronavirus. The recommendations were first released on January 10, 2020 on the WHO website, around 11 weeks prior to the release of our survey (7). The recommendations included timely and easy-to-understand measures such as regularly washing hands with soap for at least 20 seconds, covering nose and mouth while coughing or sneezing, keeping a social distance of at least 1 meter, avoid shaking hands, hugging or kissing when greeting others, using alcohol-based hand rub and avoid touching nose, eyes and mouth. In our survey, respondents were shown the graphic presentation of the six measures that was used for communication in their country and asked to rate their familiarity with the measures on a scale from "not at all familiar" (1) to "very familiar" (5). Respondents reporting a score of 4 (moderately familiar) or 5 (very familiar) are classified as being familiar with the WHO recommendations.

Figure 1: Familiarity with the WHO recommendations, by country



On average 86.3% of the respondents reported being familiar with the WHO recommended measures. Looking at country level variations (Figure 1), we see that the proportion of respondents who reported being familiar with the recommendations was the highest in Portugal (95.2%) and the lowest in the United Kingdom (81.4%; $p<0.001$).

The other countries in the sample reveal similar levels of familiarity (84-87%) with the WHO recommendations. It is noteworthy that in the Lombardy region familiarity was also very high (91.0%), but especially also that the proportion of the population „not at all familiar" (0.4%) or only „slightly familiar" (0.6%) was the lowest.

Across countries, we find a higher proportion of female (88.4% for females vs. 84.0% for males; $p<0.001$), older (89.5% for 65+ vs. 78.1 for 18-24 yo; $p<0.001$) and highly educated (87.5% for high/medium vs. 83.6% for low; $p<0.001$) respondents reporting familiarity with the WHO recommendations. The same patterns are observed within each country as well. Finally, it should be noted that respondents may overstate their familiarity resulting in self-reporting bias.

Adherence to WHO recommendations on preventive behavior

In our study, we asked respondents to rate their adherence to the six preventive measures over the past four weeks using four levels: no; yes, a bit; yes, quite strongly; yes, fully. We consider respondents to adhere to the recommendations if they reported „yes, quite strongly" or „yes, fully" to each of the six recommendations. Overall, we see that 92.1% of the respondents reported to have adopted the WHO recommendations. Avoiding physical contact by not shaking hands, kissing or hugging when meeting others (93.6%) and keeping a social distance of 1 meter (91.5%) had an overall higher adherence rate, whereas using an alcohol-based hand rub (67.5%) and avoiding touching nose, eyes and mouth (62.4%) had the lowest rates of adherence (Figure 2).

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Figures 2a-2h: Adherence to WHO recommendations, by country

Figure 2a: Germany

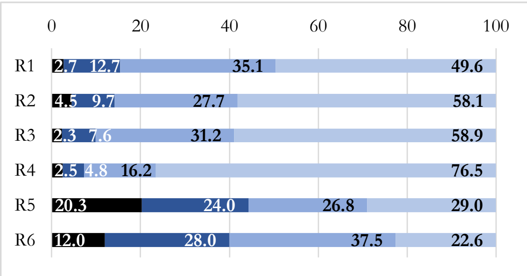


Figure 2b: The United Kingdom

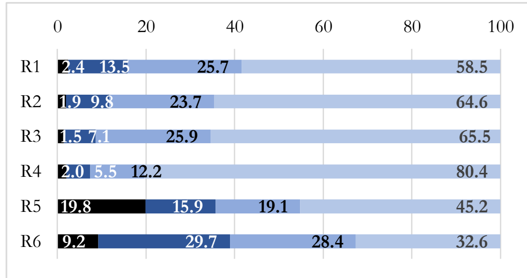


Figure 2c: Denmark

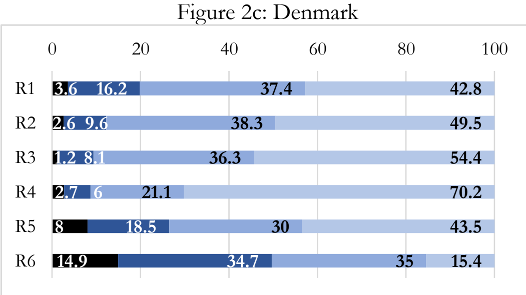


Figure 2d: The Netherlands

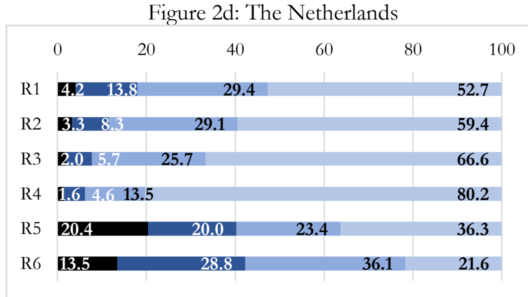


Figure 2e: France

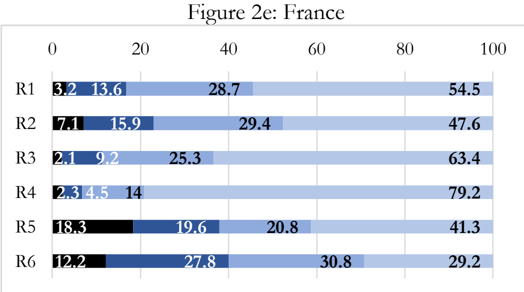


Figure 2f: Portugal

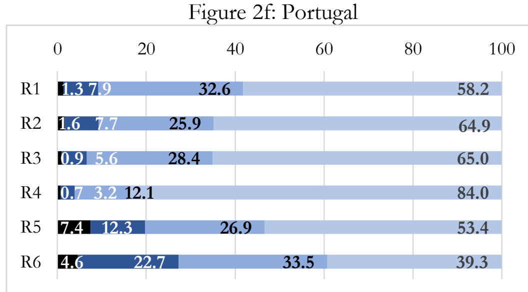
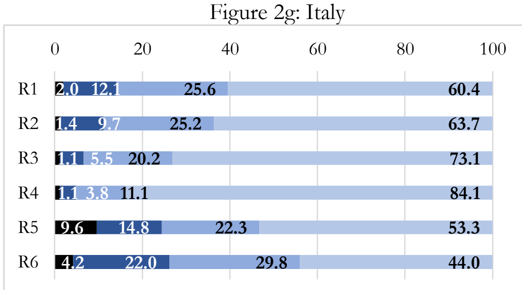


Figure 2g: Italy



■ No ■ Yes, a bit ■ Yes, quite strongly ■ Yes, fully

Note: ***R1****: Regularly wash my hands with soap for at least 20 seconds,* ***R2****: Cover my nose and mouth when coughing or sneezing,* ***R3****: Keep a distance of at least 1 meter from other people,* ***R4****: Avoid shaking hands, hugging or kissing when greeting others,* ***R5****: Use alcohol-based hand rub' and* ***R6****: Avoid touching my nose, eyes and mouth.*

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Comparing countries, Portugal and Italy perform best in adhering to all the WHO recommendations whereas France and Denmark perform the worst (Table 1). The difference between the top and worst adhering countries for each WHO recommendation is statistically significant ($p<0.001$).

Table 1: Rank of WHO recommendations in the order of their relative adherence.

Rank	WHO recommendations	Top adherers	Worst adherers
1	Avoid shaking hands, hugging or kissing when greeting others.	Portugal, Italy	Denmark
2	Keep a distance of at least 1 meter from other people.	Portugal, Italy	France
3	Cover my nose and mouth when coughing or sneezing.	Portugal	France
4	Regularly wash my hands with soap for at least 20 seconds.	Portugal	Denmark
5	Use alcohol-based hand rub.	Portugal	Germany
6	Avoid touching my nose, eyes and mouth.	Portugal, Italy	Denmark

Finally, the proportion reporting adherence is higher among female (94.0% for females vs. 90.0% for males; $p<0.001$) and older (95.1% for 65+ vs. 87.5 for 18-24 yo; $p<0.001$). Respondents reporting to „adhere fully" are higher among those with high/medium level of education (51.0%) compared to low (46.5%; $p<0.001$) and also among those who have family members that are vulnerable, such as elderly and those with additional comorbidities (49.7%), compared to those who indicate they do not have vulnerable family members (45.6%, $p = 0.001$). Similar results are observed within countries except for levels of education which does not follow a consistent pattern in all countries.

Perception of adherence to the WHO recommendations by others

We also asked respondents if, according to them, others in the community adhered to the six WHO recommendations over the past four weeks. Overall, the proportion of respondents who report that others adhere to the WHO recommendations is 81.3%, which is considerably lower than their own adherence (92.2%). This difference is highest in the UK (19% points difference; $p<0.001$) and the lowest in the Netherlands (3% ; $p= 0.022$) and in France (1%; $p<0.001$). Also, it should be noted that respondents could be overstating their own adherence to avoid judgement whereas adherence estimates of others could be a truer estimate of their own actual adherence.

Trust in information from the WHO

Furthermore, we asked respondents to rate their level of trust in information from the WHO in the context of COVID-19 on a scale "no trust at all" (1) to "trust very much" (5). Respondents reporting a score of 4 or 5 are classified as having trust in the information from the WHO, and those with a score of 1 or 2 as having no trust in this information. We find that on average 59.8% of the respondents from the countries included in this study trust the information on COVID-19 from the WHO, while 15.5% do not trust this information.

Table 2: Relative ranking of countries according to the proportion of respondents who trust and distrust information from the WHO

Country	Trust (%)	Rank
Denmark	64.7	1
Portugal	64.5	2
UK	61.6	3
Italy	60.9	4
Netherlands	59.7	5
Germany	56.8	6
France	49.9	7
Country	**Distrust (%)**	**Rank**
France	22.6	1
Italy	16.4	2
Germany	15.7	3
UK	14.1	4
Netherlands	14.0	5
Portugal	13.0	6
Denmark	12.7	7

Table 2 shows the proportion of respondents in each country reporting trust or no trust in the information from the WHO and the relative ranking among the countries in terms of trust. Marked differences in trust is observed between the countries. In particular, we find that trust is highest in Denmark and Netherlands and the lowest in France with the differences between countries being statistically significant ($p<0.001$). Similarly, Denmark scores

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the lowest on distrust whereas France scores the highest followed by Italy, two countries that were the most impacted by the COVID-19 (p<0.001).

Do Familiarity and Trust Breed Adherence?

We present evidence suggesting that familiarity and trust could be driving factors for adherence. First, looking at the piecewise relationship between familiarity and adherence, we find that overall familiarity with the six WHO recommendations is significantly correlated with adherence to these recommendations (Table 3), especially for hygiene measures (R1, R2) and avoiding physical contact (R3, R4).

Table 3: Correlations between level of familiarity and level of adherence

Adherence	Familiarity							
	Germany	United Kingdom	Denmark	Netherlands	France	Portugal	Italy	Overall
R1	0.303*	0.254*	0.255*	0.245*	0.239*	0.142*	0.218*	0.247*
R2	0.314*	0.251*	0.230*	0.258*	0.219*	0.195*	0.223*	0.246*
R3	0.275*	0.221*	0.260*	0.236*	0.308*	0.179*	0.243*	0.250*
R4	0.375*	0.276*	0.258*	0.313*	0.318*	0.261*	0.306*	0.305*
R5	0.009	0.051	0.141*	0.048	0.091*	0.105*	0.139*	0.096*
R6	0.087*	0.097*	0.110*	0.091*	0.085*	0.102*	0.093*	0.120*

*Note**:** R1-R6 corresponds to the six recommendations released by the world health organization. They are as follows.* ***R1****: Regularly wash my hands with soap for at least 20 seconds,* ***R2****: Cover my nose and mouth when coughing or sneezing,* ***R3****: Keep a distance of at least 1 meter from other people,* ***R4****: Avoid shaking hands, hugging or kissing when greeting others,* ***R5****: Use alcohol-based hand rub' and* ***R6****: Avoid touching my nose, eyes and mouth. Spearman rank correlation test is used for this analysis. *, and ** denote significance at 1 and 5 percent levels respectively.*

Trust could also be a facilitator for adherence (14). In our study, we see that distrust was lower among those who adhered (14.5%) compared to those who did not adhere to the WHO recommendations (29.3%). Overall, at first sight this would mean familiarity implies adherence and trust is a catalyst for this relationship.

However, the relationship between familiarity, adherence and trust is not so direct. Factors such as the severity of the COVID-19 crisis and other perceived worries could be influencing each of these factors independently and together. For instance, respondents from Italy and Portugal reported the highest levels of familiarity and adherence, but at the same time showed diverging profiles on case prevalence (15) and trust in WHO information during the period of our study. In Italy, adherence to physical distancing recommendations is as high as in

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Portugal, although Italy reports lower trust compared to Portugal. That this high adherence in Italy is narrowed to only physical distancing measures could be attributed to the necessity of adherence given the severity of the pandemic. However, Portugal still tops adherence in all measures (including hygiene), which could be facilitated by the high levels of trust in information. This is suggestive of the ability of the WHO to act without any coercion when there are high levels of trust, especially when adherence corresponds to recommendations that are difficult to enforce socially or legally such as hand hygiene.

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DISCUSSION

The ongoing threat to global health from COVID-19 poses critical challenges to governments, medical communities, health organizations, businesses and the public in responding to the evolving pandemic. With limited knowledge and an abundance of misinformation on the disease, governments and health organizations need to be meticulous in disseminating up to date and evidence-based information to the public. The guidelines and recommended preventive behaviors as put forward by WHO and other national level public health agencies is of immense importance given the unavailability of vaccine for COVID-19. The WHO mainly recommends hygiene and physical contact precautions to the public given that coronavirus is mainly transmitted through droplets and aerosols. This highlights the importance of non-pharmaceutical interventions such as social distancing, use of protective equipment such as face masks and other hygiene behaviors in containing the coronavirus (16). Given that the pandemic is still ongoing, and yet to reach the peak in many countries, we used data from a pan European survey collected in April 2020 to evaluate the efficiency and effectiveness of the risk communication strategies put in place by the WHO so far during the pandemic. Following are some insights and attention points on risk communication as learned from our findings.

First, our survey results suggest that overall familiarity and adherence with the recommendations is quite high in most countries in Europe. This indicates both the effectiveness of the WHO risk communication strategy and the interest among the public to seek and follow better practices. Countries reporting high levels of familiarity

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(Portugal and Italy) were also the top adherers. Similarly, countries reporting lower levels of familiarity (UK, Netherlands and Germany) performed worse on adherence. Although there could be other factors influencing this relationship, our results suggest that increasing familiarity with preventive measures could lead to higher levels of adherence among the public, and hence is an effective way to help contain and mitigate the spread of infectious diseases.

Second, we observe considerable heterogeneity in adherence to the different recommendations. Overall, people complied better with avoiding physical contact, but less with hand hygiene and avoiding touching eyes, nose or mouth. Both sets of recommendations involve behavioral modifications with the exception that during the first stage of the pandemic, social distancing was legally and socially enforced, which could be one explanation for the higher adherence rates. Literature also shows that non-adherence to be high especially when recommendations involve behavioral modifications (17). Given that exit strategies from lockdown are currently being unfolded in most countries, strict regulations regarding social distancing may be relaxed. However, at the same time the WHO warns of a potential second wave of coronavirus transmission following relaxed restrictions (18), highlighting the need to make sure that people keep up with social distancing measures even when not legally enforced.

Although social distancing measures has been mostly recommended given the nature of coronavirus transmission, hand washing is also important given that there could be indirect transmission via infected surfaces (16). However, hand washing has a lower adherence rate globally given the complex interaction of many behavioral aspects that drives compliance to hand hygiene (19). Hence, there is an increased need to put higher emphasis on improving adherence to hand hygiene and, most importantly, designing policies to ensure that adherence to social distancing does not fade off without legal enforcement over time to reduce the emergence of further waves of the pandemic.

Third, our analysis suggests evidence for heterogeneities in adherence based on socio-demographic characteristics of the respondents. Particularly, we find older, female, and higher educated respondents to report higher levels of familiarity and adherence. Additionally, we also find those respondents with vulnerable household members to

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have higher levels of adherence. Therefore, steps should be taken to increase awareness among the groups that are less likely to be familiar with or adhere to the preventive measures, in particular the young, males, less educated and households with non-vulnerable family members, since they also play a role in transmitting the virus.

Older people, who are more vulnerable to COVID-19, report higher levels of familiarity and adherence. Possibly they seek more information, or risk communication has been tailored to them better. But, it is equally important to increase awareness among younger people about the risks of not adhering to recommendations, because even if they themselves are less vulnerable, as potential carriers of the virus they may infect others who are. Similarly, households that do not have a vulnerable family member might be less worried about getting infected and hence show poor adherence. Literature shows higher levels of adherence among women in general, attributing this to several factors including early cognitive maturation, capacity for self-care and the stronger perceived need to comply to social expectations (20). Higher educated respondents might have higher levels of health literacy, which is required to critically assess the information provided in relation to their behaviors (21). Thus, we might conclude that risk messages may not fit to all groups alike and, therefore, need to be customized to the specific risks and concerns in that group.

Fourth, trust in information from the WHO could influence adherence to its recommendations. Trust is an overlooked aspect in crisis management (22). Public health organizations need to be more transparent and receptive in their communication to gain the trust of citizens. Most importantly, if the severity of the pandemic in a country is high, this could imply that trust levels are already low, and people are more worried. Hence strategies to improve both adherence and trust should take into consideration the severity of the pandemic in the country and the level of worries among the population. Finally, low trust in authoritative bodies could also be associated with low interpersonal trust (perception of the adherence of others to WHO recommendations) in the society as a whole (23), resulting in covid induced worries, social fear or acts of self-interest such as panic buying and stock piling, which makes crisis management more difficult. Having a perception that others in the community do not adhere to the WHO recommendations could also reduce one‟s own level of adherence (24). Thus, during these hard times, risk communication should not miss out on messages that could improve the public"s trust in their community members and organizations that provide credible information.

CONCLUSION

Overall, we find that information from WHO in the context of COVID-19 is well trusted and acted upon by the public. However, our results suggest the need to strengthen efforts to reach the less vulnerable parts of the population in information campaigns, and to take the worries of the public into account in the design and dissemination of risk communication strategies. Furthermore, our findings call for efforts to get regular feedback from the public on their familiarity with the most recent recommendations and their support for policy measures that increase compliance with these recommendations. As both the pandemic and the recommendations evolve, risk communication needs to be tailored to the different groups in society in order to be more effective.

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Availability of data and materials: The dataset used during the current study are available from the corresponding author on reasonable request.

List of Abbreviations

WHO: World Health Organization

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Declarations

Ethics approval and consent to participate: Ethical approval for this study was provided by the University of Hamburg, Germany under the umbrella project "Countering COVID-19: A European survey on the acceptability of and commitment to preventive measures". Subject recruitment and payment was done through the Agency Dynata. Proprietary panels used double opt-in recruitment and a written informed consent was obtained from individual participants by Dynata. Confidentiality and anonymity of the participants were ensured by issuing a unique identifier to each respondent. Study participants were informed about their freedom to opt-out of the study at any point of time.

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From villains to heroes? The economics profession and its response to the pandemic[1]

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The unprecedented crisis caused by the coronavirus pandemic has prompted a spontaneous collective effort by the economics profession to contribute both to the immediate policy response to the shock, and also to the debate about the character of the subsequent recovery. This paper describes the current contributions of economists, largely from a UK perspective, and compares – and contrasts – this episode with the activities of economists during WW2. In both cases economists have collectively responded to crisis demands with a strong sense of public service. There are also key differences, including the presence of a formal economics profession in government now in contrast to the earlier period, and also prior critiques of economics as a discipline since at least the 2008 financial crisis. The second world war led to significant innovations in economics and its professional status; the scale of the current crisis may in turn lead to an evolution in the professional character of the discipline.

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The coronavirus pandemic is an unprecedented event in our lifetime, and its impact on society and the economy around the globe has been extraordinary. It will be years before the consequences can be fully assessed. The crisis has prompted a spontaneous collective effort by the economics profession to contribute both to the immediate policy response to the shock, and also to the debate about the character of the subsequent recovery. This paper describes the current contributions of economists, largely from a UK perspective, and compares – and contrasts – this episode with the activities of economists during WW2. In both cases economists have collectively responded to crisis demands with a strong sense of public service, but there are also some significant differences. Among these is the damage – deserved or not – that the 2008 financial crisis inflicted on the reputation of economics. Among the similarities is the possibility that the scale of the crisis will lead to an evolution in the professional character of the discipline.

What have economists contributed since March 2020?

European countries, including the UK, entered periods of lockdown from March 2020, involving government shutdowns of a large part of economic activity, at a time when many academic economists were involved in teaching and the sudden switch to online methods. Nevertheless, there was an immediate and substantial response by research-active economists to carry out and publish relevant work as quickly as possible. One metric is the 60 submissions the CEPR's Covid Economics received in its first two weeks of existence; it has to date 45 weekly issues.[1] The VoxEU website had 510 columns related to Covid19 by the end of August 2020. There have also been many online conferences and seminars dedicated to exploring how to manage and mitigate the economic effects of the pandemic. Many economists across the profession, from the most senior ranks down, have switched from their existing research to Covid19-related research, and have

[1] https://cepr.org/content/covid-economics-vetted-and-real-time-papers-0

been swiftly publishing the results as working papers and in journal special issues. Some journals have published numerous Covid19-related papers, at a greatly accelerated pace compared to their usual timetable, implying a similarly responsive effort from reviewers.

Although some economists had for previously worked on epidemiological models, including the interaction between disease and economic activity (eg Chen & Toxvaerd 2017, Goenka 2014), there has unsurprisingly been a surge of interest in such work (a few of the many published include Acemoglu et al 2020, Gonzalez-Eiras & Niepelt 2020, Rowthorn & Toxvaerd 2020). A second priority area where economists leapt into action was macroeconomic policy, with governments and central banks having to take extraordinary measures to support their economies, and subsequently start to plot a route out of the crisis. The debate has covered issues such as the winding down of furlough schemes, the most effective forms of fiscal stimulus, the recovery or write-off of debt from short-term business support schemes, and the role of monetary policy in monetising government debt.

These two key areas of research and policy only scratch the surface of the economic research the crisis has galvanised, however. Other contributions range across areas such as: mitigating the impact of disrupted schooling on educational outcomes; analysing the socio-economic contributors to disproportionate rates of infection and death from Covid19 among ethnic minority and low income communities; discussing support measures for badly-affected sectors from air travel to the performing arts; and investigating potential impacts on agglomeration economies and urban real estate markets. Economists have also contributed to the emerging debate about how to enable the recovery, and what kind of recovery the public would like to see, with a particular focus on the opportunities for green transition and on the relationship between GDP growth and wider measures of economic welfare. For the crisis has touched everything, and will continue to do so, possibly for years to come.

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One downside, however, is that the differential impact of the lockdowns on men and women means both the proportion and (for most levels of seniority) the absolute number of submissions by women has declined, with a particularly stark gender gap for mid-career researchers (Amano-Patino et al 2020). This echoes the experience in other disciplines (Viglione 2020).

It is important to underline the speed and extent to which the crisis has galvanised the economics profession into spontaneous collective action. Taking just two working paper series, CEPR and NBER, the first four months of 2020 saw 798 new working papers published, most in March and April, compared with a our-month average of 606 in 2015-2019 (Amano-Patino et al 2020). A number of focal points for these activities emerged quickly. In addition to CEPR, these included the European Economic Association, which established an online hub for research,[2] and a UK online observatory, ECO, set up in less than two months.[3] This latter is designed for policy makers and members of the public to get answers to their questions about the economics of the pandemic, hosting commissioned syntheses of areas of research, pointing to experts in each case, and also acknowledging what is *not* known. From first discussions in early April (following the 23 March UK lockdown), it went live on 1 June and had posted 100 articles by mid-August. The authors came from institutions (not just universities) across the whole of the country, ranging from PhD students to some of the most senior figures in the profession. Of course, this spontaneous response has not been confined to the UK or the US. Figure 1 below gives an indication of the economics profession's global instinct to contribute to combating the pandemic.

Figure 1: Location of Covid19 economics research initiatives

[2] https://www.eeassoc.org/index.php?site=JEEA&page=298&trsz=299

[3] https://www.coronavirusandtheeconomy.com/ ECO also compiles a list of external Covid19 resources https://www.coronavirusandtheeconomy.com/external-resources

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https://www.coronavirusandtheeconomy.com/ongoing-research-map accessed 28/8/20

A final crucial and more traditional public service role has been the more formal engagement of economists with decision-makers in government. This is the aspect most directly comparable to the role of economists during World War 2, as described below. The key UK scientific committee advising the government about the pandemic, SAGE, lacked economists and other social scientists as members,[4] although their invited presence at its meetings increased as the weeks went by, and policymakers realised that they faced an economic and social emergency as well as a health emergency. Indeed, the interaction of health and economic outcomes has underlined the need for interdisciplinary work (Coyle 2020). The integration of epidemiological and economic models has been imperative to assess the extent to which there is a trade-off between 'health and wealth' as was alleged at the start of the pandemic, and to consider the economic effects of various distancing measures. As noted, a number of economists were swift to incorporate the epidemiological approaches. The Royal Society established early on an

[4] https://www.gov.uk/government/publications/scientific-advisory-group-for-emergencies-sage-coronavirus-covid-19-response-membership/list-of-participants-of-sage-and-related-sub-groups

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influential interdisciplinary group modelling pandemic outcomes, DELVE, which included economists from the start.[5] Although independent, it clearly has significant influence with policymakers. Many individual economists, who often act as formal or informal advisers to the UK government in normal times, continued to do so. For example, the Treasury called on experts in bodies such as the Institute for Fiscal Studies and National Institute of Economic and Social Research to advise on pressing economic policy decisions such as the design of furlough schemes or the public finance issues.

The UK government itself employs many economists, many (although not all) being members of the Government Economic Service (GES). Others work across regulatory bodies and local government. The presence of so many economists in government is an obvious difference between the current crisis and World War 2. As described below, economists were drafted into public service to play significant roles during the war. Post-war, however, they left and there were few economists in UK government until the GES was founded by Sir Alec Cairncross in 1964 under the Labour Government of Harold Wilson. The introduction of the service was part of that government's wider project of rationalist planning and industrial policy, and represented a (modest) shift away from the Whitehall tradition of employing Oxbridge humanities generalists (Allan 2008).

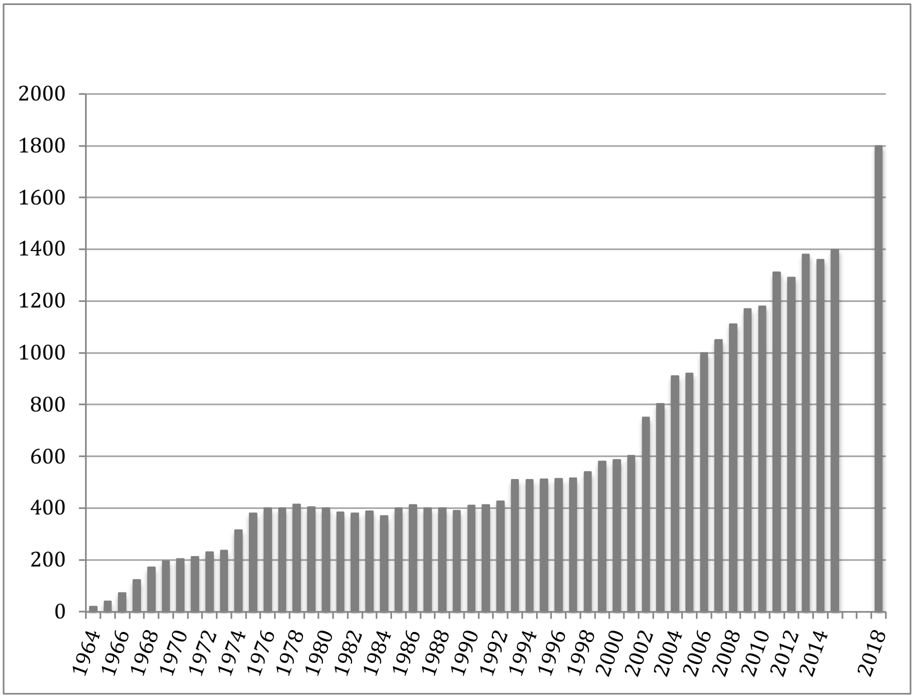
GES numbers have steadily increased (Figure 2), and it is the single biggest employer of economists in the UK. The Brexit process had already led to an increase in recruitment, taking numbers to 1800. Following the onset of the pandemic, many government economists, and also many of the economic statisticians at the Office for National Statistics, saw their work redirected toward the more pressing emergency. The Treasury's economists in particular have been acknowledged as having played a vital role in preparing

[5] https://royalsociety.org/news/2020/04/royal-society-convenes-data-analytics-group-to-tackle-COVID-19/ and https://rs-delve.github.io/

an emergency stimulus package within a week of the lockdown being introduced.

Figure 2: Number of GES members

Source: GES



Economists in World War 2

The existence now of a formal structure of economic advice within government means the current context differs from the wartime experience. Although the UK government in 1939 had economic advisers, these were external to departments – albeit establishment figures and often highly influential. Keynes of course stands out among them, but as Skidelsky observes in his authoritative biography, it was in an unpaid, unofficial role. Although hugely influential, both during and in the aftermath of war, this reflected Keynes's personal authority rather than any official appointment (Skidelsky 2000, pp135ff).

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However, the outbreak of hostilities brought many pressing economic imperatives, for innovation and the effective deployment of new military technologies, for the management of supply chains and organisation of production, for 'manpower' management, for price controls, and for wartime financing. Economists were drafted in to relevant official ministries and other agencies on both sides of the Atlantic and indeed in all the belligerent countries (Bollard 2019, 2020; Lacey 2011; Tooze 2001, 2016). This included intelligence activities (Gugliemo 2008).

As Backhouse & Fontaine (2018) note, economics had begun to professionalise in the late 19th-early 20th century, with the introduction of formal degrees and formation of professional societies. In the first part of the 20th century, the discipline remained pluralistic and close to its political economy roots. World War 2 marked a turning point in disciplinary terms, with the well-documented formalisation of macroeconomic and microeconomic theory in the postwar period. Backhouse & Fontaine write: "Whatever the nature of their wartime experience, a perception had emerged by the late 1940s that economics could be like engineering – a technical discipline that possessed mathematical tools that could be used to solve logistic and other allocation problems," (p24).

They cite many examples of US economists working as general problem solvers or applied statisticians in multiple wartime roles in different branches and agencies of government and the military. But the main reason for this new sense of the technical prowess of economic knowledge lay in the intellectual innovations economists brought to the war effort – just as the exigencies of war proved to be the cradle of innovation in other scientific domains from computing to advanced materials. Operations research emerged out of the British development of radar (Rau 2005), and was swiftly adopted by the UK and US military. In the UK immediately after the war many operations researchers transitioned straight into the new nationalised industries and economic planning. Tjalling Koopmans introduced the widespread use of linear programming, his work sponsored by the US Air Force. Wassily Leontief's (1936) input-output framework was used by the Allies to analyse Germany's greatest vulnerabilities to aerial bombardment.

The key innovation in terms of economic analysis, however, was the measurement of national income and the development of the forerunner of today's System of National Accounts. Keynes famously demanded better economic statistics in his 1940 pamphlet *How To Pay For The War*, describing those available as "very inadequate". Richard Stone and James Meade in the UK Treasury, and Robert Nathan, Simon Kuznets and Stacy May in the US, developed the means for their two governments to understand the extent of the resources available to them and the demand management requirements for their economies. These efforts built on pre-war work on national income statistics by Kuznets, and by Colin Clark in the UK, but were tailored to Keynes's macroeconomics (Coyle 2014).

Parallel efforts took place in other countries, such Germany, where the Weimar Republic had begun large-scale data gathering and development of aggregate statistics, inherited and extended by the Nazi regime (Tooze 2001); or Kantorovich's work on linear programming and planning in Soviet Russia (Ward 1960). However, these were neither as comprehensive nor as timely as the Allied effort. The importance of the greater understanding of resource constraints on the side of the eventual victors is reflected in the subtitle of Jim Lacey's (2011) book *Keep From All Thoughtful Men*: 'How US economists won World War II'.[6] He writes: "The revolution in economic statistics reached a point in 1940 where those few economists intimately familiar with their intricacies could use them to determine with a considerable degree of accuracy how much and how fast US industry could expand to meet wartime demands." The same held true in the UK, albeit there

[6] British economists would naturally put in a claim to at least equal billing.

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resources were scarcer and the necessary consumer sacrifices correspondingly greater.

Then and now

There is an obvious similarity between the formal wartime public service contribution of economics and the spontaneous contribution of economists in the current coronavirus crisis to public debate and public policy. The gravity of the current moment has inspired the profession to deploy all the tools at our disposal to serve the public interest.

There are also some important differences. One is, as already noted, the existence now of a formal and extensive role for economists in government service. I have cited the UK figures but the same is true in all the developed economies. Economists have become strikingly influential in the formation of public policy and in government generally in recent decades (Coyle, 2021 forthcoming).

A further aspect of the current context that may have prompted such an extraordinary response is the recent experience economists have had in terms of their loss of public esteem as a result of the 2008-9 financial crisis. Although individual economists had certainly pointed out the potential for macroeconomic instability ahead of 2008, the profession as a whole came in for collective blame subsequently. Indeed, commentators have continued to criticise economics and economists ever since, and at least up until the onset of pandemic this showed no sign of abating (for example, Applebaum 2019, Skidelsky 2020). Nor are the critiques all external: prominent economists have also called for economists to adopt a broader range of methodologies and address important topics of pressing importance that do not lend themselves to the narrow range of ‘hard’ methods prioritized in the field (for example, Akerlof 2020).

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The crash certainly prompted significant soul-searching within the profession, which resulted in new approaches to teaching economics such as the CORE curriculum initiative,[7] substantial advances in macroeconomics (Reis 2018), and a new emphasis on communication and the public understanding of economics.[8] For UK-based economists, their experience of the lack of traction for economic arguments during the Brexit referendum campaign underlined the importance of trustworthy professional voices during moments of vital national debate. This helps explain the speed and enthusiasm with which so many embarked on the Economics Observatory resource described above.

Perhaps the most striking difference looking back to the World War 2 comparison, though, is the role disciplinary innovation – new ideas and tools – played then. For all the scale and urgency of the coronavirus economic crisis, it has not – at least yet – led to new methodologies or anything as paradigm-changing as the Keynesian national accounting and macroeconomic framework. Modern economics perhaps has less need to innovate methodologically, with the greater wealth of data, computer power, and econometric techniques available now. This is not to say there is no innovation now, particularly in the use of real-time and/or 'big' data (Carvhalo et al 2020, Haldane and Chowla 2020).

However, it is hard to believe that our societies will emerge from the double shock of the financial crisis and the pandemic with confidence in the intellectual framework of postwar economics and public policy intact. The imperative of restoring full employment will be as important in 2020-21 as it was before and after World War 2. At the same time, it has become something of a cliché to talk about 'building back better' and ensuring economic 'resilience'. The challenge to the economics profession is what these terms mean when so many people have not experienced much real income growth since 2008, when the pandemic is exposing great inequalities,

[7] https://www.core-econ.org/
[8] https://www.economicsnetwork.ac.uk/research/understandingecon/2019

and when globalisation is questioned for many reasons including excessive 'efficiencies' in supply chains.

This may lead to a revival of interest in welfare economics (Sen et al 2020). Alternatively, it may represent a demand for a more fundamental reframing of economic policy to replace the postwar centrality of consumption and growth. Some elements of this were arguably emerging pre-pandemic, with debates within the profession about issues such as addressing multiple inequalities, developing broader understanding of well-being, tackling excessive market power in major sectors including digital, incentivising the zero carbon transition, and evaluating monetary policy and asset prices. There has been debate too about the contribution of economic outcomes to political polarisation in so many western countries. The dramatic intervention of governments in the economy through the imposition of lockdowns has in itself shifted the terms of debate about the respective role of markets and state.

From its extraordinary response to the current emergency, the economics profession seems to have an appetite to engage in these bigger debates, in the public interest. While the postwar years marked the start of disciplinary specialization in economics, as in other fields, post-Covid19 public policy imperatives may call for a broader, cross-disciplinary approach to our evident major societal problems. If economists do not respond to continuing (internal and external) critiques of the discipline's narrowness and inward-focus, other disciplines may fill the gap, including in government roles.

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