COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

Covid Economics
Vetted and Real-Time Papers

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

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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.

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

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Contents

Pandemic economics: Optimal dynamic confinement under uncertainty and learning[1]

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Most integrated models of the Covid pandemic have been developed under the assumption that the policy-sensitive reproduction number is certain. The decision to exit from the lockdown has been made in most countries without knowing the reproduction number that would prevail after the deconfinement. In this paper, I explore the role of uncertainty and learning on the optimal dynamic lockdown policy. I limit the analysis to suppression strategies. In the absence of uncertainty, the optimal confinement policy is to impose a constant rate of lockdown until the suppression of the virus in the population. I show that introducing uncertainty about the reproduction number of deconfined people reduces the optimal initial rate of confinement.

1 Introduction

Academic economists have recently spent a huge amount of energy to better understand the science of pandemic dynamics in the face of the emergence of the covid-19. Economists are contributing to the analysis of the covid-19 crisis by integrating economic dimensions to the models, such as the economic cost of social distancing and the statistical value of lives lost. These are key elements necessary for public and private decision-makers interested in shaping strategies and policies that minimize the welfare cost of the crisis. My preferred reading list on this issue as I write this paper is composed of papers by Acemoglu, Chernozhukov, Werning and Whinston (2020), Alvarez, Argent and Lippi (2020), Brotherhood, Kircher, Santos and Tertilt (2020), Favero, Ichino and Rustichini (2020), Fischer (2020), Greenstone and Nigam (2020), Miclo, Spiro and Weibull (2020), Pindyck (2020) and Pollinger (2020). This investment by the profession is impressive and highly policy-relevant. It raised critical debates about, for example, when and how much to deconfine people, who should remain confined longer, the value of testing and tracing, or whether the individual freedom of movement should be limited.

One of the most striking feature of the crisis is the deep uncertainties that surrounded most parameters of the model at the initial stage of the pandemic. To illustrate, here is a short list of the sources of covid-19 uncertainties: The mortality rate, the rate of asymptomatic sick people, the rate of prevalence, the duration of immunity, the impact of various policies (lockdown, social distancing, compulsory masks,...) on the reproduction numbers, the proportion of people who could telework efficiently, and the possibility of cross-immunization from similar viruses. Still, all models that have been built over such a short period of time by economists assumed no parameter uncertainty, and I am not an exception (Gollier, 2020). This is amazing. Large discrepancies between the predictions of these models and their associated "optimal" policies do not illustrate deep disagreements about the dynamics of the pandemic, but rather deep uncertainties about the true values of its parameters. This parameter uncertainty should be recognized and integrated in the modeling. Economists are well aware that uncertainty is typically a key component to explain observed behaviors and to shape efficient policies. Precautionary savings, option value to wait before investing, risk premia on financial markets, insurance demand, risk-sharing and solidarity mechanisms, and preventive efforts are obvious examples to demonstrate that risk and uncertainty are at the heart of the functioning of our society. But in the cases of climate change and covid-19, we most often assume no uncertainty to make policy recommendations in spite of the fact that uncertainty is everywhere in these contexts. I feel this fact as an impressive failure of our profession to be useful to make the world better.

In this paper, I go one step towards including risk in the shaping of efficient pandemic policies. Suppose that a virus has contaminated a small fraction of the population, and that no treatment or vaccine is available. Because of the high lethality of the virus, I suppose that the only feasible strategy is to "crush the (infection) curve" by imposing a partial lockdown. The intensity of the confinement can be adapted in continuous-time to the evolution of the pandemic in order to minimize the total cost of the confinement. Following Pollinger (2020), I show that in the absence of uncertainty, the optimal intensity of the lockdown should be constant over time until the eradication of the virus in the population. The optimal confinement intensity is the best compromise between the short-term cost of increasing the confinement and the long-term benefit of reducing the duration of the confinement. Confining

people modifies the reproduction number. Under the standard SIR pandemic model (Kermack and McKendrick, 1927), there is a quadratic relation between the instantaneous intensity of the confinement and the instantaneous reproduction number.

Consider the situation prevailing in the western world in April 2020, after a partial lockdown was imposed. In this context, suppose that the reproduction number under full lockdown is known, but the reproduction number under full deconfinement is uncertain. This uncertainty will evaporate within a few weeks by observing the propagation of the virus under the partial lockdown. How should this uncertainty with learning affect the initial intensity of the lockdown? Surprisingly, I show that it tends to reduce it. To obtain this result, I assume that the representative agent is risk-neutral. However, risk plays a role in this model because of two non-linear interactions: the quadratic relation between the cost of confinement and the instantaneous reproduction number, and the hyperbolic relation between the reproduction number and the duration of the pandemic. This double non-linearity makes the analysis quite complex, and I have been able to prove the main result only in the case of small risk. The calibration exercise suggests that my result holds for large risks too.

There is a long tradition in decision theory and finance on optimal choice under uncertainty and learning to which this paper is related. It is closest to the literature on the option value to wait introduced by McDonald and Siegel (1984) and popularized by Dixit and Pindyck (1994). An important message from this literature is that risk-neutral agents could optimally reduce their initial effort to achieve a long-term goal in order to obtain additional information about the welfare impact of this effort. I obtain a similar result in this pandemic model.

2 The model

My model is based on the classical SIR model developed by Kermack and McKendrick (1927) to describe the dynamics of a pandemic. Each person is either Susceptible, Infected or Recovered, i.e., the health status of a person belongs to $\{S, I, R\}$. This implies that $S_t + I_t + R_t = N$ at all dates $t \geq 0$. A susceptible person can be infected by meeting an infected person. Following the key assumption of all SIR models, this number of new infections is assumed to be proportional to the product of the densities of infected and susceptible persons in the population, weighted by the intensity of their social interaction. With no further justification, this is quantified as follows:

$$\frac{dS_t}{dt} = -\beta_t I_t S_t. \tag{1}$$

I will soon describe how β_t, which measures the intensity of the risk of contagion of a susceptible person by an infected person at date t, is related to the social interactions between these two groups and by the confinement policy. Once infected, a person quits this health state at rate γ, so that the dynamics of the infection satisfies the following equations:

$$\frac{dI_t}{dt} = \beta_t I_t S_t - \gamma I_t. \tag{2}$$

$$\frac{dR_t}{dt} = \gamma I_t \tag{3}$$

The pandemic starts at date $t = 0$ with I_0 infected persons and $N - I_0$ susceptible persons. I assume that the virus is eradicated when the number I_t of infected persons goes below I_{min}, in which case an aggressive tracing-and-testing strategy is implemented to eliminate the last clusters of the epidemic.

Because on average an infected person remains contagious for a duration $1/\gamma$, and because the instantaneous number of susceptible persons infected by a sick person is $\beta_t S_t$, the reproduction number at date t equals

$$r_t = \frac{\beta_t S_t}{\gamma}. \tag{4}$$

Herd immunity is obtained when the number of infected persons start to decrease over time. From equation (2), this is obtained when the number of susceptible persons goes below the herd immunity threshold $S^* = \gamma/\beta_t$, i.e., when the reproduction number goes below 1. In this paper, I focus on policies aimed at "crushing the curve", where r_t remains permanently below unity. Other policies, such as the laissez-faire policy or policies aimed at "flattening the curve", consist in building herd immunity through a rapid or gradual infection of a large fraction of the population, implying a large health cost but a limited economic cost. When crushing the curve, a sufficiently strong confinement is imposed to the population to maintain the reproduction number permanently below 1, so that the virus is eradicated relatively quickly. Under this family of scenarios, the number S_t of susceptible persons remain close to unity, very far from herd immunity under the laissez-faire policy. This implies that the changes in $I_t S_t$ in equation (2) mostly comes from changes in I_t. Following Pollinger (2020), I therefore simplifies the SIR dynamic described above into a single differential equation:

$$\frac{dI_t}{dt} = (\beta_t I_t S - \gamma)I_t, \tag{5}$$

where S is the average number of susceptible persons during the pandemic. This approximation of the SIR model is exact when the ratio of infected to susceptible is close to zero.

I examine policies of social distancing and lockdown. Let x denote the intensity of this policy. One can interpret x as a measure of the fraction of people that are confined. For simplicity, I assume that infected people are asymptomatic and that there is no PCR test, so that one cannot discriminate the intensity of confinement on the basis of the health status. This means that x is the fraction of people, both infected or susceptible, who are confined. A free infected person has a reproduction number $r_f = \beta_f S/\gamma$. I assume that there is no herd immunity at the start of the pandemic, i.e., that r_f is larger than unity, or $\beta_f S > \gamma$. The confinement reduces this number to $r_c = \beta_c S/\gamma$, with $\beta_c \le \beta_f$. I assume that the full confinement of the population crushes the curve in the sense that $r_c < 1$, or $\beta_c S \le \gamma$.

As said earlier, a crucial element of the SIR model is that the speed of infection is proportional to the product of the numbers of people infected and susceptible. Confining people reduces both the number of infected people and the number of susceptible persons, implying a quadratic relation between the intensity x of the confinement and propagation of the virus in the population (Acemoglu, Chernozhukov, Werning and Whinston (2020)). From this observation, the pandemic parameter β_t takes the following form:

$$\beta_t = \beta(x_t) = (\beta_c x_t + \beta_f(1 - x_t))(1 - x_t). \tag{6}$$

The true contagion rate $\beta_c x_t + \beta_f(1 - x_t)$ of infected people is a weighted average of the contagion rates β_c and β_f of infected people who are respectively confined and let free to live their life. They meet a reduced fraction $1 - x$ of susceptible people, because the remaining fraction x is lockdown. The quadratic nature of this relation plays a crucial role in this paper. The lockdown has also an economic cost. I assume that the instantaneous cost of confining a fraction x of the population at date t equal to wx, where $w > 0$ can be interpreted as the sum of the wage and psychological costs of confinement. Abstracting from discounting given the short duration of the pandemic when crushing the curve, the objective of the policy is to minimize the total cost of the health crisis. This yields the following value function:

$$V(I) = \min_{x(.)} \quad w \int_0^T x(t)dt \quad \text{s.t.} \ I_0 = I \text{ and } I_T = I_{min}, \tag{7}$$

where I is the current rate of prevalence of the virus in the population. The termination date corresponds to the time when the rate of prevalence of the virus attains the eradication threshold I_{min}. Observe that I assume an objective that ignores the potential lethality of the virus. But even when the virus is lethal, policies aimed at crushing the curve typically yields economic costs that are at least one order of magnitude larger than the value of lives lost (Gollier (2020)), thereby justifying this objective of minimizing costs.

3 Optimal suppression under certainty

Pollinger (2020) derives the solution of a more general version of this dynamic problem under certainty. Using backward induction, problem (7) can be rewritten as follows:

$$
\begin{aligned}
V(I) &= \min_x \quad wx\Delta t + V(I + (\beta(x)S - \gamma)I\Delta t) \\
&\approx \min_x \quad wx\Delta t + V(I) + (\beta(x)S - \gamma)IV'(I)\Delta t,
\end{aligned}
$$

or, equivalently,

$$0 = \min_x \ wx + (\beta(x)S - \gamma)IV'(I). \tag{8}$$

The first-order condition of this problem is

$$w = -\beta_x(x^*)SIV'(I), \tag{9}$$

Under this notation, β_x is the derivative of β with respect to x. Equation (9) expresses the optimal intensity $x^*(I)$ of confinement as a function of the rate of prevalence of the virus. However, let us guess a constant solution x^* independent of I. From equation (9), this would be the case if $IV'(I)$ is a constant. In that case, the duration T of the pandemic will be such that

$$I_{min} = I \exp((\beta(x^*)S - \gamma)T). \tag{10}$$

This equation tells us that there is an hyperbolic relation between the reproduction number and the duration of the pandemic. The total cost under such a constant strategy is

$$V(I) = wx^*T = \frac{-wx^*}{\beta(x^*)S - \gamma} \ln\left(\frac{I}{I_{min}}\right). \tag{11}$$

This implies that $IV'(I)$ is a constant, thereby confirming the guess that it is optimal to maintain a constant intensity of lockdown until the eradication of the virus. Combining equations (9) and (11) yields the following optimality condition for x^*:

$$x^* = \frac{\beta(x^*)S - \gamma}{\beta_x(x^*)S}. \tag{12}$$

The optimal intensity of lockdown is a best compromise between the short-term benefit of easing the lockdown and the long-term cost of a longer duration of the pandemic. Under the quadratic specification (6) for beta, equation (9) simplifies to

$$x^* = \sqrt{\frac{\beta_f S - \gamma}{\beta_f S - \beta_c S}} = \sqrt{\frac{r_f - 1}{r_f - r_c}}. \tag{13}$$

Because $r_c < 1 < r_f$, the optimal intensity of confinement is between 0 and 1. For example, if the reproduction number goes from 2 to 0.5 when moving from the laissez-faire to the 100% lockdown, the optimal intensity of confinement is $\sqrt{2/3} = 81\%$. I summarize my results under certainty in the following proposition. Its first part is a special case of Pollinger (2020).

Proposition 1. *Under certainty, the optimal suppression strategy is to impose a constant intensity of confinement until the virus is eradicated. In the quadratic case (6), the optimal intensity of confinement is $\sqrt{(r_f - 1)/(r_f - r_c)}$, where r_f and r_c are the reproduction numbers under respectively the laissez-faire and the full lockdown.*

4 Optimal suppression under uncertainty

Suppose that some parameters of the pandemic are unknown at date 0. Suppose also that the only way to learn the true value of these parameters is to observe its dynamics over time. How should this parameter uncertainty affect the optimal effort to fight the virus in the population? I have not been able to solve the continuous-time version of this dynamic learning problem. I therefore simplified the problem as follows. I assume that parameter β_f is unknown. At date 0, a decision must be made for an intensity x_0 of confinement under uncertainty about β_f. This intensity of confinement will be maintained until date τ.[1] Between dates 0 and τ, the observation of the propagation of the virus will inform us about β_f. Therefore, at date τ, β_f is known and the intensity of confinement is adapted to the information. My objective is to compare the optimal x_0 under uncertainty to the x_0 that would be optimal when ignoring the fact that β_f is uncertain.

This is thus a two-stage optimization problem that I solve by backward induction. From date τ on, there is no more uncertainty. As observed in the previous section, it is optimal to revise the confinement policy to the information about the true β_f. We know from the previous section that the optimal contingent policy $x^*(\beta_f)$ is constant until the eradication of the virus. The minimal total cost of this policy is denoted $V(I_\tau, \beta_f)$. Combining equations (11) and (12), it is equal to

$$V(I_\tau, \beta_f) = \frac{-w}{\beta_x(x^*(\beta_f))S} \ln\left(\frac{I_\tau}{I_{min}}\right). \tag{14}$$

---

[1] I assume that τ is small enough so that I_τ is larger than I_{min} with probability 1.

It is a function of the rate of prevalence I_τ of the virus observed at date τ and of the pandemic parameter β_f observed during the first stage of the pandemic.

The first stage of the pandemic takes place under uncertainty about β_f. I assume risk neutrality, so that the objective is to minimize the expected total cost of the suppression strategy:

$$W_0 = \min_{x_0} wx_0\tau + EV(I_\tau, \beta_f),\qquad (15)$$

where $I_\tau = I_0 \exp((\beta(x_0, \beta_f)S - \gamma)\tau)$ is also a function of random variable β_f. The first-order condition of this stage-1 problem can be written as follows:

$$E[F(x_0^*, \beta_f)] = 1,\qquad (16)$$

with

$$F(x_0, \beta_f) = \frac{\beta_x(x_0, \beta_f)}{\beta_x(x^*(\beta_f), \beta_f)}.\qquad (17)$$

In the absence of uncertainty, i.e., when β_f takes value β_{f0} with probability 1, the optimal solution is the solution of equation (16) in that particular case, which implies

$$x_0^* = x^*(\beta_{f0}).\qquad (18)$$

How does the uncertainty and learning about β_f affect the optimal effort to mitigate the pandemic? Because β is a convex function of the mitigation effort x, function F is increasing in x_0. By Jensen's inequality, equation (16) implies that the uncertainty affecting β_f reduces the optimal initial mitigation effort if an only if F is convex in its second argument. I have not been able to demonstrate a general result of this nature. I therefore limited my analysis to the case of a small risk surrounding β_f. More precisely, suppose that β_f is distributed as $\beta_{f0} + h\epsilon$, where β_{f0} is a known constant, ϵ is a zero-mean random variable and h is an uncertainty-intensity parameter. I examine the sensitivity of the optimal confinement x_0^* as a function of the intensity h in the neighborhood of $h = 0$. In the Appendix, I demonstrate that F is locally convex in its second argument, i.e., that $x_0^*(h)$ is decreasing in h in the neighborhood of $h = 0$. More precisely, I show that $x_0^{*'}(0) = 0$ and $x_0^{*''}(0) < 0$. This yields the following main result of the paper.

Proposition 2. *Consider the quadratic case (6). Introducing a small risk about the transmission rate β_f reduces the optimal initial intensity of confinement.*

Proof: See Appendix.

5 Calibration exercise

In this section, I quantify the negative impact of uncertainty on the optimal confinement in the learning stage 1. I solve numerically the optimality condition (16) in the quadratic context. This equation takes the following form in that case:

$$E\left[\frac{(2\beta_f - \beta_c)S - 2(\beta_f - \beta_c)Sx_0^*}{(2\beta_f - \beta_c)S - 2\sqrt{(\beta_f - \beta_c)S(\beta_f S - \gamma)}}\right] = 1\qquad (19)$$
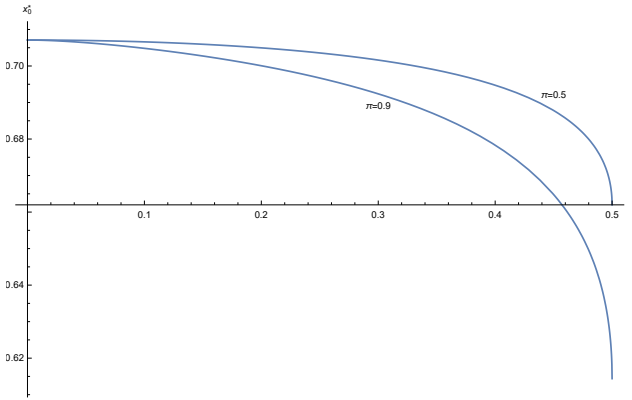
Figure 1: Optimal confinement x_0^* in stage 1 as a function of the intensity h of the uncertainty. I assume that $r_c = 0.5$ and $r_f = 1.5 + h\epsilon$, with $\epsilon \sim (-1, \pi; \pi/(1-\pi), 1-\pi)$.

It yields the following solution:

$$x_0^* = \frac{E\left[\frac{\sqrt{(r_f-r_c)(r_f-1)}}{2r_f-r_c-2\sqrt{(r_f-r_c)(r_f-1)}}\right]}{E\left[\frac{r_f-r_c}{2r_f-r_c-2\sqrt{(r_f-r_c)(r_f-1)}}\right]}, \tag{20}$$

where $r_f = \beta_f S/\gamma$ and $r_c = \beta_c S/\gamma$ are the reproduction numbers in the laissez-faire and total lockdown respectively. I first describe a simulation in the spirit of the covid-19. There has been much debate about the reproduction number under the laissez-faire policy. Ferguson et al. (2020) assumed that it was between 2 and 2.6 at the beginning of the pandemic. However, I focus in this paper on a post-lockdown situation in which people have learned the benefit of washing hands, bearing masks and basic social distancing behaviors. Therefore, the expected reproduction number under the laissez-faire in this new situation is probably smaller than 2. I assume an expected value of $Er_f = 1.5$. For France, Santé Publique France[2] has estimated the reproduction number at different stages of the pandemic. It was estimated at 0.8 at the end of the strong confinement period in May. Because the confinement was partial, this observation is compatible with a r_c equaling 0.5.

In Figure 1, I describe the optimal intensity x_0^* in stage 1 as a function of the intensity h of the uncertainty surrounding r_f, with $r_f = 1.5 + h\epsilon$, with $E\epsilon = 0$. More specifically, I consider binary distribution with $\epsilon \sim (-1, \pi; \pi/(1-\pi), 1-\pi)$. In order to keep r_f above 1 with probability 1, I consider risk intensities h between 0 and 0.5. Under certainty ($r_f = 1.5$ with certainty, or $h = 0$), the optimal intensity of confinement is a constant $\sqrt{0.5} = 70.7\%$.
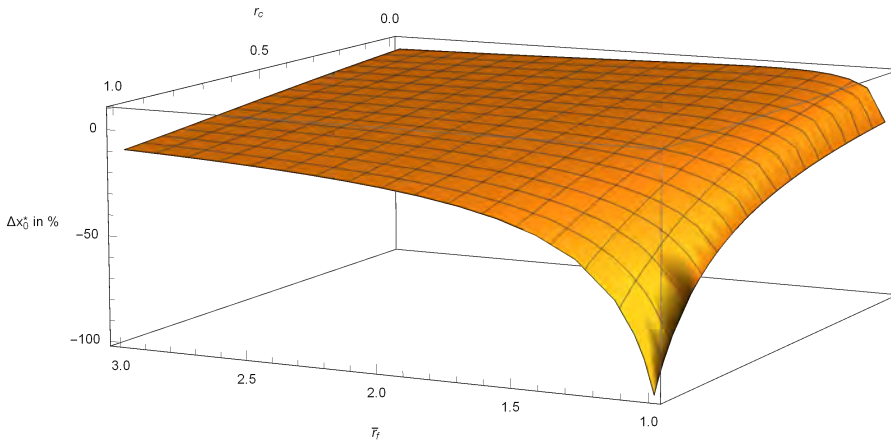
Figure 2: Percentage reduction in the optimal confinement x_0^* in stage 1 due to uncertainty for different values of $(r_c, \overline{r}_f)$. I assume that r_f is distributed as $(1, 1/2; 2\overline{r}_f - 1, 1/2)$.

Suppose alternatively that r_f is either 1 or 2 with equal probabilities. In that case, the optimal confinement goes down to 66.2%. If our beliefs about the reproduction number r_f are distributed as 1 with probability 0.9 and 6 with probability 0.1, then the optimal initial confinement goes down to 61.4%.

In Figure 2, I describe the percentage reduction in the optimal initial confinement for different r_c and $r_f \sim (1, 1/2; 2\overline{r}_f - 1, 1/2)$. We see that the impact of uncertainty on the optimal confinement is largest when the reproduction numbers in the pre- and post-confinement are close to unity. Suppose for example that $r_c = 0.9$ and $r_f = 1.1$. In this context of certainty, the optimal confinement is 70.7%. If r_f is distributed as $(1, 1/2; 1.2, 1/2)$, the optimal initial confinement goes down to 34.7%, a 51% reduction in the initial mitigation effort.

6   Concluding remarks

The uncertainty surrounding the reproduction number when reducing the strength of the lockdown is an argument in favor of lowering the intensity of this lockdown in the learning phase of the pandemic. This rather surprising result is the outcome of two non-linearities of the model. First, the duration of the pandemic is an hyperbolic function of the reproduction number. Second, the reproduction number is a quadratic function of the cost of confinement. These two non-linearities explain why one should be sensitive to the uncertainty when shaping the confinement policy, but I confess that these observations do not explain why this uncertainty should reduce the optimal confinement at the first stage of the pandemic. More work should be done to explain this result.

This research opens a new agenda of research that I am glad to share with the readers of this paper. For example, shame on me, I assume here risk neutrality, in spite of the large size

of the risk and its correlation with aggregate consumption. Could there be a precautionary motive for a larger initial intensity of the confinement? No doubt that my result should be refined in that direction. Also, I limited the analysis to suppression policies. This restriction was necessary to simplify the dynamic equations of the generic SIR model, so that the assumption of an almost constant number of susceptible people in the population is a reasonable approximation. This excludes the possibility to compare the optimal solution among this family of policies to other plausible policies, in particular policies aimed at attaining a high rate of herd immunity. Introducing uncertainty in the generic SIR model and measuring its impact on the optimal policy is another promising and useful road for research. In my to-do list, I also have the exploration of other sources of uncertainty, such as not knowing the rate of prevalence, the fraction of the population already immunized, or the time of arrival of a vaccine. Finally, because the value of lives lost associated to most suppression strategies is typically one or two orders of magnitude smaller than the direct economic cost of the lockdown, I assumed that the objective of the social planner is to minimize the economic cost incurred to eradicate the virus in the population. It would be useful, as in Pollinger (2020), to incorporate the value of lives lost in the objective function.

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Appendix: Proof of Proposition 2

In the quadratic case (6), we have that

$$\beta(x)S - \gamma = (\beta_c x + \beta_f(1-x))(1-x)S - \gamma = ax^2 - bx + c,$$

with

$$
\begin{aligned}
a &= (\beta_f - \beta_c)S > 0 \\
b &= (2\beta_f - \beta_c)S > 0 \\
c &= \beta_f S - \gamma > 0
\end{aligned}
$$

Remember that we assume that $\beta_f S > \gamma$ and that $\beta_c S < \gamma$, so the signs of coefficients (a, b, c), which are functions of β_f. This also implies that $\beta(x)S - \gamma$ alternates in sign, implying $b^2 - 4ac > 0$. We have that

$$x^*(\beta_f) = \sqrt{\frac{c}{a}} = \sqrt{\frac{\beta_f S - \gamma}{(\beta_f - \beta_c)S}}$$

Observe that $\beta_c S < \gamma$ implies that the optimal stage-2 confinement is smaller than unity. Stage-1 optimality condition (16) is now rewritten as follows:

$$E\left[\frac{2ax_0^* - b}{2\sqrt{ac} - b}\right] = 1. \tag{21}$$

As stated in the main part of the paper, let me parametrize the uncertainty by assuming that β_f is distributed as $\beta_{f0} + h\epsilon$, where β_{f0} is a known constant, ϵ is a zero-mean random variable and h is a measure of the uncertainty. The optimal stage-1 confinement is a function of h, and is denoted $x_0^*(h)$. I examine the properties of this function in the neighborhood of $h = 0$. When h equals zero, the above equation is solved with

$$x_0^*(0) = x^*(\beta_{f0}) = \sqrt{\frac{\beta_{f0}S - \gamma}{(\beta_{f0} - \beta_c)S}}.$$

I now estimate $x_0^{*\prime} = \partial x_0^*/\partial h$. To do this, I fully differentiate the optimality condition (21) with respect to h, taking account of the fact that (a, b, c) are functions of $\beta_f = \beta_{f0} + h\epsilon$. Let d be equal to ac. I obtain

$$E\left[\frac{(2a'x_0^* - b')\,\varepsilon + 2ax_0^{*\prime}}{2\sqrt{d} - b} - \frac{(2ax_0^* - b)\varepsilon}{(2\sqrt{d} - b)^2}\left(\frac{d'}{\sqrt{d}} - b'\right)\right] = 0. \tag{22}$$

When h equals zero, coefficients a, b, c and d are constant. Because $E\epsilon$ equals zero, the above equation has a single solution

$$x_0^{*\prime}(0) = 0 \tag{23}$$

when evaluating it at $h = 0$. At the margin, introducing a zero mean risk for the reproduction number has no effect on the optimal mitigation effort in stage 1.

Let me now turn to $x_0^{*''} = \partial^2 x_0^*/\partial h^2$. Let me specifically evaluate this second derivative at $h = 0$. Fully differentiating equation (22) with respect to h, and using property (23) yields

$$
0 = \frac{\left(2a''x_0^* - b''\right)\sigma^2 + 2ax_0^{*''}}{2\sqrt{d} - b} - 2\frac{\left(2a'x_0^* - b'\right)\sigma^2}{\left(2\sqrt{d} - b\right)^2}\left(\frac{d'}{\sqrt{d}} - b'\right) - \frac{(2ax_0^* - b)\sigma^2}{(2\sqrt{d} - b)^2}\left(\frac{d''}{\sqrt{d}} - \frac{1}{2}\frac{d'^2}{d^{\frac{3}{2}}} - b''\right)
$$
$$
+ 2\frac{(2ax_0^* - b)\sigma^2}{(2\sqrt{d} - b)^3}\left(\frac{d'}{\sqrt{d}} - b'\right)^2,
$$

where $\sigma^2 = E\epsilon^2$ is the variance of ϵ. This is equivalent to

$$
2a\sigma^{-2}x_0^{*''}(0) = -\left(2a''\sqrt{\frac{c}{a}} - b''\right) + 2\frac{\left(2a'\sqrt{\frac{c}{a}} - b'\right)}{2\sqrt{d} - b}\left(\frac{d'}{\sqrt{d}} - b'\right) + \left(\frac{d''}{\sqrt{d}} - \frac{1}{2}\frac{d'^2}{d^{\frac{3}{2}}} - b''\right)
$$
$$
- \frac{2}{2\sqrt{d} - b}\left(\frac{d'}{\sqrt{d}} - b'\right)^2.
$$

We have that $a' = S$, $b' = 2S$, $d' = S(b - \gamma)$ and $d'' = 2S^2$. This allows me to rewrite the above equation as

$$
\frac{2a\sigma^{-2}}{S^2}x_0^{*''}(0) = \frac{4\left(\sqrt{\frac{c}{a}} - 1\right)}{2ac - b\sqrt{ac}}\left((b - \gamma) - 2\sqrt{ac}\right) + \frac{2ac - \frac{1}{2}(b - \gamma)^2}{(ac)^{3/2}} - \frac{2}{2(ac)^{3/2} - abc}\left((b - \gamma) - 2\sqrt{ac}\right)^2.
$$

Because $b^2 - 4ac$ is positive, we obtain that $x_0^{*''}(0)$ is negative if and only if

$$
\left(3(b - \gamma)^2 - 4c(b - \gamma) - 4ac\right)(ac)^{1/2} - 2abc + 4ac\gamma + 8ac^2 \le \frac{1}{2}b(b - \gamma)^2, \tag{24}
$$

or, equivalently,

$$
\left(3S^2\beta_c^2 - 2S\left(2S\beta_f + \gamma\right)\beta_c + \left(4\gamma S\beta_f - \gamma^2\right)\right)^2\left(\beta_f(\beta_f S - \gamma) - (\beta_f S - \gamma)\beta_c\right)
$$
$$
- S(-\frac{1}{2}S^2\beta_c^3 + \left(5S^2\beta_f - 3S\gamma\right)\beta_c^2 + \left(-4S^2\beta_f^2 - 2\gamma S\beta_f + \frac{7}{2}\gamma^2\right)\beta_c + 4S\gamma\beta_f^2 - 3\gamma^2\beta_f)^2 \le 0.
$$

Let me use the following notation:

$$
v = (\beta_c S/\gamma) - 1
$$
$$
z = \beta_f S/\gamma.
$$

After tedious manipulations, the above inequality is true if and only if

$$
H(v, z) = 4(1 - z)^2 + v(8.75 - 13z + 4z^2) + v^2(4.5 - 4z) - 0.25v^3 \tag{25}
$$

is positive in the relevant domain of (v, z), i.e., $v \in [-1, 0]$ and $z \ge 1$. Notice that H is clearly non-negative at the boundaries of the relevant domain:

$$
H(0, z) = 4(1 - z)^2 \ge 0
$$

$$
H(-1, z) = z \ge 0
$$

$$H(v,1) = 0.25v(1-v)^2 \geq 0$$

$$\lim_{z \to +\infty} H(v,z) = \lim_{z \to +\infty} 4(1+v)z^2 = +\infty.$$

More generally, H is non-negative in the relevant domain $D = \{(v,z) \mid (v,z) \in [-1,0] \times [1,+\infty[\}$. This implies that $x_0^{*''}(0)$ is negative, or that $x_0^*(h)$ is smaller than $x_0^*(0)$ in the neighborhood of $h = 0$. In other words, any small zero-mean risk surrounding β_f reduces the optimal confinement at stage 1. This concludes the proof of Proposition 2. ∎

Nature of work and distribution of risk: Evidence from occupational sorting, skills, and tasks[1]

Egor Malkov[2]

How does the nature of work – teleworkability and contact intensity – shape the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic? To answer this question, we consider two contexts. First, we show that the existing spousal nature-of-work-based occupational sorting in the United States matters for the distribution of these risks. In particular, we show that it mitigates the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. Furthermore, we show that it creates a larger fraction of couples, who are excessively exposed to labor income and unemployment risks, relative to the case of zero sorting. Second, we document that teleworkable occupations require higher education and experience levels as well as greater cognitive, social, character, and computer skills relative to non-teleworkable occupations. This discrepancy affects labor income and unemployment risks by increasing the likelihood of skill mismatch for newly unemployed workers. Our results imply that the current economic downturn may have long-run effects on employment prospects and earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak. We discuss the relevant policy implications and associated policy constraints that follow from our findings.

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1 Introduction

Coronavirus disease 2019 (COVID-19) pandemic created substantial challenges for health systems and economies all over the world. To reduce the spread of disease, many countries imposed various mitigation measures, such as lockdowns and stay-at-home orders. These policies forced many workers to work from home. However, a sizeable fraction of jobs, e.g. in the United States it is equal to 63 percent, see Dingel and Neiman (2020), cannot be performed remotely. Therefore, the nature of work became one of crucial factors behind the distribution of health, labor income, and unemployment risks.

In this paper, we ask the following question. How does the nature of work — teleworkability and contact intensity — shape the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic? We consider two contexts. First, we study whether the existing spousal nature-of-work-based occupational sorting in the United States matters for the distribution of these risks. Second, we study how different are the skill requirements and task content in teleworkable versus non-teleworkable and low-contact-intensity versus high-contact-intensity occupations. The answer to the second question may inform about labor income and unemployment risks of workers, who lost their non-teleworkable or high-contact-intensity jobs during the COVID-19 pandemic, in the long run. To address the first question, we use data from the American Community Survey (ACS). To address the second question, we employ data from O*NET and online vacancy postings data from Gartner TalentNeuron.

The main contribution of this paper is threefold. First, we show that the existing spousal occupational sorting in the United States mitigates the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. We document that about 67 percent of the U.S. dual-earner couples are exposed to excessive health risk through this transmission channel. Second, we show that the existing spousal occupational sorting creates a larger fraction of couples, who are excessively exposed to labor income and unemployment risks, relative to the case of zero sorting. We document that they constitute about a quarter of all the U.S. dual-earner couples. These are the couples where both spouses work in non-teleworkable occupations. Counterfactual shift from the actual to zero sorting would reduce this fraction down to about 19 percent. Our results imply that nature-of-work-based occupational sorting in couples *matters* for the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic. Third, we document a significant differences in skill requirements between teleworkable and non-teleworkable as well as low- and high-contact-intensity occupations. Teleworkable occupations require higher education and experience levels as well as greater cognitive, social, character, and computer skills. This discrepancy increases the likelihood of skill mismatch for workers who lost their jobs during the economic downturn following the COVID-19 outbreak. This, in turn, may leave a scarring effect that reduces their wages in future occupations. To complement the discussion, we consider the patterns of labor market mobility for occupations of different teleworkability and contact intensity, using data from the Current Population Sur-

vey (CPS) and occupational mobility data from Schubert et al. (2020). Overall, our results imply that the current economic downturn may have long-run effects on employment prospects and earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak.

The results of this paper have important policy implications. First, since about 67 percent of the U.S. dual-earner couples are exposed to excessive health risk through intra-household contagion, then targeting individuals who work in occupations that require high contact intensity with testing, vaccination, and providing them with protective equipment would allow to mitigate this transmission channel. Second, a significant fraction of couples where both spouses have non-teleworkable jobs and hence exposed to greater unemployment risk suggests that occupation-specific transfers or transfers based on joint spousal earnings can be potentially desirable. Finally, we stress that while the unemployment benefits or stimulus payments for COVID-19 relief can insure the workers against short-run losses, they fall short of insuring long-run losses originated from skill mismatch. We also emphasize that existing differences in skill requirements may create constraints on policies that propose training programs for the unemployed. While some hard skills, e.g. the basic computer skills, can be acquired through training, social and character skills are much harder to develop.

This paper contributes to active and growing literature studying the effects of COVID-19 on the labor markets. In what follows we briefly describe the related studies and explain how our paper complements them. Using the data on online job postings provided by Burning Glass Technologies, Kahn et al. (2020a) document a significant drop in vacancies in the second half of March 2020. The U.S. labor market collapsed across occupations and states regardless of the initial virus spread intensity or timing of mitigation measures. They also show that unemployment insurance claims demonstrated similar patterns. Next, Coibion et al. (2020) use a repeated large-scale survey of households in the Nielsen Homescan panel and document a sharp decline in the employment-to-population ratio along with a much smaller increase in the unemployment rate. The reason is that many of the newly non-employed report that they do not actively look for work and hence they are not counted as part of the unemployed. Using February-April 2020 data from the CPS, Cowan (2020) study transitions of workers between the labor-market states — out of the labor force, employed, absent from work, and unemployed — and between full-time and part-time status. He documents that racial and ethnic minorities, individuals born outside the United States, women with children, the least educated, and disabled workers experience the largest decline in the likelihood of full-time work. In this paper, we study the distribution of labor market transitions across jobs of different teleworkability and contact intensity. This may have a crucial importance for the future prospects of individuals who lost their jobs as a result of the COVID-19 pandemic.

We also complement the literature that study alternative work arrangements and, given the concerns created by the COVID-19 pandemic, jobs that differ in teleworkability and contact intensity at the workplace. Mas and Pallais (2020) provide an excellent literature review on the

topic of alternative work arrangements. Using O*NET data, Dingel and Neiman (2020) classify the occupations into those that can and cannot be performed from home. Leibovici et al. (2020) characterize the U.S. occupations in terms of their contact intensity. Since the same occupations may have different task content across countries, some papers study teleworkability by employing data from various countries. Using data from the Skills Toward Employability and Productivity survey, Saltiel (2020) examines the feasibility of working from home in ten developing countries. Delaporte and Peña (2020) analyze the potential to work from home across occupations, industries, regions, and socioeconomic characteristics of workers in 23 Latin American and Caribbean countries. Hatayama et al. (2020) use skills surveys from 53 countries to estimate the feasibility of working from home. They show that the more developed is the country, as measured by the GDP per capita PPP, the greater is the amenability of jobs to working from home. This finding is consistent with the results by Gottlieb et al. (2020) who show that the share of employment that can work from home is around 20 percent in poor countries compared to about 40 percent in rich countries.

Our work is mostly related to the papers that study the implications of teleworkability and contact intensity of occupations for health and economic outcomes. Mongey et al. (2020) show that workers in low-work-from-home (non-teleworkable) or high-physical-proximity occupations are less educated, have lower income, fewer liquid assets relative to income, and are more likely to be renters. Next, using data from the CPS, they document that workers employed in non-teleworkable occupations experienced greater declines in employment. Using the Real-Time Population Survey, Bick et al. (2020) also document several facts about working from home following the COVID-19 outbreak. In particular, they show that 35.2 percent of the workforce worked entirely from home in May 2020, while in February 2020 this fraction was 8.2 percent. Using the estimates of the potential number of home-based workers from Dingel and Neiman (2020), they conclude that more than 70 percent of the U.S. workers that could work from home did so in May 2020. Using data from the American Time Use Survey (ATUS) in 2017 and 2018, Papanikolaou and Schmidt (2020) measure the industry exposure to the lockdowns using information on the share of the workforce than can work from home. They show that sectors in which a higher fraction of workers is not able to work remotely experienced greater declines in employment, greater reductions in expected revenue growth, worse stock market performance, and higher expected likelihood of default. Furthermore, they document that lower-paid workers, especially female workers with young children, were affected most.

Teleworkability and contact intensity at the workplace are also tightly connected to the household structure and division of labor. First, the presence of the other family members raises the concerns of intra-household COVID-19 contagion. Almagro and Orane-Hutchinson (2020) show the importance of exposure to human interactions across occupations in explaining the disparities in COVID-19 incidence across New York City neighborhoods. Furthermore, they provide suggestive evidence that the stay-at-home order is helpful at mitigating contagion at work or in public spaces but can raise the likelihood of intra-household contagion. Second, the presence of

another employed family member serves as partial insurance against labor income and unemployment shocks. Lekfuangfu et al. (2020) construct indices that capture the extent to which jobs can be adaptable to work from home and the degree of infection risk at workplace. Using the data from Thailand, they show that low-income married couples are much more likely to sort into occupations that are less adaptable to work from home. As a result, these couples tend to face a significantly higher income risk resulted from lockdown measures. Third, because of school and day care closures, the presence of children becomes a crucial factor behind employment prospects for many individuals, especially women. Kahn et al. (2020b) discuss how childcare and the presence of COVID-19-high-risk household members can limit the ability to return to work. They document that about a quarter of the workforce may be constrained from full-time work because they have young children. Next, roughly one-fifth of the workforce is either in a high-risk group or live with someone who is more likely to suffer from COVID-19. Alon et al. (2020) study the implications of the COVID-19 pandemic for gender inequality. First, they provide supporting evidence that the current recession will have disproportionately negative effect on women and their employment opportunities while the "regular" recessions, such as the Great Recession, affect men's employment more severely. Second, they discuss the potential forces that may ultimately reduce gender inequality in the labor market. These include the increasing adoption of flexible work arrangements that may persist over time and changes in social norms about the division of labor in housework and child care within a household. We contribute to this literature by studying the occupational sorting of spouses in married couples in the United States and its implications for the distribution of health and unemployment risks.

Furthermore, our paper bridges the studies of alternative work arrangements to several other strands of the literature. First, it is related to the literature that study multidimensional skill requirements of occupations. Using the 1979 National Longitudinal Survey of Youth (NLSY79) and O*NET data, Guvenen et al. (2020) construct the empirical measure of skill mismatch and show that it is informative about current and future wages and occupational switching. Lise and Postel-Vinay (2020) extend a standard job-search model allowing for multidimensional skills — cognitive, manual, and interpersonal — and on-the-job learning. In their model, cognitive, manual, and interpersonal skills have different returns and speed of adjustment. Abstracting from this multidimensionality and assuming that a worker's skills are described by a single scalar index leads to overestimation of the importance of unobserved heterogeneity and underestimation of the contribution of career shocks relative to observed initial skills. Our characterization of occupations that differ in teleworkability and contact intensity in terms of multiple skill requirements may be informative about the prospects of labor market mobility following the COVID-19 outbreak.

To construct the measures of skill requirements, we use online job ads data. Therefore our work is also related to the growing literature that use the vacancy ads data for studying the labor markets, see Deming and Kahn (2018), Hershbein and Kahn (2018), Hazell and Taska (2019), Marinescu and Wolthoff (2020), and Schubert et al. (2020) among many others.

Furthermore, our work bridges the papers on alternative work arrangements with studies that use the "task approach" to labor markets and the literature on labor market polarization, see Autor et al. (2003), Acemoglu and Autor (2011), and Foote and Ryan (2015). First, our characterization of occupations of different teleworkability and contact intensity in terms of task routineness can guide the modeling choice for studying the changing nature of work following the COVID-19 outbreak. Second, it can be informative about the groups of tasks that are mostly affected in the current economic downturn. Foote and Ryan (2015) document that job losses during the Great Recession were concentrated among middle-skill workers, those who worked in routine cognitive occupations. Next, Hershbein and Kahn (2018) show that the Great Recession accelerated the process of restructuring of production toward routine-biased technologies and the more-skilled workers that complement them.

Finally, this paper is also related to the literature studying the patterns of labor market mobility, see Moscarini and Thomsson (2007), Kambourov and Manovskii (2008), Kambourov and Manovskii (2009), and Schubert et al. (2020). Our finding that teleworkable occupations feature significantly higher skill requirements — cognitive, social, character, and computer — than non-teleworkable occupations have direct implications for the employment prospects of individuals who lost their jobs during the COVID-19 pandemic. We emphasize the constraints imposed by the differences in skill requirements: while some hard skills, e.g. basic computer skills, can be acquired through the training courses, the social or character skills are significantly more difficult to adjust. See Kambourov et al. (2020) for the discussion of relationship between occupational switching and the returns to training.

The rest of the paper is organized as follows. In Section 2, we describe the datasets and construction of the variables. In Section 3, we provide the empirical results. Section 4 concludes.

2   Data

To study how teleworkability and contact intensity of occupations affect the distribution of health and unemployment risks, created by the COVID-19 pandemic, we employ several data sets. First, we use the classifications of occupations by teleworkability and contact intensity from Dingel and Neiman (2020), Leibovici et al. (2020), and Mongey et al. (2020). These classifications are based on O*NET data. We also construct the continuous measures of teleworkability and contact intensity using the similar inputs as in the papers mentioned above. Second, we use O*NET data to measure the task content of occupations. Third, to measure the skill requirements, we use the proprietary online vacancy posting data from Gartner TalentNeuron with access provided by RealTime Talent. Next, to show the patterns of occupational sorting of spouses in married couples we use the ACS data. Finally, to study the labor market mobility associated with occupations of different teleworkability and contact intensity we employ two sources: Annual Social and Economic Supplement of the CPS (CPS ASEC) and the Burning Glass Technologies occupational mobility data constructed by Schubert et al. (2020). In what follows, we describe these datasets and construction the variables of interest in more detail.

2.1 Teleworkability and Contact Intensity Classification

To classify the occupations in terms of teleworkability, we use the classifications developed by Dingel and Neiman (2020) and Mongey et al. (2020). These papers use similar inputs from O*NET survey responses but follow different methodologies to construct the resulting indices. In Appendix, we provide the list of job attributes that they employ.

Dingel and Neiman (2020) classify an occupation as one that can or cannot be performed at home based on the conditions defined over the listed inputs (e.g., if, in a given occupation, an average respondent says they are exposed to diseases or infection at least once a week, then this occupation is classified as non-teleworkable). As a result, their classification is done at the O*NET SOC level. Totally, there are 968 classified occupations. We use this classification to study the differences in task content, skill requirements, and labor market mobility for teleworkable and non-teleworkable occupations.

In turn, Mongey et al. (2020) exploit a different approach to construct the measure of teleworkability. They classify the occupations at the 3-digit Census OCC level that is less finer than O*NET SOC level. To do this, they aggregate 6-digit SOC level O*NET scores using employment from the Occupational Employment Statistics (OES) as weights. As a result, they get a continuous measure of teleworkability at the 3-digit Census OCC level. Next, using this measure, they construct a binary variable that divides occupations into high work-from-home (more likely to be able to work remotely, i.e. teleworkable) and low work-from-home (less likely to be able to work remotely, i.e. non-teleworkable) such that each of both groups is comprised of half of employment. Totally, there are 511 classified occupations. See Mongey et al. (2020) for more details. We use their binary classification to study the occupational sorting of spouses in couples and labor market mobility because ACS and CPS define occupations at the 3-digit Census OCC level. To avoid confusion, we always clearly specify which binary measure of teleworkability, either from Dingel and Neiman (2020) or Mongey et al. (2020) we use. We define an occupation to be *WFH* (work-from-home) if it is classified as teleworkable. We define an occupation to be *NWFH* (not-work-from-home) if it is classified as non-teleworkable.

We also construct a continuous measure of teleworkability at the O*NET SOC level. For each job attribute listed in Appendix, we standardize the score to have mean zero and standard deviation one.[1] Next, we sum the standardized scores and standardize the sum to have mean zero and standard deviation one.[2] Since we are interested in the distribution of teleworkability across occupations, not workers, we do not use the employment weights when constructing the indices. The higher values of this measure — we define it as *WFH Index* — correspond to greater feasibility

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[1] We take the reverse of all the attributes except "Electronic Mail".

[2] When we sum the scores, we assign weight 0.5 to "Repairing and Maintaining Mechanical Equipment", "Repairing and Maintaining Electronic Equipment", "Outdoors, Exposed to Weather", "Outdoors, Under Cover", "Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets", and "Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection", and weight 1 to all the other attributes.

of working from home.

In addition to teleworkability, we also employ the measures of contact intensity (or physical proximity) constructed by Leibovici et al. (2020), and Mongey et al. (2020). Using "Physical Proximity" from O*NET Work Context module as an input, Leibovici et al. (2020) classify the occupations at the O*NET SOC level. They divide the occupations into three groups: (i) low contact-intensity (*low CI*) if O*NET score is between 0 and 49, (ii) medium contact-intensity (*medium CI*) if O*NET score is between 50 and 74, and (iii) high contact-intensity (*high CI*) if O*NET score is between 75 and 100. We use this classification to study the differences in task content, skill requirements, and labor market mobility for more and less contact-intensive occupations.

Next, Mongey et al. (2020) construct the measures of physical proximity in a way similar to teleworkability measures. We use their binary classification, defined at the 3-digit Census OCC level, to study the occupational sorting in couples and labor market mobility. To avoid confusion with the contact-intensity categories from Leibovici et al. (2020), we define an occupation to be *low PP* (low physical proximity) if it is classified by Mongey et al. (2020) as requiring lower physical proximity at the workplace. We define an occupation to be *high PP* (high physical proximity) if it is classified as requiring higher physical proximity at the workplace.

Finally, we also construct a continuous measure of contact intensity. To do this, we standardize the reversed score for "Physical Proximity" from O*NET Work Context module to have mean zero and standard deviation one. As with the WFH Index, we do not use the employment weights when constructing this index. Higher values of this measure — we define it as *CI Index* — correspond to lower contact intensity at the workplace.

2.2 Occupational Sorting of Spouses in Couples

To document the patterns of occupational sorting in married couples, we use data from the ACS in 2018, the most recent available release.[3] In Online Appendix we also show the results for the earlier years, namely, 2010-2018. ACS defines the occupations using the Census OCC codes, and we merge it with the teleworkability and contact-intensity classification from Mongey et al. (2020). We keep the different-sex married couples where both spouses aged 20 to 65. Since our primary interest is in occupational sorting, we keep only those couples where both spouses are employed. Furthermore, we also separately consider the couples with children, couples with children under the age of 5, and couples without children.

2.3 Task Content

To study the task content of occupations that differ in teleworkability and contact intensity, we use O*NET 24.2 data. We construct the composite measures proposed by Acemoglu and Autor

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[3] The data is extracted from IPUMS at https://usa.ipums.org/usa/.

(2011) and additionally consider a measure of computer usage at the workplace. In Appendix, we provide the list of job attributes that are used for constructing these indices.

For each attribute, we standardize the score to have mean zero and standard deviation one. Next, we sum the standardized scores within each composite task measure (e.g. routine cognitive). Finally, we restandardize the sum to have mean zero and standard deviation one. All the measures are constructed at the O*NET SOC level. Since we are interested in the distribution of routineness/offshorability/computer usage across occupations, not workers, we do not use the employment weights when constructing the indices. To compare the task content between occupations of different teleworkability and contact intensity, we merge these measures with the classifications from Dingel and Neiman (2020) and Leibovici et al. (2020).

2.4 Skill Requirements

To compare the skill requirements between occupations of different teleworkability and contact intensity, we use the online vacancy posting data from Gartner TalentNeuron. Gartner Talent-Neuron collects the data from more than 65000 global sources and continuously retests it for quality, accuracy, and consistency. We have the data for five states — Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin — that covers the period between September 2014 and September 2018. Gartner TalentNeuron uses algorithms to extract the data on a job title, occupation at the O*NET SOC level, industry, location, posted wage, and also education, experience, and skill requirements from the description of the job posting. In Malkov (2020), we show that the distribution of our Gartner TalentNeuron data by occupations and industries closely matches the Burning Glass Technologies data used by Deming and Kahn (2018). Overall the dataset contains over 14 million non-duplicated online job ads. We use this data to construct the indices of character, cognitive, and social skill requirements across the occupations defined in O*NET. We proceed in the following way. First, we use the keywords and phrases to determine whether each listed skill requirement falls into *cognitive*, *social*, or *character* category. The list of these keywords and phrases is given in Table A.1. To create it, we use the categorization from Atalay et al. (2020), Deming and Kahn (2018), and Hershbein and Kahn (2018), and add several more keywords by ourselves. In our dataset, we have 9924 unique skill requirements. Each vacancy may have from zero to many posted skill requirements. Second, we code a vacancy as falling into a skill category if at least one posted skill requirement falls into this category. The skills are mutually exclusive but not collectively exhaustive, i.e. there are ads that fall neither in cognitive, nor social, nor character category. Next, for each occupation defined at the O*NET SOC level, we calculate the share of ads containing each skill category. Finally, we standardize the index for each skill category to have mean zero and standard deviation one using the number of ads as weights. We merge our constructed indices with the teleworkability and contact intensity classifications from Dingel and Neiman (2020) and Leibovici et al. (2020).

Furthermore, to get additional validation of our results, we also construct the measure of social-skill intensity of occupations considered by Deming (2017). In particular, we use the following four attributes from O*NET: "Coordination" (adjusting actions in relation to others' actions), "Negotiation" (bringing others together and trying to reconcile differences), "Persuasion" (persuading others to change their minds or behavior), and "Social Perceptiveness" (being aware of others' reactions and understanding why they react as they do). For each attribute, the score is standardized to have mean zero and standard deviation one. Next, we sum the standardized scores and restandardize the sum to have mean zero and standard deviation one.

2.5 Labor Market Mobility

To document the distribution of labor market mobility for occupations of different teleworkability and contact intensity, we use CPS ASEC data in 2019.[4] In Online Appendix we also show the results for the earlier years, namely, 2011-2019. We consider labor market mobility over the year preceding the survey by taking advantage of the questions that ask the respondent's current occupation and their occupation in the previous year.[5] CPS defines the occupations using the Census OCC codes, and we merge it with the classification from Mongey et al. (2020). We keep the individuals aged 25 to 60. We also consider the distribution of labor market transitions separately for men and women.

To complement our analysis, we also employ the Burning Glass Technologies occupational mobility data from Schubert et al. (2020). To construct this dataset, the authors use 16 million unique resumes with more than 80 million job observations over 2002-2018, with the majority of observations in the later years. The advantage of this data is that it defines the occupations at the 6-digit SOC level. This level of granularity is not available in such datasets as CPS where the transitions within broader occupation categories cannot be observed. See Schubert et al. (2020) for more details. We merge this dataset with the teleworkability and contact intensity classifications from Dingel and Neiman (2020) and Leibovici et al. (2020).

3 Empirical Results

This section contains our empirical findings. We begin by documenting the patterns of occupational sorting of spouses in married couples in the United States. We proceed with the task content and skill requirements of occupations that differ in teleworkability and contact intensity. Finally, we document the patterns of labor market mobility for these groups of occupations.

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[4] The data is extracted from IPUMS at https://cps.ipums.org/cps/.

[5] We intentionally do not define it as annual mobility because, as discussed by Kambourov and Manovskii (2013), CPS ASEC data most likely measure mobility over a much shorter period.

3.1 Occupational Sorting of Spouses in Couples

One of the features associated with the COVID-19 outbreak and subsequent economic downturn is the interaction between unemployment risk and health risk. The extent of exposure to these risks greatly depends on the type of occupation that an individual has. Workers who have teleworkable jobs face lower unemployment risk than those who have non-teleworkable jobs. Workers whose occupations require less contact intensity at the workplace face lower risk of being infected than those who work in high physical proximity to the other individuals. Note that we discuss the feasibility of working from home or in low physical proximity at the workplace rather than actual behavior of individuals. However, as Bick et al. (2020) show, most of the U.S. workers that can work from home actually do so in May 2020. Several studies document that low-income individuals are, in general, more vulnerable to both types of risk. For example, Mongey et al. (2020) show that in the United States workers in less teleworkable or high-contact-intensity jobs are less educated, have lower income, and fewer liquid assets relative to income.

Married couples constitute a significant fraction of the U.S. population. According to the U.S. Bureau of the Census, in 2019 there were almost 62 million married couples. This accounts for 48 percent of all the U.S. households. The sign and extent of actual occupational sorting in couples plays an important role during the COVID-19 pandemic because it can either exacerbate or mitigate health and labor income risks relative to the case of zero sorting. In what follows we briefly discuss this idea. First, the presence of the other family members raises the concerns of intra-household COVID-19 contagion. Under perfect positive contact-intensity-based sorting, i.e. when both spouses have either high-contact-intensity or low-contact-intensity jobs, the risk of intra-household contagion is heavily concentrated in high-contact-intensity couples. Under perfect negative contact-intensity-based sorting, i.e. when in each couple there is a spouse in a high-contact-intensity-based job and a spouse in a low-contact-intensity-based job, the risk of intra-household contagion is evenly distributed across the couples. In general, more negative contact-intensity-based occupational sorting is associated with greater fraction of individuals who are exposed to health risk. Second, the presence of another employed family member serves as insurance against labor income shocks. Under perfect positive teleworkability-based sorting, i.e. when both spouses have either teleworkable or non-teleworkable jobs, labor income risks are heavily concentrated in non-teleworkable couples. Given the results of Mongey et al. (2020), these individuals also have lower income. Under perfect negative teleworkability-based sorting, i.e. when in each couple there is a spouse in a teleworkable job and a spouse in a non-teleworkable job, labor income risks are distributed across the couples more evenly and are easier to insure. In general, more positive teleworkability-based occupational sorting is associated with greater fraction of individuals who are heavily exposed to labor income risk. Third, because of school and day care closures, the presence of children becomes a crucial factor behind employment prospects for many individuals, especially women. Couples face higher unemployment risk because at least

one spouse has to be responsible for childcare. In the families, where at least one spouse has a teleworkable job, the impact of children on employment and labor income is likely to be mitigated.

Overall, the patterns of occupational sorting in couples have crucial importance for the distribution of health and labor income risks over the population and, as a consequence, may have different policy implications. What are the sign and level of occupational sorting is an empirical question that we address in this section.

We show the distribution of occupations in terms of teleworkability and contact intensity for dual-earner married couples in the United States in 2018 in Table 1.[6] In addition, we separately consider the couples with children, couples with children under the age of 5, and couples without children. To study the patterns of occupational sorting, we also refer to Table 2 that contains the actual distribution of spouses across occupations from Table 1 and compares them with two counterfactual benchmark distributions. The first benchmark is the distribution under zero sorting. The second benchmark is the distribution under "ideal" sorting. For teleworkability-based distribution, we define "ideal" sorting as the situation when the fraction of couples where both spouses have non-teleworkable jobs is minimized. For contact-intensity-based distribution, we define "ideal" sorting as the situation when the fraction of couples where one spouse has a high-contact-intensity job and another one has a low-contact-intensity job is minimized, i.e. the risk of intra-household contagion is minimized.

We begin with teleworkability-based distribution. In the data, there is positive sorting: in about 60 percent of couples both spouses work in either teleworkable or non-teleworkable occupations. Almost a quarter of couples have spouses that both work in non-teleworkable occupations, and hence are exposed to greater unemployment risk. Under zero sorting, this fraction goes down to 18.7 percent. Under "ideal" sorting, it further reduces to zero as more males and females form mixed (one has a teleworkable job and another one has a non-teleworkable job) couples. Therefore, the actual teleworkability-based occupational sorting in the U.S. couples creates a greater fraction of individuals who are excessively vulnerable to labor income and unemployment risks relative to the case of zero sorting.

Next, we turn to contact-intensity-based distribution. In the data, there is weak positive sorting: in about 54 percent of couples both spouses have either high-physical-proximity or low-physical-proximity jobs. Around 67 percent of couples include a spouse whose job requires a high contact intensity at the workplace, and hence are exposed to greater intra-household contagion risk. Under zero sorting, this fraction goes up to 69.5 percent. Under "ideal" sorting, it falls to 52.1 percent because more males and females form couples where both spouses have low-physical-proximity jobs. Therefore, the actual contact-intensity-based occupational sorting in the U.S. couples creates a lower fraction of individuals who are excessively exposed to intra-household contagion risk relative to the case of zero sorting.

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[6] Table 1 uses 2018 ACS data. When we use 2019 ASEC CPS data, we get very close results. They are available upon request.

Table 1: Occupational distribution of couples, by family type (with/without children) (%)

	All	With children	With children under 5	Without children
Male (WFH) – Female (WFH)	36.0	35.4	36.7	36.9
Male (NWFH) – Female (WFH)	27.9	27.4	25.4	28.9
Male (NWFH) – Female (NWFH)	23.9	24.9	24.4	22.1
Male (WFH) – Female (NWFH)	12.2	12.3	13.6	12.1
Spouses have similar WFH-type jobs	59.9	60.3	61.1	59.0
At least one spouse cannot work from home	64.0	64.6	63.3	63.1
Male (low PP) – Female (low PP)	32.7	31.3	28.9	35.4
Male (low PP) – Female (high PP)	30.9	31.6	32.4	29.6
Male (high PP) – Female (high PP)	21.2	22.2	25.2	19.5
Male (high PP) – Female (low PP)	15.1	14.9	13.5	15.5
Spouses have similar PP-type jobs	54.0	53.5	54.1	54.8
At least one spouse should work in high phys. proximity	67.3	68.7	71.1	64.6

Note: We use 2018 American Community Survey data to produce this table. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. Low PP (low-physical-proximity) stands for occupations that require low contact intensity at the workplace. High PP (high-physical-proximity) stands for occupations that require high contact intensity at the workplace. To obtain the results, we use household weights provided by IPUMS. Percentages may not add up to 100% due to rounding.

Table 2: Distribution of males and females in dual-earner couples : actual occupational sorting / zero occupational sorting / "ideal" occupational sorting (%)

	Teleworkable and non-teleworkable jobs		
	Female (WFH)	Female (NWFH)	Total
Male (WFH)	36.0 / 30.8 / 12.1	12.2 / 17.4 / 36.1	48.2
Male (NWFH)	27.9 / 33.1 / 51.8	23.9 / 18.7 / 0.0	51.8
Total	63.9	36.1	100.0

	Low- and high-physical-proximity jobs		
	Female (low PP)	Female (high PP)	Total
Male (low PP)	32.7 / 30.4 / 47.8	30.9 / 33.2 / 15.8	63.6
Male (high PP)	15.1 / 17.4 / 0.0	21.2 / 18.9 / 36.3	36.3
Total	47.8	52.1	100.0

Note: We use 2018 American Community Survey data to produce this table. Numbers correspond to the first column of Table 1. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). To obtain the results, we use household weights provided by IPUMS.

Another observation from Table 1 is related to the differences in job characteristics by gender. Consider the classification of occupations in terms of teleworkability. Women more likely work in teleworkable than non-teleworkable occupations. Furthermore, they more likely have teleworkable jobs than males. Men are equally distributed between teleworkable and non-teleworkable jobs. Next, consider the classification of occupations in terms of contact intensity. Men more likely work in low-physical-proximity than high-physical-proximity occupations. This highlights the difference between teleworkability and contact intensity. Men more likely work in occupations that cannot be performed at home but at the same time do not require close contact intensity at the workplace. In the classification from Mongey et al. (2020), 147 out of 511 occupations satisfy these criteria.[7] Men also more likely have low-physical-proximity jobs than women. Women are almost equally distributed between low-physical-proximity and high-physical-proximity jobs. In Online Appendix, we show that the patterns documented in Table 1 were stable over the last decade, see Figures O.1-O.5.[8]

Our findings have several policy implications. First, we document that about 67 percent of the U.S. dual-earner couples are exposed to excessive health risk through intra-household contagion. Therefore, targeting individuals who work in occupations that require high contact intensity with testing, vaccination, and providing them with protective equipment would allow to mitigate this transmission channel. However, we also show that the patterns of spousal occupational sorting in the United States reduce the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. Second, a significant fraction of couples where both spouses have non-teleworkable jobs and hence exposed to greater unemployment risk suggests that occupation-specific transfers or transfers based on joint spousal earnings can be potentially desirable. Formal study of this policy proposal is an important avenue for future research.

3.2   Skills and Tasks

We turn to the discussion of characteristics of occupations per se. How different are the task content and skill requirements for jobs that can or cannot be performed at home and require high or low contact intensity at the workplace? The answers to this question have direct implications for employment prospects and future earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak.

The differences in task content of jobs, considered through the lens of routine and non-routine occupations, may matter for the discussion about the U.S. labor market polarization. Foote and Ryan (2015) document that job losses during the Great Recession were concentrated among middle-skill workers, those who worked in routine cognitive occupations. How different is the economic downturn that follows the COVID-19 outbreak?

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[7] For example, "Postal service mail carriers" or "Aircraft mechanics and service technicians".

[8] The classification from Mongey et al. (2020), that we use both in Table 1 and Figures O.1-O.5, by construction depends on the distribution of employment by occupations in 2018. We fix it and use for the pre-2018 years as well.

To study this question, we estimate two regressions for a set of of outcomes y that include the measures of non-routine cognitive (analytical and interpersonal), routine cognitive, routine manual, and non-routine manual physical content of occupations defined at the O*NET SOC level. In addition, we also estimate regressions for the measures of offshorability and computer usage. All outcome variables y are standardized to have mean zero and standard deviation one, see details about their construction in Section 2.3.

For teleworkability-based classification we estimate

$$y_i = \alpha_0 + \alpha_1 WFH_i + \varepsilon_i \tag{1}$$

where $WFH_i = 1$ if occupation i is teleworkable and $WFH_i = 0$ otherwise.

Next, for contact-intensity-based classification we estimate

$$y_i = \beta_0 + \beta_1 LCI_i + \beta_2 MCI_i + v_i \tag{2}$$

where $LCI_i = 1$ if occupation i is low-contact-intensity and $LCI_i = 0$ otherwise, $MCI_i = 1$ if occupation i is medium-contact-intensity and $MCI_i = 0$ otherwise.

We plot the values for estimates $\hat{\alpha}_1$ in the left panel, and the values for estimates $\hat{\beta}_1$ and $\hat{\beta}_2$ in the right panel of Figure 1. The left panel demonstrates that teleworkable occupations are, in average, have higher score of non-routine cognitive tasks, both analytical (+0.88 st.dev.) and interpersonal (+0.41 st.dev.), than non-teleworkable occupations. The greatest differences are observed along non-routine manual physical (teleworkable is 1.33 st.dev. less) and routine manual (teleworkable is 1.16 st.dev. less) dimensions. The right panel shows that low-contact-intensity occupations are less likely to be classified as non-routine cognitive (interpersonal), routine cognitive, routine manual, and non-routine manual physical than high-contact-intensity occupations. Medium-contact-intensity occupations are not significantly different from high-contact-intensity occupations except non-routine cognitive (interpersonal) dimension. Furthermore, Figure 1 demonstrates that teleworkable occupations and occupations of lower contact intensity are more likely to be offshorable and require greater use of the computer. The latter argument, coupled with the observation about excessive job loss for workers in non-teleworkable occupations, may lead to large and persistent decline in earnings for these workers, see Braxton and Taska (2020).

In comparison with the results of Foote and Ryan (2015) for the Great Recession, job losses during the COVID-19 economic downturn do not seem to be concentrated in routine occupations only. Both non-teleworkable and high-contact-intensity occupations, that suffer most, are also heavily represented in non-routine manual occupations.

Our characterization of occupations of different teleworkability and contact intensity in terms of task routineness can guide the modeling choice for studying the changing nature of work following the COVID-19 outbreak.
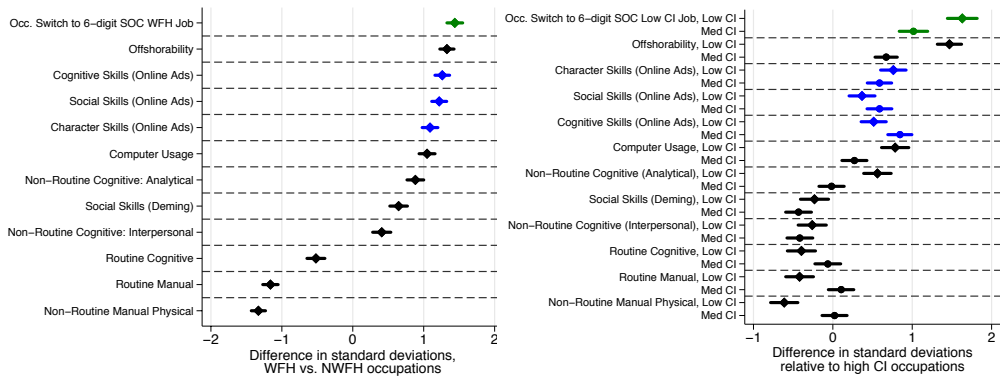
Figure 1: Left panel — Difference between characteristics of teleworkable (WFH) and non-teleworkable (NWFH) occupations. Right panel — Difference between characteristics of low-contact intensity (low CI)/medium-contact-intensity (medium CI) occupations and high-contact-intensity (high CI) occupations

Note: The left panel illustrates the results of estimated $\hat{\alpha}_1$ from regression (1). The right panel illustrates the results of estimated $\hat{\beta}_1$ and $\hat{\beta}_2$ from regression (2). The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. The classification of occupations in terms of contact intensity (low CI/medium CI/high CI) is from Leibovici et al. (2020). The outcome variables are standardized to have mean zero and standard deviation one. Point estimates are given by the markers, and 95 percent confidence intervals are given by the lines through each marker. We use black color for results obtained from O*NET data, blue color for results obtained from Gartner TalentNeuron online vacancy posting data, green color for results obtained from Schubert et al. (2020) data. For results in black and blue, the occupations are defined at the O*NET SOC level. For results in green, the occupations are defined at the 6-digit SOC level.

We turn to the differences in skill requirements. A fraction of individuals who lost their non-teleworkable or high-contact-intensity jobs during the current economic downturn, will probably want to find a job that can be performed at home. Skill mismatch, or discrepancy between the portfolio of skills required by an occupation and the portfolio of worker's skills, constitutes one of the factors that affect the likelihood of finding a new job. The greater are the differences in skill requirements between teleworkable and non-teleworkable or high- and low-contact-intensity occupations, the less likely a displaced worker can switch an occupation. Moreover, if these differences exist, it is also important what are the skill dimensions where the gaps are greater. While some hard skills, e.g. basic computer skills, can be acquired through the training courses, the social or character skills are significantly more difficult to adjust, see Lise and Postel-Vinay (2020).

Table 3: Descriptive statistics of online job ads data

	WFH Jobs		NWFH Jobs		Low CI Jobs		Medium CI Jobs		High CI Jobs	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Full-time job (%)	94.2	23.4	88.2	32.3	95.9	19.9	89.5	30.7	84.5	36.2
Wage is posted (%)	13.1	33.8	17.7	38.2	17.7	38.1	16.5	37.1	12.9	33.5
Posted full-time wage, 2012 USD	57641	34983	51953	40847	63105	39417	44282	28189	56041	53523
Education is posted (%)	52.4	49.9	29.5	45.6	36.2	48.1	41.9	49.3	33.8	47.3
GED/High School	19.1	39.3	48.5	50.0	16.4	37.0	43.4	49.6	37.5	48.4
Associate Level	9.0	28.6	13.7	34.4	7.8	26.8	12.5	33.1	13.9	34.6
Bachelor's Degree	67.2	47.0	30.5	46.0	71.4	45.2	40.9	49.2	34.5	47.5
Master's Degree	3.1	17.3	2.8	16.6	2.8	16.6	2.1	14.4	5.0	21.7
Doctoral Degree	1.7	12.8	4.4	20.6	1.6	12.5	1.1	10.5	9.2	28.9
Experience is posted (%)	78.8	40.8	65.1	47.7	75.4	43.1	71.4	45.2	61.1	48.8
0-2 years	38.6	48.7	58.8	49.2	43.3	49.6	51.3	50.0	60.3	48.9
3-7 years	37.8	48.5	31.1	46.3	37.2	48.3	32.7	46.9	30.8	46.2
8+ years	23.6	42.5	10.1	30.1	19.5	39.6	16.0	36.6	8.9	28.4
Social Skills (%)	42.1	49.4	21.1	40.8	28.9	45.3	32.6	46.9	22.5	41.8
Cognitive Skills (%)	37.4	48.4	12.5	33.1	26.9	44.3	23.4	42.4	11.8	32.3
Character Skills (%)	44.3	49.7	25.9	43.8	32.5	46.8	38.1	48.6	23.8	42.6
Number of observations	4744107		7998162		4303069		5340712		3098488	

Note: We use 2014-2018 Gartner TalentNeuron data on online vacancy ads in Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin for September 2014-September 2018 to produce this table. Occupations are defined at the O*NET SOC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. The classification of occupations in terms of contact intensity (low CI/medium CI/high CI) is from Leibovici et al. (2020). Posted full-time wages are adjusted for inflation to 2012 dollars using the personal consumption expenditures (PCE) price index.

To address this question, we use Gartner TalentNeuron data on online vacancy ads. Table 3 contains the descriptive statistics. We divide the sample in two ways. First, we compare teleworkable and non-teleworkable occupations. Relative to non-teleworkable occupations, vacancy postings in teleworkable occupations more likely advertise full-time jobs, more likely post education and experience requirements, but less likely post a wage. Conditional on posting an education requirement, teleworkable occupations more likely require college degree. Conditional on posting an experience requirement, teleworkable occupations more likely require longer experience. Finally, teleworkable jobs significantly more likely require social, cognitive, and character skills.

Second, we compare the occupations of low, medium, and high contact intensity. Vacancy postings in low-contact-intensity occupations more likely advertise full-time jobs, post a wage and experience requirement. Conditional on posting an experience requirement, low-contact-intensity occupations also more likely require longer experience. Conditional on posting an education requirement, these occupations more likely require college degree. Finally, comparing low- and high-contact-intensity occupations, we see that former more likely require social, cognitive, and character skills.

When comparing posted full-time annual wages, we observe the following patterns. First, teleworkable occupations are, in average, offer higher wages than non-teleworkable occupations.

Second, low-contact-intensity occupations are, in average, offer higher wages than high-contact-intensity occupations. As Hazell and Taska (2019) show, wages posted in online ads is a good proxy for the wages for new hires. When we consider the distribution, shown in Figure A.1, we see that non-teleworkable and high-contact-intensity occupations are characterized with higher posted wages at the top of it. This result is mostly driven by occupation group "Health Diagnosing and Treating Practitioners" (29-1000 SOC code).

To get additional evidence, we also consider the O*NET-based measure of social skill intensity of occupations used by Deming (2017). We show the relation between measures constructed from the online ads and O*NET data at the O*NET-SOC-occupation level in Figure O.6 in Online Appendix. Correlation between the online-ads-based measure and the measure from Deming (2017) is 0.42.

Figure 1 contains the results of estimated regressions (1) and (2) for four skill measures — cognitive, character, and social from the online ads data and social from Deming (2017). Teleworkable occupations, in average, have higher requirements of cognitive, social, and character skills, than non-teleworkable occupations. Despite work can be performed remotely, workers in teleworkable occupations still need to demonstrate the ability to communicate, cooperate, and negotiate. This observation is consistent with the idea of complementarity between cognitive and social skills, see Weinberger (2014). The right panel of Figure 1 shows that low-contact-intensity occupations, in average, have higher requirements of cognitive and character skills, than high-contact-intensity occupations. Two measures of social skill requirements deliver the opposite results.

To summarize, we find evidence that the skill requirements between teleworkable and non-teleworkable or low- and high-contact-intensity occupations are significantly different. Teleworkable occupations have higher requirements in terms of education and experience. Furthermore, they require better cognitive, social, and character skills. This difference may matter a lot for the labor market prospects of newly unemployed individuals. While the cognitive skills can be acquired through training, social and character skills are much harder to develop. The skill requirements may respond to the crisis as well. For example, Hershbein and Kahn (2018) show that routine cognitive occupations demonstrated increase in skill requirements during the Great Recession.

3.3 Labor Market Mobility

If an unemployed individual finds a new job, how likely is this new occupation teleworkable? If an individual switches from a non-teleworkable occupation to another occupation, how likely is this new occupation teleworkable? Having discussed the differences in skill requirements, we document patterns in labor market transitions before the COVID-19 outbreak. We consider it at two levels of granularity, 3-digit Census OCC and 6-digit SOC classifications.

Table 4: Distribution of labor market transitions in the United States, (%)

	All	Males	Females
From WFH to WFH occupation	38.5	32.8	44.8
From NWFH to NWFH occupation	37.6	45.3	29.1
From WFH to NWFH occupation	12.4	12.0	12.9
From NWFH to WFH occupation	11.5	9.9	13.3
From unemployment to WFH occupation	39.7	32.0	46.3
From unemployment to NWFH occupation	60.3	68.0	53.7
From low PP to low PP occupation	37.1	40.2	33.7
From high PP to high PP occupation	27.3	20.9	34.4
From high PP to low PP occupation	18.9	20.9	16.6
From low PP to high PP occupation	16.7	18.0	15.3
From unemployment to low PP occupation	45.8	50.3	41.9
From unemployment to high PP occupation	54.2	49.7	58.1

Note: We use 2019 Annual Social and Economic Supplement of the Current Population Survey data to produce this table. Occupations are defined at the 3-digit Census OCC level. Occupational switching is defined as change of occupation over the year preceding the survey. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). To obtain the results, we use ASEC individual weights.

We use CPS ASEC data to document the distribution of labor market transitions between 2018 and 2019. Consider the teleworkability-based classification of occupations. The upper panel of Table 4 shows that occupational mobility mostly occurs within teleworkable and non-teleworkable groups of occupations. Between-group mobility accounts for about a quarter of all switches. The fraction of switches from non-teleworkable to teleworkable occupations accounts for 11.5 percent of the total occupational mobility. The distributions for males and females follow a similar pattern. Turning to unemployment-to-employment transitions, we see that about 60 percent of newly-hired individuals work in non-teleworkable occupations. This result is mostly driven by male workers. Next, we turn to physical-proximity-based classification of occupations. The lower panel of Table 4 demonstrates that 35.6 percent of switches occur between low-physical-proximity and high-physical-proximity groups. Women demonstrate smaller between-group mobility than men, 31.9 percent against 39.7 percent. The fraction of switches from high-physical-proximity to low-physical-proximity occupations accounts for 18.9 percent of the total occupational mobility. Among the unemployment-to-employment transitions, about 55 percent of new hires are in high-physical-proximity occupations. Females, who move from unemployment to employment, more likely start working in high-physical-proximity occupations. In Online Appendix, we show that the patterns documented in Table 4 were stable over the last decade, see Figure O.7.

Next, we use the data on occupation-to-occupation transitions, defined at the finer 6-digit SOC level, from Schubert et al. (2020). We should note that the results for this dataset, shown in Tables A.2 and A.3, are not directly comparable to those from Table 4. The first reason is that Table 4 shows the results for labor market mobility between 2018 and 2019, while the data from Schubert et al. (2020) contains occupation-to-occupation transitions averaged over all observations over starting years 2002-2015. Second, we use different classifications of occupations: in Table 4 we use the classification from Mongey et al. (2020), while in Tables A.2 and A.3 we use the classifications from Dingel and Neiman (2020) and Leibovici et al. (2020). Finally, the finer level of granularity implies that in the data from Schubert et al. (2020) we observe more job-to-job transitions within broader categories (e.g., defined by 3-digit Census OCC) that are not observed in the CPS data. Besides that, it is still instructive to document two observations. First, from Table A.2, about 45 percent of occupational switches occur between teleworkable occupations, while the remaining 55 percent is almost evenly distributed between the other types of transition. Second, from Table A.3, most of occupational switches are concentrated in low- and medium-contact-intensity occupations. Workers more rarely switch from or to the occupations that require high contact intensity at the workplace. Green markers in Figure 1 illustrate that (i) if a worker has a teleworkable occupation, then, conditional on switching, they more likely switch to another teleworkable occupation than if they had a non-teleworkable occupation, and (ii) if a worker has low- or medium-contact-intensity occupation, then, conditional on switching, they more likely switch to a low-contact-intensity occupation than if they had a high-contact-intensity occupation.

To draw a line under our empirical findings, we consider correlations between continuous measures of teleworkability (WFH Index) and contact intensity (CI Index) and the other characteristics of occupations. Table A.4 contains the results. Teleworkability is positively correlated with the measures of computer usage, social, cognitive, and character skills. Furthermore, conditional on occupational switch, the level of teleworkability of a current occupation is positively correlated with the probability of moving to another teleworkable occupation. Occupations characterized by lower contact intensity (higher values of CI Index) demonstrate similar patterns.

We conclude this section by emphasizing that teleworkable and low-contact-intensity occupations significantly differ along multiple characteristics, namely skill requirements and task content, from non-teleworkable and high-contact-intensity occupations respectively. This implies that workers in non-teleworkable and high-contact-intensity occupations, who bear higher risk of losing a job during the economic downturn that follows the COVID-19 outbreak, may incur not only short-run but also long-run losses (scarring effects) originated from skill mismatch. Our findings have important policy implications. While the unemployment benefits or stimulus payments for COVID-19 relief can insure these workers against short-run losses, they fall short of insuring long-run losses. The observation that scarring effects are typically larger for low-earnings workers, see Guvenen et al. (2017), strengthens our arguments even further. Study of

optimal policies that can provide insurance against short-run and long-run losses is an important avenue for future research. We also emphasize that existing differences in skill requirements may create constraints on policies that propose training programs for the unemployed. While some hard skills, e.g. basic computer skills, can be acquired through training, social and character skills are much harder to develop.

4   Conclusion

We study how the nature of work — teleworkability and contact intensity — shapes the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic. To answer this question, we consider two contexts. First, we show that the existing spousal nature-of-work-based occupational sorting in the United States matters for the distribution of these risks. In particular, we show that it mitigates the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. Next, we show that it creates a larger fraction of couples, who are excessively exposed to labor income and unemployment risks, relative to the case of zero sorting. Second, we document a significant differences in skill requirements between teleworkable and non-teleworkable as well as low- and high-contact-intensity occupations. Teleworkable occupations require higher education and experience levels as well as greater cognitive, social, character, and computer skills relative to non-teleworkable occupations. This discrepancy increases the likelihood of skill mismatch for workers who lost their jobs during the economic downturn following the COVID-19 outbreak. This, in turn, may leave a scarring effect that reduces their wages in future occupations. Our results imply that the current economic downturn may have long-run effects on employment prospects and earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak.

While in the text we briefly discuss several policy implications that follow from our analysis, more careful and formal study of optimal policies is necessary. Baqaee et al. (2020) is an example of a quantitative paper that studies the economic reopening using the data on teleworkability and contact intensity by sector. Current evidence suggests that firms rapidly adopt flexible work arrangements and highly likely this tendency will persist in the future. An important question that needs a careful study is how working from home affects productivity, see Bloom et al. (2015) for a recent contribution to this topic. Using data from a field experiment with national scope, Mas and Pallais (2017) show that the average worker is willing to give up 20 percent of wages to avoid a schedule set by an employer, and 8 percent for the option to work from home. Has COVID-19 shifted the preferences for work from home? Answers to these questions are fruitful avenues for future research.

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Appendix

O*NET Job Attributes used by Dingel and Neiman (2020) and Mongey et al. (2020)

- **Work Activities:** Performing General Physical Activities; Handling and Moving Objects; Controlling Machines and Processes; Operating Vehicles, Mechanized Devices, or Equipment; Performing for or Working Directly with the Public; Repairing and Maintaining Mechanical Equipment; Repairing and Maintaining Electronic Equipment; Inspecting Equipment, Structures, or Materials.

- **Work Context:** Electronic Mail; Outdoors, Exposed to Weather; Outdoors, Under Cover; Deal With Physically Aggressive People; Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets; Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection; Spend Time Walking and Running; Exposed to Minor Burns, Cuts, Bites, or Stings; Exposed to Disease or Infections.

O*NET Job Attributes used by Acemoglu and Autor (2011)

- **Non-Routine Cognitive (Analytical):** Analyzing Data or Information; Thinking Creatively; Interpreting the Meaning of Information for Others.

- **Non-Routine Cognitive (Interpersonal):** Establishing and Maintaining Interpersonal Relationships; Guiding, Directing, and Motivating Subordinates; Coaching and Developing Others.

- **Routine Cognitive:** Importance of Repeating Same Tasks; Importance of Being Exact or Accurate; Structured versus Unstructured Work (reverse).

- **Routine Manual:** Pace Determined by Speed of Equipment; Controlling Machines and Processes; Spend Time Making Repetitive Motions.

- **Non-Routine Manual Physical:** Operating Vehicles, Mechanized Devices, or Equipment; Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls; Manual Dexterity; Spatial Orientation.

- **Offshorability:** Face-to-Face Discussions (reverse); Assisting and Caring for Others (reverse); Performing for or Working Directly with the Public (reverse); Inspecting Equipment, Structures, or Material (reverse); Handling and Moving Objects (reverse); $0.5 \times$ Repairing and Maintaining Mechanical Equipment (reverse); $0.5 \times$ Repairing and Maintaining Electronic Equipment (reverse).

- **Computer Usage:** Interacting with Computers. *Not used by Acemoglu and Autor (2011).*

Table A.1: Keywords and phrases for skill category classification

Skill Category	Keywords and Phrases
Cognitive	Analy, Arithmetic, Assess, Brainstorming, Cognitive, Critical, Decision, Economics, Estimating, Financial, Forecasting, Intelligence, Learn, Math, Modelling, Numer, Problem, Quantitative, Research, Solving, Science, Statistics, Thinking
Social	Collaboration, Communication, Conjunction, Cooperation, Interpersonal, Listening, Negotiation, Partnership, People Skills, Presentation, Public Speaking, Relationship Building, Social, Teamwork
Character	Administrative, Ambitious, Assertive, Autonomy, Bright, Career-Minded, Character, Charismatic, Detail-Oriented, Dynamic, Energetic, Enterprising, Enthusiastic, Hardworking, Initiative, Inquisitive, Intellectual Curiosity, Leadership, Meeting Deadlines, Minded, Motivated, Multi-Tasking, Organizational Skills, Organized, Responsibility, Time Management

Note: This table contains the list of keywords and phrases that we use to determine whether a skill requirement falls into one of categories, cognitive, social, or character. To create this list, we use the categorization from Atalay et al. (2020), Deming and Kahn (2018), and Hershbein and Kahn (2018), and add several more keywords by ourselves. We apply this classification to the online vacancy postings data from Gartner TalentNeuron.

Table A.2: Distribution of occupational switches in the United States: teleworkable and non-teleworkable occupations, (%)

	To WFH	To NWFH	Total
From WFH	45.8	16.4	62.2
From NWFH	20.5	17.2	37.8
Total	66.3	33.7	100

Note: We use the data from Schubert et al. (2020) to construct this table. Occupations are defined at the 6-digit SOC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations.

Table A.3: Distribution of occupational switches in the United States: low-, medium-, and high-contact-intensity occupations, (%)

	To low CI	To medium CI	To high CI	Total
From low CI	16.2	16.2	3.0	35.4
From medium CI	18.9	23.2	6.1	48.2
From high CI	4.7	7.7	4.1	16.5
Total	39.7	47.1	13.2	100

Note: We use the data from Schubert et al. (2020) to construct this table. Occupations are defined at the 6-digit SOC level. The classification of occupations in terms of contact intensity (low/medium/high CI) is from Leibovici et al. (2020). Low CI stands for low contact intensity. Medium CI stands for medium contact intensity. High CI stands for high contact intensity. Percentages may not add up to 100% due to rounding.

Table A.4: Correlations for continuous measures of teleworkability and contact intensity

	WFH Index	CI Index
WFH Index		0.42
CI Index	0.42	
Non-Routine Cognitive (Analytical)	0.48	0.20
Non-Routine Cognitive (Interpersonal)	0.16	-0.11
Routine Cognitive	-0.19	-0.16
Non-Routine Manual Physical	-0.88	-0.22
Offshorability	0.81	0.57
Computer Usage	0.62	0.27
Social Skills (Deming)	0.34	-0.10
Social Skills (Online Ads)	0.72	0.15
Cognitive Skills (Online Ads)	0.74	0.34
Character Skills (Online Ads)	0.66	0.22
Transition to a new WFH job	0.81	0.73
Transition to a new low CI job	0.58	0.66

Note: Construction of WFH Index (WFH stands for "work-from-home") and CI Index (CI stands for "contact intensity") is described in Section 2.1. Higher values of WFH Index correspond to greater teleworkability of occupation. Higher values of CI Index correspond to lower requirements of contact intensity at the workplace. Construction of measures of task content (lines 3-8) is described in Section 2.3. Construction of measures of skill requirements (lines 9-12) is described in Section 2.4. Transition probabilities (lines 13-14) are calculated using the data from Schubert et al. (2020). For lines 1-12, correlations are calculated using occupations at the O*NET SOC level. For lines 13-14, correlations are calculated using occupations at the 6-digit SOC level, and we use WFH Index and CI Index for the starting occupations. Correlations in lines 10-12 are calculated using the number of posted ads for each O*NET SOC occupation as weights.

(a) Teleworkability classification

(b) Contact intensity classification
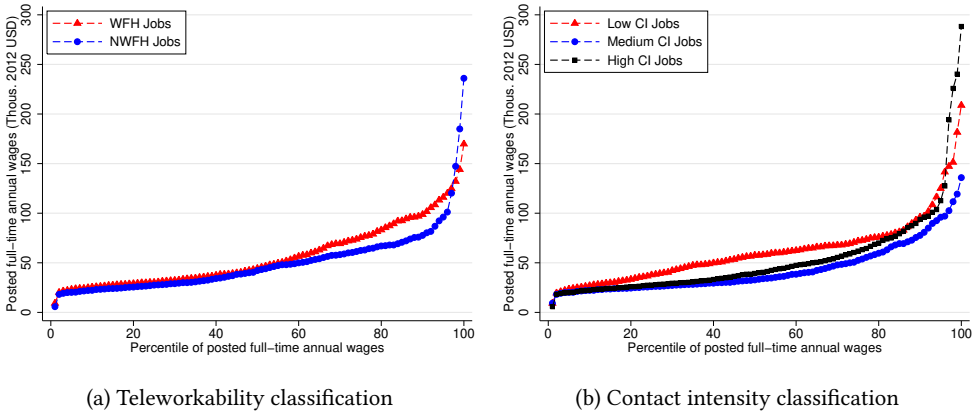
Figure A.1: Cumulative distribution of full-time annual posted wages

Note: We use 2014-2018 Gartner TalentNeuron data on online vacancy ads in Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin for September 2014-September 2018 to produce these figures. Occupations are defined at the O*NET SOC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. The classification of occupations in terms of contact intensity (low/medium/high CI) is from Leibovici et al. (2020). Low CI stands for low contact intensity. Medium CI stands for medium contact intensity. High CI stands for high contact intensity. For each percentile, statistics are based on the minimum full-time posted wage in that percentile. Posted wages are adjusted for inflation to 2012 dollars using the PCE price index.

Online Appendix

(a) All couples

(b) Couples with children

(c) Couples with children under 5

(d) Couples without children
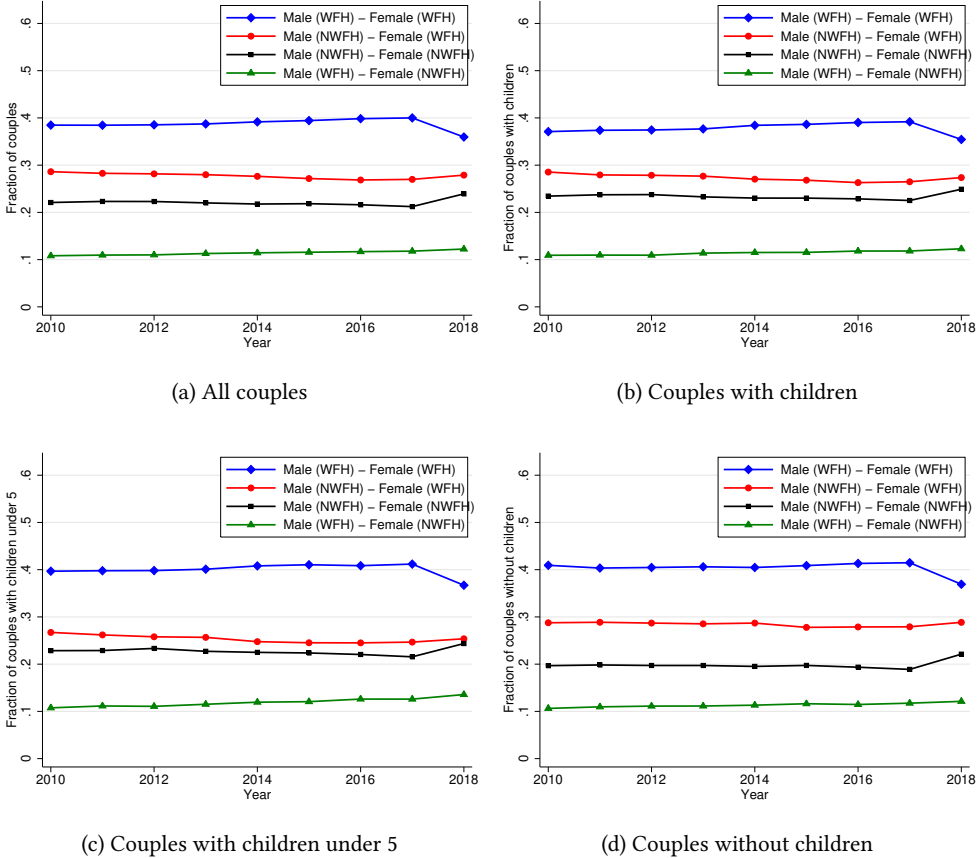
Figure O.1: Distribution of WFH/NWFH occupations within dual-earner married couples

Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Mongey et al. (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. To obtain the results, we use household weights provided by IPUMS.
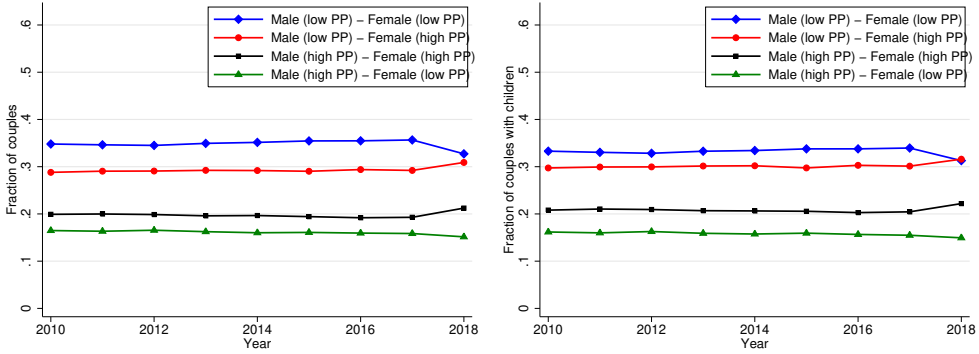
(a) All couples

(b) Couples with children
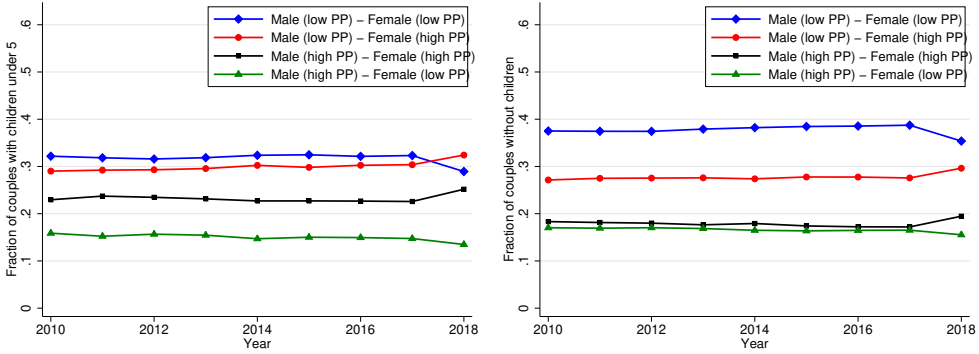
(c) Couples with children under 5

(d) Couples without children

Figure O.2: Distribution of low PP/high PP occupations within dual-earner married couples

Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of physical proximity (low PP/high PP) is from Mongey et al. (2020). Low PP (low-physical-proximity) stands for occupations that do not require close physical proximity at the workplace. High PP (high-physical-proximity) stands for occupations that require close physical proximity at the workplace. To obtain the results, we use household weights provided by IPUMS.

(a) All couples

(b) Couples with children

(c) Couples with children under 5

(d) Couples without children
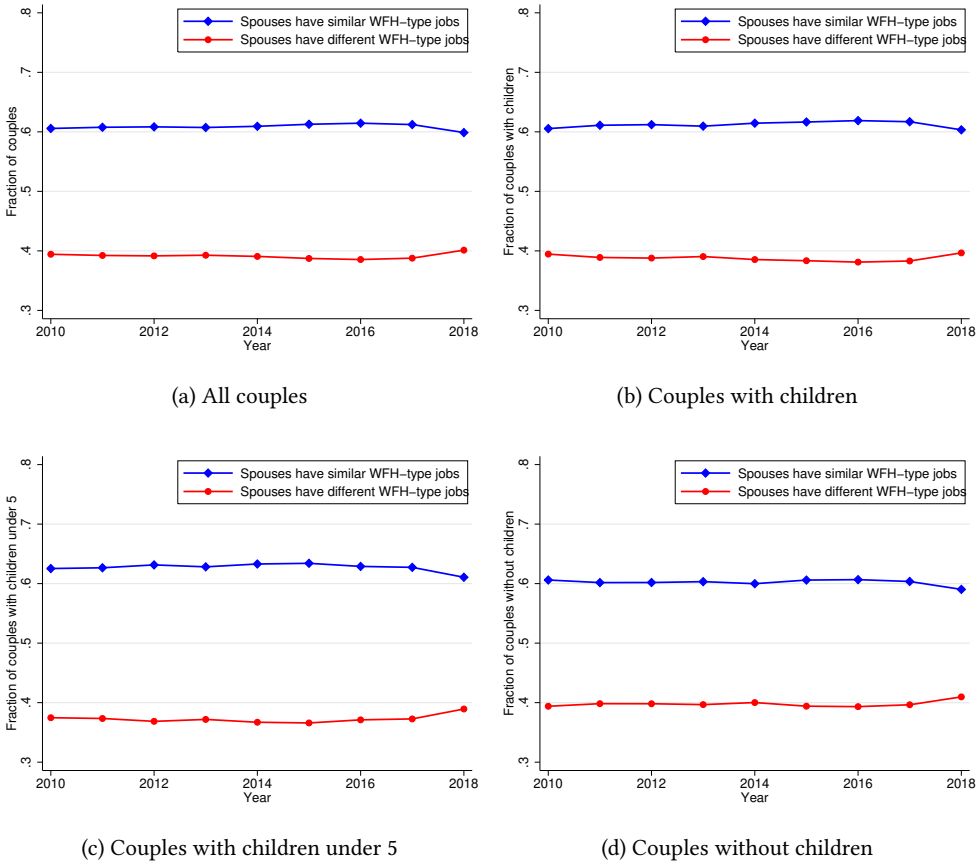
Figure O.3: Fraction of dual-earner married couples where spouses have similar/different WFH-type jobs

Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Mongey et al. (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. Couples with similar WFH-type jobs are those where both spouses have either WFH or NWFH jobs. Couples with different WFH-type jobs are those where one spouse has WFH job and another spouse has NWFH job. To obtain the results, we use household weights provided by IPUMS.
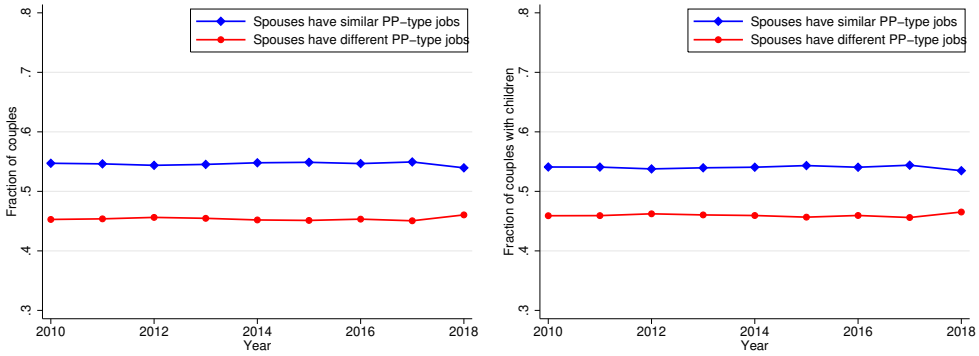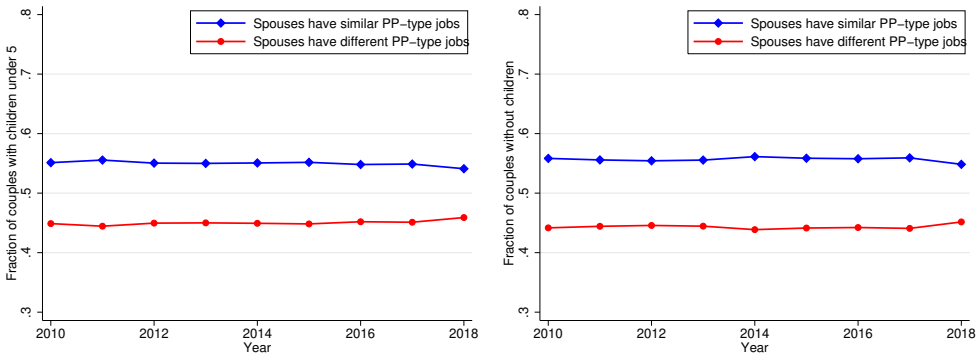
Figure O.4: Fraction of dual-earner married couples where spouses have similar/different PP-type jobs

Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of physical proximity (low PP/high PP) is from Mongey et al. (2020). Low PP (low-physical-proximity) stands for occupations that do not require close physical proximity at the workplace. High PP (high-physical-proximity) stands for occupations that require close physical proximity at the workplace. Couples with similar PP-type jobs are those where both spouses have either low PP or high PP jobs. Couples with different PP-type jobs are those where one spouse has low PP job and another spouse has high PP job. To obtain the results, we use household weights provided by IPUMS.
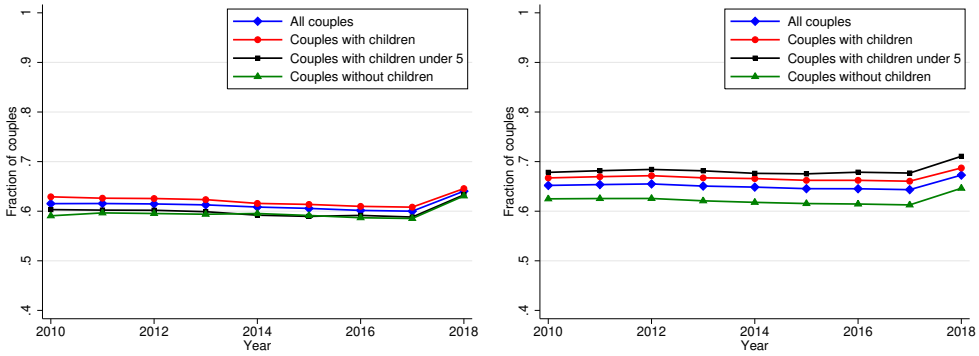
Figure O.5: Left panel — Fraction of dual-earner married couples where at least one spouse cannot work from home (has NWFH job). Right panel — Fraction of dual-earner married couples where at least one spouse should work in physical proximity (has high PP job)

Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). To obtain the results, we use household weights provided by IPUMS.

(a) Social skills

(b) Social skills vs. non-routine cogn. (interpersonal)

(c) Cognitive skills vs. non-routine cogn. (analytical)
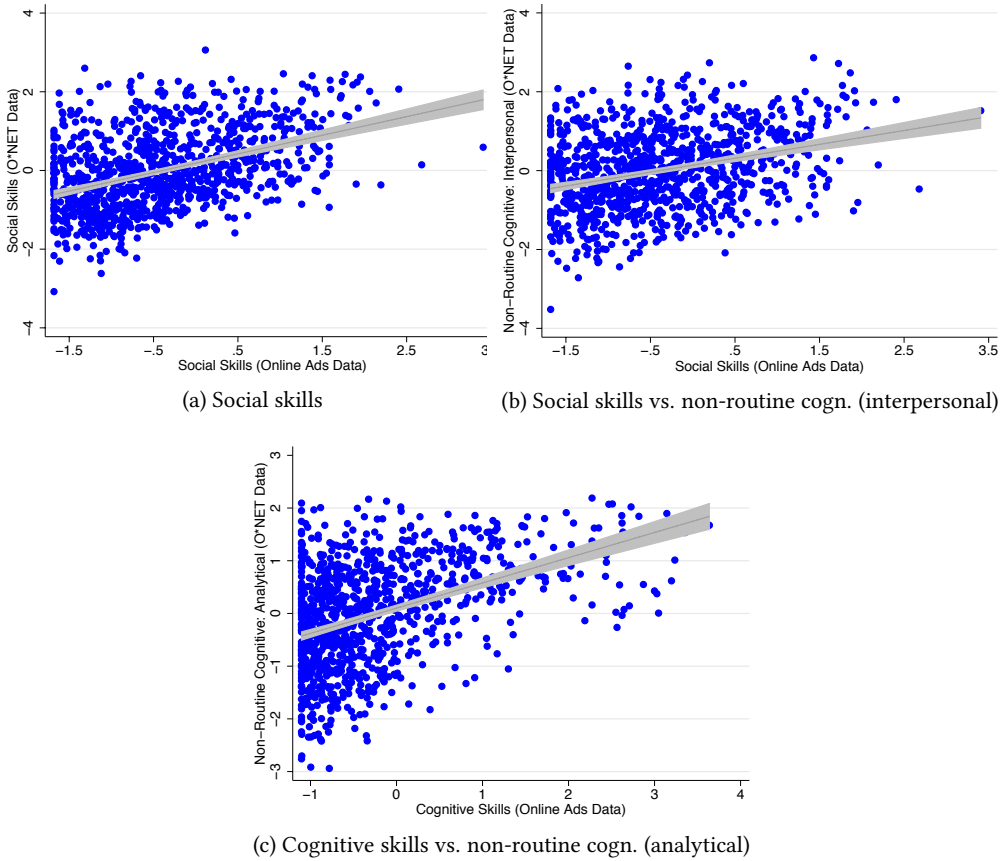
Figure O.6: Association between measures constructed from the online job ads data and measures constructed from O*NET data

Note: Blue dots represent occupations defined at O*NET SOC level. The grey shaded area represents the 95% confidence interval. In these figures, we show the relationship between the measures of skill requirements, constructed using Gartner TalentNeuron online ads data, and the measures, constructed using O*NET data. Social-skill measure from O*NET data, used in Figure O.6a, corresponds to the measure used by Deming (2017). Non-routine cognitive measures, interpersonal and analytical, from O*NET data, used in Figure O.6b and Figure O.6c, correspond to the measures proposed by Acemoglu and Autor (2011).
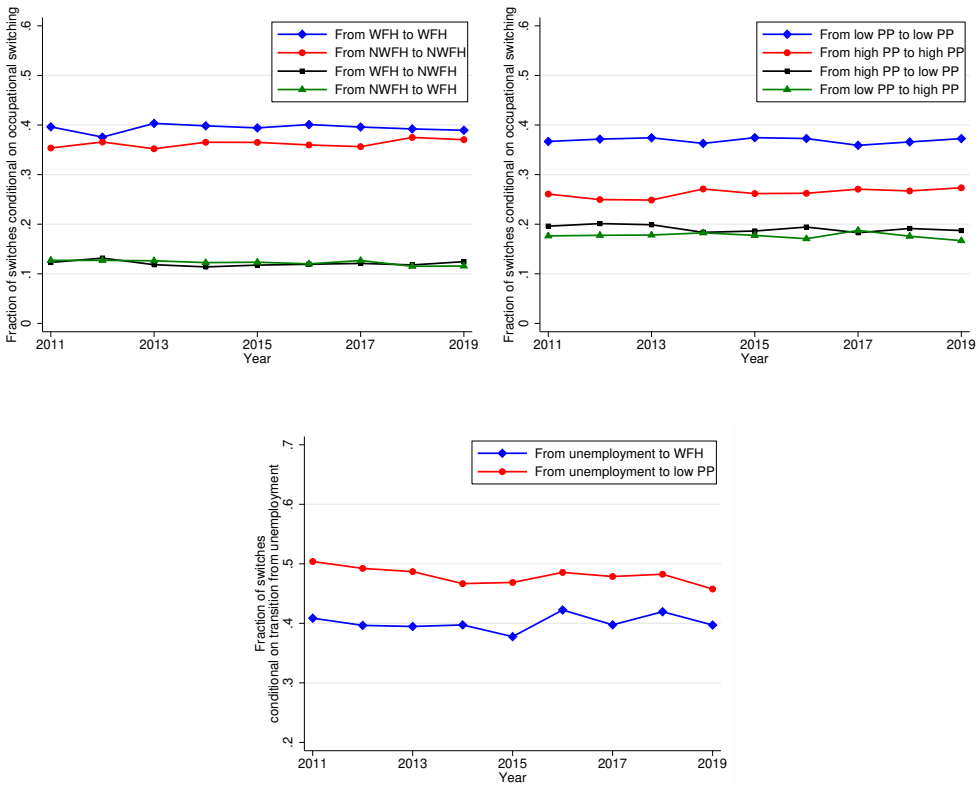
Figure O.7: Left upper panel — Distribution of occupational switching over teleworkable (WFH) and non-teleworkable (NFWH) occupations. Right upper panel — Distribution of occupational switching over occupations that require (high PP) and do not require (low PP) close physical proximity at the workplace. Bottom panel — Distribution of unemployment-to-employment transitions

Note: We use 2011-2019 Annual Social and Economic Supplement of the Current Population Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. Occupational switching is defined as change of occupation over the year preceding the survey. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). To obtain the results, we use ASEC individual weights.

The real cost of political polarization: Evidence from the COVID-19 pandemic[1]

Christos A. Makridis[2] and Jonathan T. Rothwell[3]

While the SARS-CoV2 pandemic has led to a rapid increase in unemployment across the United States, some states have fared better than others at minimizing economic damage and suppressing the disease burden. We examine the political factors behind these outcomes at the individual and institutional levels. First, using new daily data from the Gallup Panel between March and June on roughly 45,000 individuals, we document that heterogeneity in beliefs about the pandemic and social distancing behaviors is driven primarily by political affiliation. In fact, it is systematically more predictive than factors directly connected to the disease, including age, county infections per capita, and state public health policies. Second, we investigate how partisanship led states to adopt laxer or stricter policies during the pandemic. While the more extreme policies have had negative effects on either economic activity or public health, middle-of-the-road policies (e.g., mask-mandates) have been more effective at curbing infections without significant economic damages. However, the effectiveness of these policies—and compliance with them—is mediated by political affiliation. Our results suggest that partisanship can have persistent effects on economic activity and health beyond its effects on sentiment, moving individuals and institutions away from optimal policy.

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I.   Introduction

There is now a large literature examining the effects of the COVID-19 pandemic, especially the resulting state and national quarantines, on employment (Coibion et al., 2020a; Cajner et al., 2020), consumption (Baker et al., 2020; Chetty et al., 2020), and real output (Guerrieri et al., 2020; Makridis and Hartley, 2020). Although national guidelines had an effect, states hold considerably more power in the United States than the Federal government in terms of setting and enforcing public health regulations. For example, there is already evidence that state policymaking has had a substantial effect on household expectations (Coibion et al., 2020b) and job postings (Ali et al., 2020). Along these lines, several papers have found that state health policies have had real effects on social-distancing behaviors and slowing the growth rate of infections (Sears et al 2020; Courtmanche et al. 2020; David et al 2020; Lyu et al ,2020). However, there is still an ongoing debate about the economic consequences of these policies, with Chetty et al., 2020 arguing that health concerns were more important than state policies in affecting consumption expenditures.

This paper explores the role of political affiliation as a mediating factor for public health policy and decentralized beliefs and behaviors during the SARS-CoV2 pandemic. Following Allcott et al. (2020) and Bursztyn et al. (2020) about the role of political affiliation and information, we show that these partisan differences affect beliefs about the pandemic and its economic disruption, including forecasted economic disruption, fear, compliance with public health guidelines, and the avoidance of other people. For example, according to Gallup in late May 2020, 79% of Republicans reported that the coronavirus situation was getting better, compared to only 22% of Democrats.[2]

Moreover, these individual partisan differences have real economic effects: they correspond with meaningful institutional differences across states. For example, Figure 1 shows that political affiliation is closely tied with policy decisions: there is a 20 percentage point (pp) difference in the

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[2] https://news.gallup.com/poll/312014/optimism-pandemic-less-duration.aspx

probability that a state adopts a state shut down order based on the winner of the 2016 election.[3]
Nearly all residents of states won by Hillary Clinton require masks to be worn in public-facing
businesses, whereas just over half of residents in Trump-won states face this requirement.

Beyond documenting these differences systematically, this paper asks: Do partisan
differences in policies affect how successfully different areas mitigate the disease, and do these
policies have real economic affects? We present evidence for both.

Figure 1: State Policy Decisions and Economic Outcomes by Winner of 2016 Election

Note: Weighted by state population. Sources: U.S. DOL; IHME; Boston University; Google, 7-day mean;
Federal Elections data. Opportunity Insights: Affinity for consumer spending; Womply for revenue
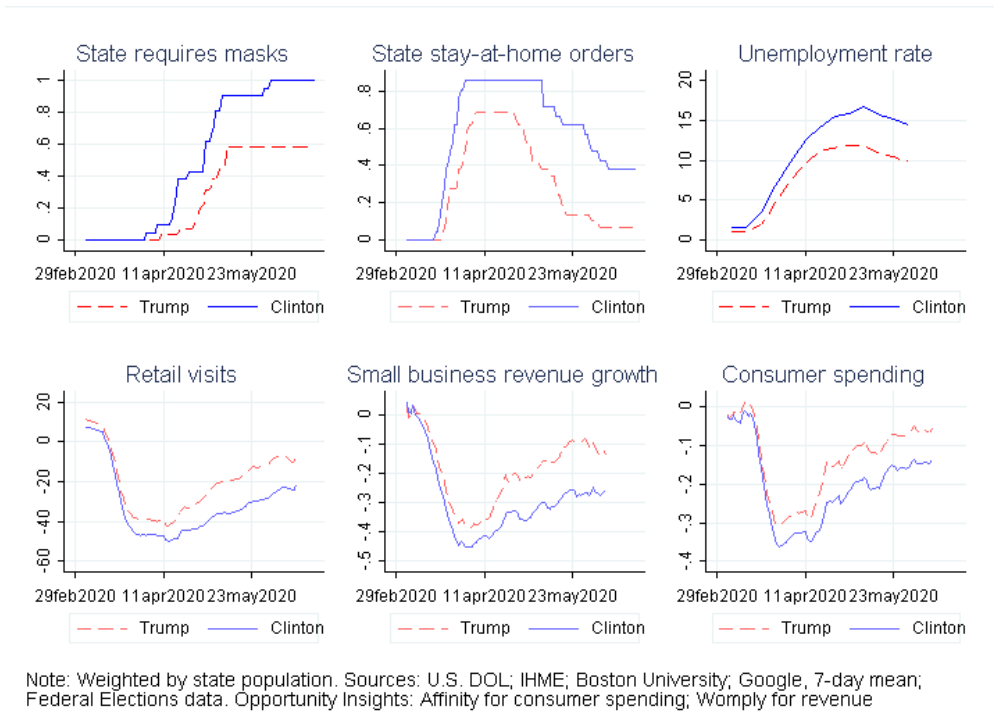
The first part of the paper introduces our data from Gallup between March 13th and June
14.th. We document substantial differences in attitudes about the pandemic and economic disruption
across party lines and over time since the declaration of a national emergency by President Trump

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[3] Figure A.1 in the Online Appendix shows that the 2016 Trump vote share is representative of current attitudes.

on March 13. These differences are not explained by local exposure to the virus, population density, or other observable factors. We show that our data is nationally representative, in relation with the Current Population Survey, with the advantage of having daily variation and county identifiers.

The second part of the paper quantifies the quantitative importance of political affiliation of typical determinants of beliefs about the pandemic and the economy. In contrast with the large literature on the role of personal experience (Malmendier and Nagel, 2011; 2016), even among firms (Coibion et al., 2018), we find that local fluctuations in new infections per capita and unemployment insurance claims have very weak predictive power over our measures of beliefs. Moreover, we also find that measures of infections mediated through social networks also play less of a role, in contrast to Makridis and Wang (2020). One potential explanation arises from the fact that people are not interacting as much with one another, meaning that there is less margin for personal encounters and information gathering through observation of the local environment to inform beliefs—and greater reliance on media sources, which are heavily filtered by partisanship (Gallup and Knight Foundation 2018). Instead, political affiliation remains the most important predictor—even more significant than, for example, age, gender, race, college attainment, or even whether the person has a serious medical condition. The fact that political affiliation matters so much provides microeconomic evidence for models of belief distortions and their aggregate effects, as in Bianchi et al. (2020). We also speak to the potential for scarring, as in Kozlowski et al. (2020), that can arise when individuals with different political affiliations observe the same shock, but arrive at different conclusions. Our ongoing work exploits the panel structure of our data to examine whether updates to beliefs are correlated with political affiliation and local and/or aggregate changes in economic activity.

The third part of the paper investigates whether political affiliation also plays a mediating role on real economic outcomes. After controlling semi-parametrically for the age, education, race, and even industry distribution, we show that a 1% increase in the share of individuals voting for

Trump in 2016 is associated with a 1.5% and 2% decrease in the probability of a state passing a stay-at-home order (SAHO) and a nonessential business closure. In turn, states that adopted stricter policies also exhibited sharper declines in economic activity. For example, the adoption of a SAHO and nonessential business closure is associated with a sharp decline in retail visits and more modest 1-3.5% declines in credit card spending and small business revenue growth, relative to the baseline. Interestingly, however, the adoption of mask policies is not statistically related with declines in credit card spending or small business revenue growth. While these state interventions had economic consequences, we find that they had some effect on curbing the spread of the virus, which is not surprising. Importantly, we find that political affiliation mediates the effects of these state policies on both economic and health outcomes, driven by the beliefs that individuals in these states had in the policies. In this vein, we follow Acemoglu et al (2020) in acknowledging that the optimal disease-suppression policy balances economic concerns with minimizing mortality through lockdown requirements. Given the wide variation in risk by age, they conclude that targeted lockdowns could limit mortality with only modest economic losses. Version of this approach appear to have been implemented in countries such as Hong Kong, Taiwan, Japan, South Korea, and Iceland, which minimized economic harm, while deploying mask-wearing, contact tracing, quarantine, and testing to various degrees not observed in the United States (Cheng et al 2020; Rothwell, 2020).

This paper contributes to two literatures. The first is a rapidly growing empirical literature tracking the effects of the COVID-19 pandemic. However, much less work has been done on the role of expectations. We build most closely on Coibion et al. (2020b) who conduct a survey of over 10,000 respondents, finding that households living in states that entered into lockdowns earlier expect that the unemployment rate over the next year would be 13 percentage points higher, on top of expecting lower future inflation and higher uncertainty for the next decade. Building on their results, while we find that the adoption of SAHOs and business closure policies are associated with

increases in beliefs about economic disruption, Republicans respond differently than Democrats: they become systematically more pessimistic. These differences remain even after controlling for state × month fixed effects, suggesting that the results are not an artifact of self-selection of individuals into states that vary in their propensity to enact different regulations. These findings apply beyond formal policies to voluntary disease-suppression behaviors. We find similar effects of beliefs about self-reported mask-usage and social distancing as in Allcott et al. (2020) and Bursztyn et al. (2020) who show that political affiliation and the exposure to different information sources affects beliefs about the pandemic and the resulting disease-mitigation behaviors.

We also build on several recent large-scale surveys. For example, Wozniak (2020) developed the COVID Impact Survey (CIS) to track well-being and physical health at a high frequency, finding large declines in self-reported well-being across space and demographic brackets. Our results are also consistent with Papageorge et al. (2020) who use the large-scale survey effort from Belot et al. (2020) to study the correlation between attitudes about the pandemic and socio-economic characteristics. They find that individuals with lower income and less flexible income arrangements are less likely to engage in social distancing behaviors. We also extend these results to additional measures, including beliefs about economic disruption, mask-usage, visiting work, and worrying about the virus.

The second is a larger literature about the role of partisanship and its potential effect on real economic activity. While Mian et al. (2018) argue that that political partisanship affects economic sentiment, but sentiment does not affect consumption. However, an ongoing debate remains. For example, using the University of Michigan Survey of Consumer Sentiment, Benhabib and Spiegel (2019) provide state-level evidence that changes in economic activity are correlated with changes in sentiment about national conditions. Moreover, Gillitzer and Prasad (2018) exploit changes in the government party in power to identify the effects of expectations on an intent to spend more in the future. Makridis (2020) uses additional data from Gallup to quantify the effects of beliefs about the

economy on non-durables consumption, finding that the decline in beliefs during the financial crisis can account for up to 60% of the decline in consumption in the sluggish recovery that followed. Kamdar and Ray (2020) also build a model where disagreement about macroeconomic fundamentals leads to changes in consumption and Bianchi et al. (2020) show how distortions in beliefs can create overoptimism that leads to systematic changes in aggregate productivity.

The structure of the paper is as follows. Section II summarizes our data and measurement strategy focusing on the new facts from the Gallup micro-data. Section III quantifies the factors that affect beliefs about the pandemic and predict the adoption of state disease-suppression policies. Section IV estimates how these policies affect health outcomes and economic outcomes, and how politics does or does not mediate these outcomes. Section V concludes.

II.   Data and Measurement

Our individual survey-based data are from Gallup's COVID Tracking Survey. Gallup fielded the survey on March 13, 2020 and collected roughly 1000 responses per day until April 26th when the sample declined to roughly 500 responses per day. The survey remains in the field, but we restrict our analysis to June 14th as the cutoff date. Our sample is a subset of the Gallup panel, which is representative of the U.S. population with approximately 100,000 members contacted via random-digit dialing. Our sample has 81,516 responses from 45,054 unique individuals who completed the survey online or using a smartphone after receiving an emailed invitation. While no one in the sample has more than three responses, the presence of at least some longitudinal variation is a substantial advantage over traditional surveys in this literature because it allows us to trace out how a given individual has adjusted their expectations over the duration of the pandemic, rather than relying on repeated cross-sections based on limited observable characteristics. Nonetheless, we use weights based on age, gender, education, region, race, and Hispanic ethnicity to ensure the sample is

nationally representative. Out of an abundance of caution, we benchmark the sample with the Current Population Survey between March and April in Table A.1 of the Online Appendix.

Our Gallup data has contains the zip code for every respondent, allowing us to match confirmed COVID-19 cases and deaths from USA Facts at the county-level, together with county unemployment insurance (UI) claims from various state agencies and demographic characteristics from the Census Bureau's American Community Survey (ACS).

We focus on six major outcome variables, which we detail in Table 1. We have a mix of economic sentiment and pandemic response variables. For example, our measure of expected disruption captures the degree of economic impact from COVID-19 on business and organizational closures. We also have several variables measuring expectations about the severity of the virus and individual responses to these concerns. Individuals report their degree of social distancing, self-isolation, and wearing a mask. Broadly speaking, these variables reflect expectations about the pandemic, rather than specifically about the economy as in Coibion et al. (2020).

Figure 2 documents significant cross-sectional and time series variation in these attitudes. For example, in early April, roughly 32% of Republicans were visiting the workplace, whereas only 20% of Democrats were. By June, those shares climbed to roughly 43% and 33%, respectively, continuing to demonstrate a large partisan gap. We also observe substantial differences in expectations about the COVID-19 disruption lasting at least until the end of the year. For example, whereas only 15% of Republicans anticipated a large disruption as of early April, as many as 38% of Democrats expected a disruption. Moreover, these differences have widened over time with roughly 38% of Republicans expecting a disruption and 80% of Democrats expected one. We see similar patterns among other variables, particularly wearing masks. These patterns provide a preview for the quantitative importance of political affiliation over other individual or local characteristics.

Table 1: Definition of Economic and Pandemic Expectation Variables

Variable	Survey Question	Categorical Values
Expected Disruption	How long do you think the level of disruption occurring to travel, school, work and public events in the U.S. will continue before it starts to improve?	1. A few more weeks 2. A few more months 3 For the rest of the year 4. Longer than this year
Worried About Illness	How worried are you that you will get the coronavirus (COVID-19)?	1. Not worried at all 2. Not too worried 3. Somewhat worried 4. Very worried
Social Distancing	Over the past 24 hours, how often have you been practicing social distancing?	1. Always 2. Very often 3. Sometimes 4. Rarely 5. Never
Self Isolation	Next, thinking about everything you've done in the past 24 hours, which of the following comes closest to describing your in-person contact with people outside your household?	1. Completely isolated yourself, having no contact with people outside your household 2. Mostly isolated yourself, having very little contact with people outside your household 3. Partially isolated yourself, having some contact with people outside your household 4. Isolated yourself a little, still having a fair amount of contact with people outside your household 5. Did not make any attempt to isolate yourself from people outside your household.
Wearing Masks	There are some things people may do because of their concern about the coronavirus. For each one of the following, please indicate if this is something you have done, are considering doing or have not considered in the past 7 days. Worn a mask on your face when outside your home?	1. Have done 2. Considering doing 3. Have not considered
Visited Work	In the past 24 hours have you visited your place of work?	Binary

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Figure 2: Evolution of Beliefs About the Pandemic and Economy, by Political Affiliation
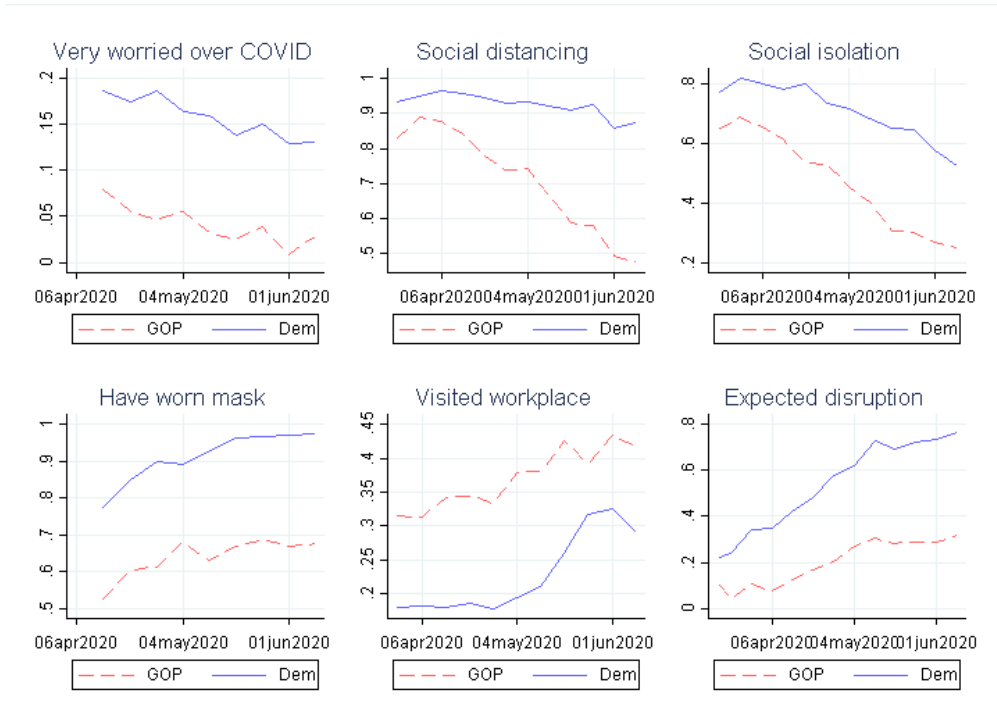
To understand how beliefs translate into differences in state policies, we obtain the start and end dates of state stay-at-home-orders and closures of non-essential businesses from Institute for Health Metrics and Evaluation (IHME). Using data current to June 15th, we code a policy as "1" if active on that day and "0" otherwise. We have also examined other policies (e.g. bans on social gatherings and school closures), but, because there is much less within-state variation, we focus on important policies with greater variation. We follow Lyu et al (2020) and use Boston University School of Public Health's COVID-19 policy database to measure variation in the start-date of mask

policies.[4] This database includes the start-date of policies that require face masks to be worn in public and those that require workers to wear them in public-facing businesses (e.g., grocery stores).

Our daily data on positive tests confirming COVID-19 cases and deaths are from USAFacts, which pulls the original data from state health departments.[5] We have these data through June 14, 2020. We also pull state and county demographic data from the U.S. Census Bureau, land area data from the Missouri Census Data Center's geographic correspondence engine, the U.S. Department of Labor on state unemployment insurance claims, and the Opportunity Insights Project for other county-level economic outcomes. Data on 2016 Presidential election results by county are from Tony McGovern who created the database from news sources.[6]

III.   Evaluating the Determinants of Household Expectations and Behaviors

To estimate the determinants of household expectations about the pandemic and degree of economic disruption, we consider regressions of the following form:

$$y_{ict} = \gamma P_{ict} + \zeta COVID_{ct} + \phi D_{ict} + \eta_c + \lambda_t + \epsilon_{ict} \tag{1}$$

where y denote individual i's outcome in county c and day-of-the-year t, P denotes indicators for Republican and Democrat political affiliation (normalized to moderates), $COVID$ denotes the logged number of new COVID-19 cases per capita, and D denotes a vector of individual demographic characteristics, and η and λ denote fixed effects on county and day-of-the-year. We cluster standard errors at the county-level to allow for arbitrary degrees of autocorrelation (Bertrand et al., 2004). We focus on the six major outcome variables from Section II, which we bin as a binary variables and estimate linear probability models so that we can easily include fixed effects. We also experimented with the number of unemployment insurance claims as a share of the county

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[4] We are not aware of states that have lifted their mask-wearing policies as of writing in late June, and the database does not indicate end dates
[5] https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/ (accessed June 25, 2020).
[6] https://github.com/tonmcg/US_County_Level_Election_Results_08-16

workforce and a proxy for exposure to COVID-19 from the respondent's social network from Makridis and Wang (2020), but we omit these from the main results because they are insignificant.

Table 2 documents these results. Measured by the t-statistic, we find that political affiliation is the most important predictor of expectations of economic disruption and mask-usage, and second-only to either educational attainment or the existence of a medical condition on other outcomes regarding fear, social-distancing, and visits to work. For example, Republicans are 18% less likely to believe that the COVID-19 disruption will last until the end of the year, whereas Democrats are 11% more likely, relative to independents or those who prefer an "other" party. To put that in perspective with other correlates, we see that a 10% rise in the number of new infections per capita is associated with a 0.2% increase in the probability of expected disruption. Moreover, political affiliation is even more predictive of economic expectations than employment status (employed are 8% less likely to expect significant disruption), education (those with graduate degrees are 3% more likely), or even health (those with a medical condition are 5% more likely).[7]

In unreported results, we find that the unemployment rate—the number of UI claims divided by the employment level in 2018—and the SCI-weighted infections per capita are uncorrelated with these attitudes about the pandemic with the exception of economic disruption as an outcome variable. But, even here the magnitude of these two factors is economically insignificant. The fact that unemployment is not correlated with beliefs about the pandemic and disruption suggests that local factors and personal experience are dwarfed in significance by the role of political affiliation, which influences the way people process and attend to different information.

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[7] We do not believe that these trends can be explained by partisan differences in the levels of trust in government. In separate surveys, Democrats and Republicans have similar levels of trust in local or state government, and Republicans report far higher levels of trust in the current Executive Branch and slightly higher levels of trust for the legislative and judicial branch than Democrats. https://news.gallup.com/poll/243563/americans-trusting-local-state-government.aspx and https://news.gallup.com/poll/243293/trust-legislative-branch-highest-nine-years.aspx

We see similar patterns when we look at other outcome variables. For example, Republicans are 5% less likely to report being somewhat or very worried about getting the illness, Democrats are 6% more likely, relative to moderates. Again, we see that increases in actual local infections raises concerns about contracting the virus, but a fifth to a sixth as much as political affiliation. Here, employment status matters relatively more: those employed in a job are 6% less likely to worry about getting sick, perhaps reflecting that many are working remotely. Not surprisingly, we see that those with serious medical problems are 8% more likely to worry about getting sick, which reflects not only a potential selection effect, but also the possible heightened exposure to COVID-19.

Turning to our remaining attitudinal outcomes, we see that Republicans are 7% less likely to social distance very often or always, 8% less likely to self-isolate mostly or completely, and 10% less likely to wear a mask, relative to moderates, whereas Democrats are 6%, 6%, and 8% more likely, respectively. Interestingly, increases in infections per capita are not statistically or economically associated with attitudes or behaviors around social distancing and self-isolation. We also find that Republicans are 5% more likely to visit work at least once in the past day, whereas Democrats are 3% less likely. Educational attainment predicts each outcome except fear of getting the virus with high levels of significance, and the patterns suggest compliance with public health guidelines rises strongly with education. Future work could explore to what extent this is related to being more informed about those guidelines and their value or other factors, such as the ease of working remotely (Makridis and Hartley, 2020).

The inclusion of individual political affiliation represents a major advantage in our data. Because political affiliation is correlated with both demographic characteristics, failing to control for it produces biased estimates of how these factors correlate with behavior and attitudes during the pandemic. For example, we find that African Americans are 9% more likely to anticipate that economic disruption will last at least until the end of the year when we fail to control for political

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affiliation. However, after adding these controls, we find that the magnitude drops to 4% and becomes less statistically significant. Similarly, those with a bachelor's degree and those with a post-graduate degree are 6% and 8% more likely to anticipate economic disruption that will last at least until the end of the year, but the coefficients drop to 1% (not statistically significant) and 3% (significant at the 5% level) once political affiliation is included. We find similar patterns for our measures of social distancing and wearing masks.

Table 2: Baseline Determinants of Individual Beliefs about the Pandemic

	Expected disruption	Worry about illness	Social distancing	Self-Isolating	Wearing mask	Visited work
	(1)	(2)	(3)	(4)	(5)	(6)
log(New Infections, 7-day Avg)	0.02**	0.01**	0.00	0.01	0.03***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Republican	-0.18***	-0.04***	-0.07***	-0.08***	-0.10***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Democrat	0.11***	0.06***	0.06***	0.06***	0.08***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employed	-0.08***	-0.06***	-0.05***	-0.15***	0.02	0.39***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Out of workforce	-0.05**	-0.06***	0.00	0.05**	0.03	-0.07***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Male	-0.00	-0.03***	-0.04***	-0.06***	-0.05***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age/10	-0.01***	-0.01*	0.01***	-0.01***	0.02***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Some College	0.04***	0.01	0.02**	0.03***	0.05***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bachelors degree	0.01	0.00	0.07***	0.15***	0.08***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Graduate degree	0.03**	0.01	0.09***	0.17***	0.08***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hispanic	0.00	0.02	0.01	-0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Black	0.04**	-0.00	-0.01	-0.06***	0.02	0.02

	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Asian	0.02	0.06	0.04***	0.03	-0.00	-0.09***
	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)	(0.03)
American Indian	0.02	0.00	0.01	0.01	0.01	0.02
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Native Hawaiian	0.06	0.16*	-0.04	-0.03	-0.03	0.10*
	(0.08)	(0.08)	(0.07)	(0.09)	(0.06)	(0.06)
Other Race	0.04	0.02	-0.01	-0.06*	-0.02	0.07*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Has medical condition	0.05***	0.08***	0.04***	0.05***	0.05***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lives with children	-0.00	0.01	-0.01	-0.01	-0.02*	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adj. R2	0.25	0.14	0.23	0.23	0.31	0.39
Sample Size	61687	38423	61625	61646	42139	49699
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes.—Sources: Gallup Panel. The table reports the coefficients associated with regressions of indicators for different beliefs about the pandemic and its economic implications on the logged number of new infections over the past seven days, political affiliation, and demographic controls, including age: race, employment status, living with children, having a medical condition. Standard errors are clustered by county and observations are weighted by the sample weights.

One shocking result is that age becomes insignificant in predicting fear of contracting the virus after we control for political affiliation, despite the striking relationship between age and mortality-risk documented by the CDC.[8] Indeed, age is much less powerful than political affiliation in explaining all of our attitudes and behaviors.

This explains the departure of our results from Wozniak (2020) or Papageorge et al. (2020) who find statistically significant correlations between age and race, for example, and beliefs about the pandemic. However, like them, we continue to find that those with medical conditions are more likely to self-isolate, social distance, and avoid the workplace.

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[8] https://data.cdc.gov/NCHS/Provisional-COVID-19-Death-Counts-by-Sex-Age-and-S/9bhg-hcku

IV.   State Policymaking and Political Polarization

Motivated by our result that political affiliation is a robust and important determinant of household expectations, attitudes, and behaviors related to the pandemic, we now examine the role that political affiliation plays in affecting the adoption of different state public health policies through regressions of the form:

$$STPOL_{st} = \zeta TRUMP_s + \zeta COVID_s + g(D_{st}, \theta) + \epsilon_{st} \qquad (2)$$

where $STPOL$ denotes an indicator for the adoption of a specific state policy, $TRUMP$ denotes the 2016 share of voters within a state that voted for Trump, $COVID$ denotes the logged number of new infections over the past 7 days, $g(D, \theta)$ denotes a semi-parametric function of demographic to control for a wide array of differences across states.[9] Our baseline controls include the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (less than high school, high school, some college, college, more than college), and the race distribution (white, black). Our industry controls include the full industry distribution, especially the share of workers in retail trade and food and hospitality. These controls help mitigate against concerns about the cross-sectional variation, but we nonetheless caution against a causal interpretation: our goal is simply to quantify the relation between political affiliation and state policy.

Table 3 documents these results. We find that a 1pp rise in the Trump share in 2016 is associated with a 0.65pp (1.2pp) decline in the probability that the state adopts a nonessential business closure (stay-at-home order, SAHO). While the former is not statistically significant at the 10% level, the latter is at the 1% level. Not surprisingly, we also find that increases in infections are positively associated with the adoption of nonessential business closures, but not statistically related with the adoption of SAHOs. On top of our existing controls (e.g., population density and cases),

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[9] We use the 2016 share of voters for Trump as a proxy for contemporaneous political affiliation because it is a salient, well-defined, and comprehensive measurement. However, Figure A.1 in the Online Appendix plots the degree of persistence between these two terms at the state-level using more recent data from Gallup.

we introduce additional controls in columns (2) and (4) that address concerns about differences in industry composition. For example, since areas with a higher share of jobs in professional services are much less likely to have voted for Trump (correlation is -.78), but could work from home easier than jobs in mining, for example, , we might pick up confounding forces affecting policy. Following the introduction of these controls in columns (2) and (4), we find that a 1pp rise in the share of people who voted for Trump in 2016 is associated with a 1.8pp (1.5pp) decline in the probability that a state adopts a nonessential business closure law and a SAHO.

We also consider health policies with no clear economic externalities: testing and face-covering requirements. For example, states with greater testing capacity may have felt less need to implement shutdowns. Public health leaders have said that a high positive test rate indicates low testing capacity because it suggests that only the most vulnerable people are getting tested, despite the large threat of asymptomatic transmission (Collins, 2020). However, we find no significant relationship between the testing rate and party orientation. Moreover, while there is evidence from raw correlations that states with higher shares of the Trump vote in 2016 are significantly less likely to adopt mask policies, these effects are seem to be explained by differences in state demographics and become significant only at the 10% level once we add demographic controls.

Given that we have documented the quantitative significance of political affiliation as a determinant of beliefs about the pandemic and its severity, together with the effects of political affiliation on the adoption of different state policies, we now investigate whether differences in political affiliation also mediate the effects of state policies on realized economic outcomes.

Drawing on measures of economic activity, namely retail sales, small business revenue growth, and consumer spending from Chetty et al. (2020), we estimate regressions of the form:

$$y_{ct} = \phi STPOL_{st} + \zeta COVID_{ct} + \xi_s + \lambda_t + \epsilon_{ct} \tag{3}$$

where *y* denotes our outcome variable of interest, *STPOL* is an indicator for whether the state policy (e.g., business closure law) has passed, *COVID* again denotes the logged number of new infections per capita, and ξ and λ denote our usual fixed effects. Our identifying variation in estimation Equation (3) comes from the fact that counties within the same state vary in their political ideology, which influences the adoption of different policies and potentially mediates the effects on outcomes. Our estimates here resemble those from some related literature, i.e., Andersen et al. (2020), who explore the effects of national policies on economic outcomes in Scandinavia.

Table 4 documents these results. We begin by examining the effects of SAHOs and nonessential business closures on retail visits, credit card spending, and small business revenue growth with state and week fixed effects in columns (1), (4), and (7). We find statistically negative effects on retail visits and small business revenue growth. While declines in retail visits are almost mechanical, the result for small businesses is unique: the introduction of a SAHO and nonessential business closure is associated with a 3.3-3.7 percentage point decline in revenue growth for small businesses. We find no statistically significant effects on credit card spending, which could reflect the offsetting increase in spending on digital goods through online platforms (Baker et al., 2020).

We subsequently explore the robustness of these results by introducing county fixed effects in columns (2), (5), and (8). Our results are unchanged. We finally add an indicator for whether masks are required in businesses. Importantly, we find no statistically significant effect of these policies on small busines revenue growth and the effect on credit card spending is a precise zero, whereas the effects of nonessential business closure on credit card spending are negative, albeit statistically insignificant. This suggests that mask wearing policies may have no effect on economic activity, so if they are effective for combating the spread of the disease, they are an optimal policy.

Table 3: Predicting the Adoption of State Pandemic Policy Responses

	Nonessential Businesses Closure		Stay-at-Home Order		Positive Test Ratio		Masks Required in Businesses	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trump 2016 Vote, %	-0.651	-1.869***	-1.202***	-1.526**	0.144	0.0316	-0.593	-0.867*
	(0.402)	(0.385)	(0.375)	(0.613)	(0.101)	(0.127)	(0.446)	(0.444)
log(New Infections, 7-day Avg)	0.163***	0.201***	0.00413	0.0319	0.0764***	0.0661***	0.0450	0.0479
	(0.0598)	(0.0509)	(0.0781)	(0.0770)	(0.0163)	(0.0164)	(0.0403)	(0.0397)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	No	Yes	No	Yes	No	Yes
Sample Size	7,200	7,200	7,200	7,200	4,969	4,969	7,200	7,200
Adj. R2	0.508	0.550	0.528	0.559	0.333	0.361	0.586	0.613

Notes.—Sources: IHME, Chetty et al. (2020), Census 2014-2018, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with state regressions of indicators for nonessential business closures and stay-at-home orders and the positive test ratio for COVID-19 on the 2016 share of votes for Trump, conditional on the logged number of new infections per capita over the past 7 days and a flexible function of demographic controls. Our baseline controls include: population density, the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (some college, college, more than college), and the race distribution (white, black). Our industry controls include the share working in agriculture, mining, and forestry, in construction, in manufacturing, in wholesale trade, in retail trade, in transportation and utilities, in information services, in finance, insurance, and real estate (FIRE), in education and healthcare, in arts, services, and food/accommodation, and in other services. Standard errors are clustered at the state-level and observations are unweighted since we have the whole population.

Table 4: State Policies and Realized Economic Outcomes Mediated by Political Affiliation

	Retail Visits			Credit Card Spending			Small Business Revenue Growth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Stay-at-home-order	-4.929***	-5.101***	-4.624***	-0.00547	-0.00706	-0.00739	-0.0380**	-0.0378**	-0.0349**
	(0.919)	(0.899)	(0.925)	(0.00767)	(0.00777)	(0.00778)	(0.0147)	(0.0147)	(0.0157)
Nonessential Business Closure	-2.302	-2.330*	-2.554**	-0.0145	-0.0133	-0.0132	-0.0336**	-0.0334**	-0.0347**
	(1.434)	(1.339)	(1.236)	(0.0107)	(0.0112)	(0.0112)	(0.0160)	(0.0162)	(0.0159)
Masks Required in Businesses			-3.127**			0.00213			-0.0181
			(1.554)			(0.0104)			(0.0185)
log(New Infections, 7-day Avg)	-1.345***	-1.327***	-1.299***	-0.00393*	-0.00470**	-0.00472**	-0.00452	-0.00385	-0.00367
	(0.190)	(0.199)	(0.184)	(0.00230)	(0.00185)	(0.00186)	(0.00320)	(0.00305)	(0.00295)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No	Yes	No	No
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sample Size	208,694	208,961	208,961	193,345	195,230	195,230	287,513	288,878	288,878
Adj. R2	0.784	0.835	0.836	0.203	0.532	0.532	0.281	0.536	0.536

Notes.—Sources: IHME, Chetty et al. (2020), Census Bureau 2014-2018, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county regressions of indicators for economic outcomes from March 2020 to June 2020 on state public health policies, conditional on the logged number of new infections per capita over the past 7 days and a flexible function of demographic controls. Our controls include all those in Table 2: population density, the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (some college, college, more than college), and the race distribution (white, black). Our industry controls include the share working in agriculture, mining, and forestry, in construction, in manufacturing, in wholesale trade, in retail trade, in transportation and utilities, in information services, in finance, insurance, and real estate (FIRE), in education and healthcare, in arts, services, and food/accommodation, and in other services. We also add controls for the percent of households with various levels of income. Standard errors are clustered at the state-level and observations are unweighted since we have the whole population.

While county-level data on unemployment rates are not yet available for most states, we present additional results in Table A.2 of the Online Appendix showing that the adoption of these SAHOs and nonessential business closures are associated with a 1.4-1.6 percentage point increase in the state unemployment rate. However, the adoption of masks in public or in businesses are not statistically related with increases in the unemployment rate, except in one specification that is significant at the 10% level. We interpret these results as consistent with those from Table 4.

V.   Discussion and Health Consequences of State Policies

Our results suggest that beliefs about the pandemic and its economic effects are largely driven by political affiliation, rather than realized infections or even local economic activity, and that these political differences may have influenced the adoption of more extreme or relaxed state policies. We now explore whether these policies may have had benefits beyond the adverse costs that they imposed on economic activity and use these to put our estimates in perspective.

There is already a large literature on the potentially beneficial effects of SAHOs and nonessential business closure laws on infections. For example, Courtmanche et al. (2020) show that the adoption of social distancing measures reduced the daily growth rate of infections by 5.4pp after 1-5 days, which may have grown even larger over time (e.g., up to 9.1pp after 16-20 days). Similarly, Sears et al. (2020) show that the introduction of these SAHOs led to a substantial decline in average distance traveled and human encounters and a reduction in the number of infections and deaths.

How do we make sense of these competing costs and benefits? Even without empirical evidence, we are not surprised that limiting human encounters will reduce the transmission of the virus. Cross-country evidence from Scandinavia suggests, as much, since Sweden, which did close down its economy, has seen many more deaths per capita than Denmark, which did (Juranek and Zoutman 2020). Yet, the constellation of policies that work optimally in practice remains empirically

ambiguous. Japan appears to have limited both economic damage and the virus's spread with light social-distancing and testing, instead relying mask-wearing, quarantine, and contact tracing.[10]

Though still unclear how much to attribute to policies compared to avoidance behaviors, it seems clear that shut-down policies will raise unemployment and depress consumer demand, which not only affects economic activity, but also affects mortality (Sullivan and von Wachter, 2009), long-run earnings (Jacobsen et al., 1993), and mental health (Paul and Moser, 2009; Kuhn et al., 2009). As far as we can tell at the time of our writing, current analyses have not distinguished between the lives saved due to social distancing and the harm due to economic malaise. Using more comprehensive data that spans until mid-June and adding face-covering mandates, we follow Courtmanche et al. (2020) and assess the potential benefits of state mitigation policies. We adopt a difference-in-differences event-study framework with the following form:

$$COVID_{ct} = \rho COVID_{ct-1} + \phi STPOL_{sw+1} + \phi STPOL_{sw-1} + \phi STPOL_{sw-2} + \xi_c + \lambda_t \qquad 3 \\ + \epsilon_{st}$$

where $COVID$ represents the confirmed cases or deaths from COVID-19 in log form plus one to allow for county-days with zero cases to be included in the model. The time-periods for the state policies are grouped into weekly bins for reasons we explain below, which we denote as "w" to distinguish from daily changes. Our preferred specification predicts the log of cumulative cases (deaths) after controlling for the log cumulative number the day before. We also tried using one week before and found very similar results. Mathematically, subtracting the lagged log from both sides of the equation, yields the growth rate on the left-hand side, and only the policies and fixed effects on the right-hand-side. This makes the regression equivalent to predicting growth: future cases, given the starting point. As in the macroeconomic literature on convergence, there is good

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[10] https://www.wsj.com/articles/japan-declares-coronavirus-under-control-lifts-state-of-emergency-11590413785

reason to believe that the starting point matters, since new infections comes from those previous infected. Nonetheless, in Table A.4 of the Online Appendix, we report regressions that use the pure growth rate (subtracting logs) on the left-hand side without including the lagged variable as a control. The results are similar and, if anything, more suggestive that mask policies are effective.

COVID-suppression policies are not exogenously determined—they could be, as we show, endogenously a function of a dynamic bargaining game. To account for the fact that anticipated outbreaks prompt state policy makers to adopt stricter requirements, we control for the forward and lagged effects of policy and compare both to cases during the week preceding the present. Given the lag between infection and the revelation of a positive test or death, we think that the comparison to the week preceding the present is the right one. Thus, our preferred coefficients predict the effects of a policy 7 to 13 days later and 14 to 20 days later, with the latter being especially relevant for deaths. We believe deaths are more relevant than cases for two reasons: given early limits in testing capacity, many symptomatic people could not be tested in March and even April. Second, we know from serology data and other studies that most people who become infected are asymptomatic and are never revealed as a positive confirmed case, because they are not tested.

Table 5 documents these results. Not surprisingly, much of the variation is explained by the previous day's cases (deaths), but we focus on the coefficients associated with state policies. Broadly speaking, we find evidence for significant health benefits from stay-at-home orders and especially masks, but not the closure of non-essential businesses. Stay-at-home orders predict 0.7% fewer cases 14 to 20 days later and predict 0.2% fewer deaths per day. Mask requirements have a slightly larger effect: predicting roughly 0.9% fewer cases and 0.8% fewer deaths per day. Mask requirements directed at businesses or individuals appear to be roughly equally effective. When included simultaneously, both are significant, suggesting that the policies are complementary, working best in

conjunction. However, we cannot rule out the possibility that we simply observe both happening jointly in both states, so we caution against a causal interpretation.[11]

Given our findings that Republicans are less likely to wear-masks or practice social-distancing, we would expect that mask-policies would be less effective in Republican-controlled areas. Indeed, Texas offers an interesting example. The county judge of Harris County, which encompasses Houston, Texas, is a Democrat named Linda Hildago. She imposed a mask-order on April 27th.[12] Yet, in the same metropolitan area, the Republican judge of Galveston County, Mark Henry, publicly stated that he thought mask ordinances were an infringement of liberty, and he would not require them in his jurisdiction.[13] The views of these politicians are likely to be reflected in their constituents, with similar debates playing out around the country. If compliance is greater (less) in Democrat (Republican) counties than we should see that state mask ordinances are more (less) effective in Democrat (Republican) counties. We document results consistent with this hypothesis in Table A.4 of the Online Appendix. For example, daily growth in cases and deaths are 1.5% to 2% higher in counties where Trump won with a margin of 75% of the vote relative to counties in which he received just 25% of the vote. These results are statistically significant for growth in cases and deaths across both ways of measuring growth. The interaction effect is particularly strong for mask-requirements focused on private individuals wearing masks in public.

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[11] Table A.3 of the Online Appendix shows that these results are robust to working with the growth rates. Masks are roughly three times more effective at reducing the growth in deaths as stay-at-home-orders. Using 7-day growth rates instead of single day rates did not meaningfully change these results.

[12] https://www.readyharris.org/Newsroom/ReadyHarris-Alerts/All-Previous-Alerts/mandatory-face-coverings-required-starting-42720

[13] https://www.galvnews.com/opinion/guest_columns/article_3b5c58bb-6029-594a-bcd6-c66b129715f1.html

Table 5: COVID-19 Confirmed Cases and Deaths Regressed on State Policies with County and Time Fixed Effects

	log(Cumulative COVID-19 Cases)			log(Cumulative COVID-19 Deaths)		
	1	2	3	4	5	6
log(COVID-19 Cases), *t - 1 day*	0.992***	0.992***	0.992***			
	(0.000540)	(0.000576)	(0.000559)			
log(COVID-19 Deaths), *t - 1 day*				0.996***	0.996***	0.996***
				(0.000358)	(0.000349)	(0.000339)
Stay-at-home-order, *t + 1-7 days*	0.00958*	0.00934*	0.0101**	0.00182	0.00217	0.00203
	(0.00492)	(0.00492)	(0.00483)	(0.00248)	(0.00228)	(0.00239)
Stay-at-home-order, *t - 7-13 days*	-0.00466	-0.00454	-0.00464	0.00451**	0.00401**	0.00445**
	(0.00436)	(0.00427)	(0.00436)	(0.00178)	(0.00169)	(0.00181)
Stay-at-home-order, *t - 14-20 days*	-0.00672**	-0.00650**	-0.00586**	-0.00295**	-0.00236*	-0.00255*
	(0.00267)	(0.00315)	(0.00279)	(0.00139)	(0.00132)	(0.00134)
Nonessential businesses closed, *t + 1-7 days*	0.0122*	0.0120	0.0116*	0.00449*	0.00437*	0.00432
	(0.00715)	(0.00718)	(0.00691)	(0.00263)	(0.00254)	(0.00258)
Nonessential businesses closed, *t - 7-13 days*	-0.00210	-0.00225	-0.00231	0.00383**	0.00380**	0.00393**
	(0.00491)	(0.00493)	(0.00495)	(0.00172)	(0.00179)	(0.00169)
Nonessential businesses closed, *t - 14-20 days*	-0.00346	-0.00373	-0.00396	-0.00108	-0.00157	-0.00163
	(0.00356)	(0.00394)	(0.00359)	(0.00163)	(0.00172)	(0.00170)
Masks required in businesses, *t + 1-7 days*	-0.00516*		-0.00677**	0.00736**		0.00663**
	(0.00285)		(0.00325)	(0.00285)		(0.00271)
Masks required in businesses, *t - 7-13 days*	-0.00448*		-0.00353	-0.00664***		-0.00779***
	(0.00241)		(0.00308)	(0.00217)		(0.00209)
Masks required in businesses, *t - 14-20 days*	-0.00519**		-0.00188	-0.00304**		-5.77e-05
	(0.00221)		(0.00177)	(0.00138)		(0.00136)
Masks required in public, *t + 1-7 days*		-0.000496	0.00348		0.00721	0.00173
		(0.00403)	(0.00433)		(0.00442)	(0.00436)
Masks required in public, *t - 7-13 days*		-0.00539*	-0.00311		-0.00420	0.00269
		(0.00286)	(0.00381)		(0.00407)	(0.00372)
Masks required in public, *t - 14-20 days*		-0.00829**	-0.00895**		-0.00749***	-0.00815***
		(0.00358)	(0.00367)		(0.00237)	(0.00277)
Sample Size	434,148	434,148	434,148	434,148	434,148	434,148
Adj. R-squared	0.998	0.998	0.998	0.997	0.997	0.997

Notes.—Sources: IHME, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county-level regressions of public health policies on COVID-19 confirmed cases and deaths. The policies are set equal to one if implemented or zero otherwise and averaged over various time periods from March 2020 to June 2020. Standard errors are clustered on state. All models include county and time fixed effects.

Moreover, our Gallup micro-data allow us to check whether Republicans respond differently than Democrats when living under the same stay-at-home-order or mask-orders. We find that they do. We estimate our regression models from Table 2, but add SAHOs and mask requirements and interact them with Republicans-party identification. In Table A.5 of the Online Appendix, we see that Republicans are significantly less likely to wear masks than Democrats generally and that gap persists even when they live in the same county with the same state policy. The regression-adjusted gap in mask-wearing is 29pp between Republicans and Democrats when they are not living in a state that requires masks. Mask-wearing rises for both Democrats and Republicans by 5pp when they live in a state that requires mask-usage, and the gap closes to 20pp, because Republicans respond even more. Yet, a 20pp gap in compliance with a public health mandate has meaningful consequences to the economy and public health. Social-distancing is also higher in states with stay-at-home-orders and mask-orders, but again, this does not eliminate the partisan gap. This is the first evidence that clearly links the probability of compliance with public health mandates to partisan politics.

VI.   Conclusion

The COVID-19 pandemic has had a profound effect on health and the economy. Yet, as we show, neither the health nor economic consequences can be explained without understanding how partisan politics has shaped the adoption of disease-suppressing policies and behaviors. Using a uniquely high-quality sample, consisting of a large representative daily survey of U.S. adults, we find that fear, economic expectations, workplace visits, social-distancing, and mask-wearing are all driven by party-identification to a much greater extent than local public-health conditions, state economic conditions, or state public health policies. Partisanship is also more important in explaining disease-mitigation behaviors than actual individual risk of death (measured by age or self-reported risk) as well as other demographic factors, , gender, race, or ethnicity. In terms of predicting these

outcomes, party affiliation is roughly as powerful as educational attainment and the presence of pre-existing medical conditions—and in some cases more powerful.

This finding alone has enormous implications for public health campaigns, the accuracy of epidemiological models, and the realities of compliance. Relative to other democracies, the United States stands out for high levels of income inequality and political polarization and are results suggest this background has hindered the efficacy of its response to COVID-19. We also examine how partisanship affects the adoption of state policies, showing a clear and robust negative relationship between disease-suppression policies and the share of votes won by President Trump that cannot be explained by the local disease burden. Governors and state legislatures, therefore, are responding in much the same way as individuals: according to their partisan inclinations.

In the final section of the paper, we show how these partisan differences play out with respect to economic and health outcomes. Even Trump-dominated states have experienced a sharp-rise in unemployment and Trump-dominated counties have seen large losses in small business revenue and consumer spending. This suggests that the disease itself largely explains most of the economic damage the country has experienced. Still, state and counties oriented more strongly to the Republican Party have seen significantly less economic damage than those oriented toward the Democratic Party. This result cannot be explained by different rates of exposure to COVID-19, but rather the result of stricter controls and restrictions on business put in place in Democratic areas and stricter compliance with social-distancing measures by individual Democrats in these areas.

The relaxed policies and relaxed compliance found in Republican areas has meant less economic damage, but our results suggest it has also resulted in higher growth rates in cases and fatalities. These joint results suggest that Republicans and Democrats can learn from one another. Disease suppression efforts are crucial to saving lives, and the economy is unlikely to recover while the disease is out of control. Yet, some of the more extreme policies—shutting down non-essential

businesses—seem to create economic damage without bending the curve, while others (like mask-wearing) are almost costless to the economy but effective at slowing growth in mortality. In any case, the fact that policies and individual attitudes and behaviors are predicted by party identification more than actual conditions is strong evidence that the many Americans are not pursuing a disease-suppression strategy that balances concerns about infection with concerns about economic livelihood. In this sense, our results are consistent with the recommendations from Acemoglu et al. (2020) for targeted lockdowns, rather than uniform lockdowns of economic sectors and individuals.

We suggest that our research could be improved with comprehensive county or local data on public health policies that would uncover even greater variation within states. We would also like to see work that further explains the sources of geographic vulnerability to infection, beyond population density. At this stage, it remains unclear why areas like New York City faced an infection and mortality rate so much greater than any other major city, and given the international variation, there are still many unanswered questions about which disease-suppression strategies are most effective and best balance individual liberty and economic necessity, with health and safety.

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Online Appendix

Election Vote Shares in 2016 Are Correlated With Contemporaneous Political Affiliation

One concern with our use of the 2016 Trump vote share is that it is an imperfect proxy for current political attitudes. For example, attitudes may have grown closer or further away in ways that are correlated with location characteristics. Figure A.1 shows that there is a strong correlation of 0.78 between the share of 2016 election votes going towards Donald J. Trump and the share of adults identifying as members of the Republican Party in During COVID-19 Pandemic, March-June, 2020.

Appendix Figure A.1: Correlation Between 2016 Voting and 2020 Self-Reported Political Affiliation

Source: Gallup COVID Tracking Panel and Tony McGovern's election database
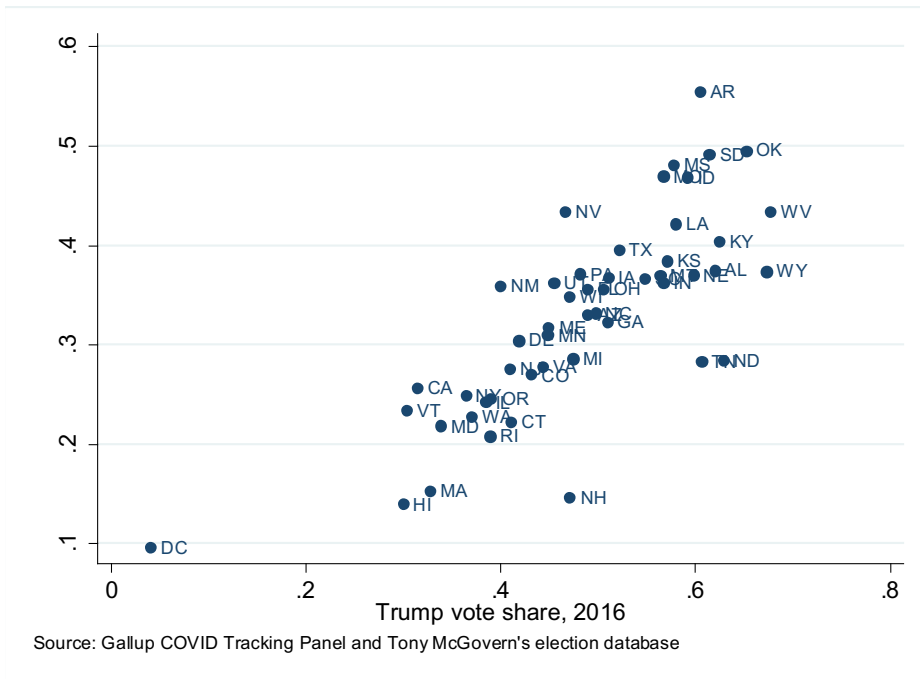
The Gallup Panel Resembles the Distribution of the Current Population Survey

We benchmark the Gallup panel with the Current Population Survey (CPS) over March to May 2020. Although there is a minor difference among the share of respondents with a bachelor's degree—that is, the Gallup Panel has a higher share of college-educated workers than the CPS—the remainder of the demographic characteristics exhibit strong balancing.

Appendix Table A.1: Comparison of the Current Population Survey and Gallup Panel

	Current Population Survey		Gallup Panel	
	Mean	Std. Dev.	Mean	Std. Dev.
Average Age	44.73	17.61	49.54	16.55
Share Age 19-29	0.21	0.40	0.11	0.31
Share Age 30-44	0.33	0.47	0.32	0.47
Share Age 45-64	0.28	0.45	0.35	0.48
Share Age 65+	0.17	0.37	0.22	0.42
Share Male	0.48	0.50	0.49	0.50
Share White	0.84	0.37	0.85	0.36
Share Black	0.12	0.32	0.13	0.33
Share Married	0.58	0.49	0.63	0.48
Share Hispanic	0.11	0.31	0.15	0.36
Share Employed	0.61	0.49	0.59	0.49
Share Some college, no degree	0.26	0.44	0.30	0.46
Share Bachelor's or higher	0.23	0.42	0.34	0.47
Observations	6925293	6925293	80,491	80,491

Notes.—Sources: Current Population Survey (March to May 2020) and Gallup Panel (March to June). The table reports the means and standard deviations of various demographic characteristics.

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Similar Results of State Policies on State Unemployment Rates

We present additional evidence on the effects of different state policies on the state unemployment rate. We find strong effects of SAHOs and nonessential business closures on the unemployment rate, even after we control for state and time fixed effects. However, we find little effects of mask wearing policies, particularly masks in public, on state unemployment. For example, the adoption of nonessential business closures and SAHOs are associated with a 0.94-1.4 (1.55-1.62) percentage point increase in the state unemployment rate, which are generally significant at the 1% level. However, mask wearing policies are not statistically related with increases in unemployment, except masks required in businesses, which is significant at the 10% level when introducing fixed effects.

Appendix Table A.2: State Policies and Unemployment Rates

	(1)	(2)
Masks Required in Public	0.815	0.633
	(1.049)	(1.082)
Masks Required in Businesses	1.200	1.470*
	(0.831)	(0.780)
Stay-at-home-order	1.551***	1.620***
	(0.578)	(0.592)
Nonessential Businesses Closure	1.403**	0.940
	(0.639)	(0.607)
log(New Infections, 7-day Avg)	-0.469	-0.402
	(0.294)	(0.308)
Time FE	Yes	Yes
State FE	No	Yes
Sample Size	969	969
Adj. R-squared	0.842	0.870

Notes.—Sources: IHME, Census Bureau 2014-2018, U.S. Department of Labor, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with state-level regressions of the insured unemployment rate on public health policies from March 2020 to June 2020, conditional on the logged number of new infections per capita over the past 7 days. Column one controls include all those in Table 2: population density, the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (some college, college, more than college), and the race distribution (white, black). Our industry controls include the share working in agriculture, mining, and forestry, in construction, in manufacturing, in wholesale trade, in retail trade, in transportation and utilities, in information services, in finance, insurance, and real estate (FIRE), in education and healthcare, in arts, services, and food/accommodation, and in other services. Column one includes state fixed-effects. Column two uses county-fixed effects. Standard errors are clustered at the state-level and observations are unweighted since we have the whole population. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Appendix Table A.3: COVID-19 Confirmed Cases and Deaths Regressed on State Policies with County and Time Fixed Effects

	100 X Log cases (t) - log cases (t-1)			100 X Log deaths (t) - log deaths (t-1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Masks required in businesses, future 1-7 days	-0.934***		-1.064***	0.622**		0.561**
	(0.298)		(0.349)	(0.275)		(0.266)
Masks required in businesses, lag 7-13 days	-0.460*		-0.328	-0.710***		-0.818***
	(0.246)		(0.317)	(0.225)		(0.214)
Masks required in businesses, lag 14-20 days	-0.520**		-0.177	-0.388**		-0.0502
	(0.257)		(0.233)	(0.152)		(0.137)
Stay-at-home-order, future 1-7 days	0.785*	0.743	0.851*	0.173	0.207	0.205
	(0.445)	(0.458)	(0.438)	(0.243)	(0.224)	(0.231)
Stay-at-home-order, lag 7-13 days	-0.606	-0.577	-0.595	0.419**	0.376**	0.419**
	(0.452)	(0.441)	(0.452)	(0.176)	(0.166)	(0.180)
Stay-at-home-order, lag 14-20 days	-0.895***	-0.887**	-0.790**	-0.383**	-0.321**	-0.328**
	(0.285)	(0.345)	(0.299)	(0.157)	(0.155)	(0.151)
Nonessential businesses closed, future 1-7 days	1.219*	1.178*	1.129*	0.487*	0.462*	0.451*
	(0.677)	(0.679)	(0.643)	(0.261)	(0.250)	(0.251)
Nonessential businesses closed, lag 7-13 days	-0.356	-0.379	-0.385	0.352**	0.345*	0.359**
	(0.508)	(0.511)	(0.513)	(0.171)	(0.176)	(0.167)
Nonessential businesses closed, lag 14-20 days	-0.506	-0.517	-0.542	-0.175	-0.219	-0.227
	(0.367)	(0.430)	(0.371)	(0.177)	(0.185)	(0.179)
Masks required in public, future 1-7 days		-0.449	0.232		0.609	0.124
		(0.490)	(0.505)		(0.410)	(0.408)
Masks required in public, lag 7-13 days		-0.574*	-0.394		-0.453	0.259
		(0.308)	(0.415)		(0.416)	(0.382)
Masks required in public, lag 14-20 days		-0.804**	-0.936**		-0.864***	-0.925***
		(0.367)	(0.376)		(0.267)	(0.304)
Sample Size	434,148	434,148	434,148	434,148	434,148	434,148
Adj. R-squared	0.086	0.085	0.086	0.044	0.044	0.044

Notes.—Sources: IHME, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county-level regressions of public health policies on COVID-19 confirmed cases and deaths. All models include county and time fixed effects. The policies are set equal to one if implemented or zero otherwise and averaged over various time periods from March 2020 to June 2020. Standard errors are clustered on state. All models include county and time fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A.4. COVID-19 County-Level Growth in COVID-19 Cases and Deaths on State Policies interacted with Presidential Voting with County and Time Fixed Effects

	100 X Log cases (t) - log cases (t-1)	100 X Log deaths (t) - log deaths (t-1)	Log of cumulative COVID-19 cases	Log of cumulative COVID-19 deaths
	1	2	3	4
Log of cumulative COVID-19 cases, lag 1 day			0.993***	
			(0.000601)	
Log of cumulative COVID-19 deaths, lag 1 day				0.997***
				(0.000397)
Stay-at-home-order, future 1-7 days	0.842*	0.192	0.00979**	0.00193
	(0.442)	(0.236)	(0.00481)	(0.00242)
Stay-at-home-order, lag 14-20 days	-0.589	0.424**	-0.00472	0.00444**
	(0.460)	(0.180)	(0.00446)	(0.00180)
Stay-at-home-order, lag 14-20 days	-0.624*	-0.292*	-0.00511*	-0.00260*
	(0.311)	(0.155)	(0.00296)	(0.00145)
Nonessential businesses closed, future 1-7 days	1.331**	0.448*	0.0131*	0.00418
	(0.646)	(0.256)	(0.00697)	(0.00263)
Nonessential businesses closed, lag 7-13 days	-0.435	0.435**	-0.00290	0.00462**
	(0.517)	(0.177)	(0.00508)	(0.00177)
Nonessential businesses closed, lag 14-20 days	-0.425	-0.174	-0.00327	-0.00141
	(0.384)	(0.157)	(0.00369)	(0.00156)
Masks required in public, future 1-7 days	-0.495	1.042	0.00314	0.0133
	(1.702)	(1.400)	(0.0144)	(0.0140)
Masks required in public, lag 7-13 days	-2.037**	-1.069	-0.0172*	-0.00985
	(0.995)	(1.258)	(0.00886)	(0.0124)
Masks required in public, lag 14-20 days	-3.320***	-3.144***	-0.0293***	-0.0279***
	(0.984)	(0.745)	(0.00874)	(0.00733)
Masks required in businesses, future 1-7 days	-6.222***	0.476	-0.0431***	0.0105
	(1.016)	(0.792)	(0.00930)	(0.00766)
Masks required in businesses, lag 7-13 days	1.143	-2.266***	0.00687	-0.0232***
	(0.711)	(0.660)	(0.00670)	(0.00653)
Masks required in businesses, lag 14-20 days	-0.428	-0.356	-0.00405	-0.00274
	(0.504)	(0.403)	(0.00457)	(0.00391)
Trump share of vote X Masks required in public, future 1-7 days	1.926	-1.575	0.00458	-0.0209
	(2.734)	(2.025)	(0.0233)	(0.0200)
Trump share of vote X Masks required in public, lag 7-13 days	2.515	2.496	0.0221	0.0240
	(1.596)	(1.811)	(0.0146)	(0.0180)

Trump share of vote X Masks required in public, lag 14-20 days	4.227***	3.885***	0.0358**	0.0340***
	(1.526)	(1.169)	(0.0141)	(0.0117)
Trump share of vote X Masks required in businesses, future 1-7 days	8.134***	0.146	0.0569***	-0.00633
	(1.644)	(1.024)	(0.0143)	(0.00992)
Trump share of vote X Masks required in businesses, lag 7-13 days	-2.247*	2.252**	-0.0160	0.0236**
	(1.237)	(1.010)	(0.0122)	(0.0100)
Trump share of vote X Masks required in businesses, lag 14-20 days	0.354	0.561	0.00344	0.00488
	(0.749)	(0.566)	(0.00682)	(0.00547)
County Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Observations	429,456	429,456	429,456	429,456
Adjusted R-squared	0.091	0.046	0.998	0.997

Notes.—Sources: IHME, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county-level regressions of public health policies on COVID-19 confirmed cases and deaths. All models include county and time fixed effects. The policies are set equal to one if implemented or zero otherwise and averaged over various time periods from March 2020 to June 2020. Standard errors are clustered on state. All models include county and time fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A.5: Regression of Attitudes and Behaviors on Local Infection Risk and Party Identification with County and Time Fixed Effects

	Expected disruption	Expected disruption	Worry about illness	Worry about illness	Social distancing	Social distancing	Isolating	Isolating	Wearing mask	Wearing mask	Visited work	Visited work
Republican w/ mask req.		-0.09***		0.03**		-0.05**		-0.06**		0.10***		-0.01
		(0.02)		(0.02)		(0.02)		(0.03)		(0.02)		(0.02)
Republican w/ SAHO		0.02		0.01		0.03*		-0.03		0.05***		0.01
		(0.01)		(0.01)		(0.02)		(0.02)		(0.02)		(0.02)
Republican	-0.18***	-0.18***	-0.04***	-0.06***	-0.07***	-0.08***	-0.08***	-0.06***	-0.10***	-0.16***	0.06***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Democrat	0.11***	0.11***	0.06***	0.06***	0.06***	0.06***	0.06***	0.06***	0.08***	0.09***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(New Infections, 7-day)	0.02**	0.02***	0.01*	0.01*	0.00	0.01	0.01	0.01	0.03***	0.03***	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Stay-at-home-order	0.01	0.00	-0.01	-0.01	0.02*	0.01	0.03**	0.04***	0.00	-0.02	0.02*	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Masks required in public	0.03*	0.05***	0.00	-0.00	0.03**	0.04***	-0.01	0.00	0.06***	0.03*	0.02	0.02*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Employed last week	-0.08***	-0.08***	-0.06***	-0.06***	-0.05***	-0.05***	-0.15***	-0.15***	0.02	0.02	0.28***	0.28***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Out of workforce	-0.05**	-0.04**	-0.07***	-0.07***	0.00	0.01	0.05**	0.05**	0.03	0.03	-0.07***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Male	-0.00	-0.00	-0.03***	-0.03***	-0.04***	-0.04***	-0.06***	-0.06***	-0.05***	-0.05***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age divided by 10	-0.01***	-0.01***	-0.01*	-0.01*	0.01***	0.01***	-0.01***	-0.01***	0.02***	0.02***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Some college no degree	0.04***	0.04***	0.01	0.01	0.02**	0.02**	0.03***	0.03**	0.05***	0.05***	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bachelors degree	0.01	0.01	0.00	0.00	0.07***	0.07***	0.15***	0.14***	0.08***	0.08***	-0.13***	-0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Graduate degree	0.03**	0.03**	0.01	0.01	0.09***	0.09***	0.17***	0.17***	0.08***	0.08***	-0.15***	-0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Hispanic	0.00	0.00	0.02	0.02	0.01	0.01	-0.00	-0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Black	0.04**	0.04**	-0.00	-0.00	-0.01	-0.01	-0.06***	-0.06***	0.02	0.02	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	0.02	0.02	0.06	0.06	0.04***	0.04***	0.03	0.03	-0.00	-0.01	0.07***	-0.07***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
American Indian	0.02	0.02	0.00	-0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Native Hawaiian	0.06	0.06	0.16*	0.16*	-0.04	-0.04	-0.03	-0.03	-0.03	-0.03	0.05	0.05
	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.06)	(0.09)	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)
Other Race	0.04	0.04	0.02	0.02	-0.01	-0.01	-0.06*	-0.06*	-0.02	-0.02	0.06*	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Has medical condition	0.05***	0.05***	0.08***	0.08***	0.04***	0.04***	0.05***	0.05***	0.05***	0.05***	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lives with children	-0.00	-0.00	0.01	0.01	-0.01	-0.01	-0.01	-0.01	-0.02*	-0.02*	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Square	0.26	0.26	0.14	0.14	0.23	0.23	0.23	0.23	0.31	0.32	0.36	0.36
Sample Size	61687	61687	38423	38423	61625	61625	61646	61646	42139	42139	53294	53294

Notes.—Source: Gallup Panel. Demographic controls included in the model but not shown: binary variables for the following: being employed last week, being out of the labor force last week; male; having some college but no degree, holding a bachelor's degree, holding a graduate degree; being Black, Asian, American Indian, Native Hawaiian, another non-White race, or Hispanic; you or household member having a medical condition that puts them at risk for COVID-19; living with a child. Standard errors are clustered at the county-level.

The 2008 global financial crisis and COVID-19 pandemic: How safe are the safe haven assets?

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This paper compares the performance of safe haven assets during two stressful stock market regimes – the 2008 Global Financial Crisis (GFC) and COVID-19 pandemic. Our analysis across the ten largest economies in the world shows that the traditional choice, gold, acts as a safe haven during the GFC but fails to protect investor wealth during COVID. Our results suggest that investors might have lost trust in gold. Furthermore, silver does not serve as a safe haven during either crisis, while US Treasuries and the Swiss Franc generally act as strong safe havens during both crises. The US dollar acts as a safe haven during the GFC for all the countries except for the United States, but only for China and India during COVID. Finally, Bitcoin does not serve as a safe haven for all countries during COVID; however, the largest stablecoin, Tether, serves as a strong safe haven. Thus, our results suggest that, during a pandemic, investors should prefer liquid and stable assets rather than gold.

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Introduction

The spread of COVID-19 – transforming from a regional crisis in China to a global pandemic within three months – has caused severe damage to human lives and the global economy. The stock markets around the world have plummeted to their lowest levels since the 2008 Global Financial Crisis (GFC) (BBC, 2020). Furthermore, the COVID-19 pandemic negatively impacted stock markets more than any previous infectious disease outbreak, including the 1918 Spanish Flu (Baker et al., 2020).

Unforeseen and unanticipated events such as the 1987 stock market crash, trigger flight to quality episodes where investors transfer their investments from risky to safe assets (e.g. Caballero and Krishnamurthy, 2008). It is well documented in the literature that gold (e.g. Baur and Lucey, 2010; Hillier et al., 2006; Pullen et al., 2014); US Treasury bills and bonds (e.g. Chan et al., 2011; Fleming et al., 1998; Hartmann et al., 2004; Noeth and Sengupta, 2010); and currencies such as the US dollar and Swiss Franc (e.g. Grisse and Nitschka, 2015; Kaul and Sapp, 2006; Ranaldo and Söderlind, 2010) act as safe havens during periods of stock market turmoil. However, Baur and Lucey (2010) and Chan et al. (2011) suggest that Treasury bonds possess better properties than gold as a safe haven during stock market crises. Moreover, Brunnermeier et al. (2020) propose US Treasuries as the global safe asset in times of the crisis.

Several recent studies argue that cryptocurrencies act as a safe haven during market turmoils (e.g. Cheema et al.; Stensås et al., 2019; Urquhart and Zhang, 2019); however, other studies view cryptocurrencies as a risky asset instead of a safe haven (e.g. Bouri et al., 2017; Smales, 2019). Most recently, Conlon and McGee (2020) and Kristoufek (2020) find that Bitcoin is not a safe haven during the COVID-19 pandemic, whereas Baur and Hoang (2020)

suggest using stablecoins, such as Tether, because it acts as a safe haven against Bitcoin during extreme market movements.[1]

The COVID-19 pandemic provides an enticing research setting in which to examine whether the traditional safe assets such as gold, US Treasury bills and bonds, US dollar, and Swiss Franc provide protection from stock market losses given the unique nature of this twin health/economic crisis. Furthermore, we take the opportunity to compare the performance of safe haven assets during the GFC versus the COVID-19 pandemic. For instance, we ask the question – do traditional assets that were safe havens during the GFC (e.g. Baur and McDermott, 2010; Low et al., 2016) maintain their safe haven status during the COVID-19 pandemic? Furthermore, COVID-19 provides an opportunity to re-examine whether the largest traditional cryptocurrency, Bitcoin, and the largest stablecoin, Tether, serve as a safe haven against stock market losses.

A growing number of studies examine the impact of COVID-19 on the financial markets and financial assets (e.g. Al-Awadhi et al., 2020; Alfaro et al., 2020; Baker et al., 2020; Conlon et al., 2020; Conlon and McGee, 2020; Corbet et al., 2020; Kristoufek, 2020; Ramelli and Wagner, 2020; Zhang et al., 2020). For instance, Baker et al. (2020), Al-Awadhi et al. (2020) and Zhang et al. (2020) find a significant negative impact of COVID-19 on stock markets. Conlon et al. (2020) show that Tether acts as a safe haven for several stock indices; whereas Bitcoin and Ethereum do not. Nonetheless, no study has compared the performance of safe haven assets between the GFC and COVID-19.

In this paper, we perform a coordinated comparative examination of the safe haven efficacy of: (a) precious metals (gold and silver); (b) currencies (US dollar and Swiss Franc); (c) US Treasuries (T-bill and T-bond); and (d) cryptocurrencies (Bitcoin and Tether) from stock

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[1] Stablecoins are cryptocurrencies that are pegged to other stable assets such as gold and the traditional currencies. Please refer to page 6 for further details.

market losses during the GFC and COVID-19. We select the stock markets of the ten largest economies; namely, the US, China, Japan, Germany, the UK, France, India, Italy, Brazil and Canada since investors prefer to invest in these markets. We estimate a GJR-GARCH model since it accounts for the asymmetric effects when the stock market returns exhibit higher (lower) volatility to bad news (good news).

Our analysis shows that gold serves as a strong, safe haven for six countries and as a weak safe haven for the other four countries during the GFC. However, notably, gold loses its safe haven status during COVID since its price has moved in tandem with the stock markets of all ten countries. The obvious question is, why? We suggest that gold loses its safe haven status because investors might have lost trust in gold as a stable asset after the precious metal lost 45% of its USD value between 2011 to 2015. Somewhat in contrast, silver does not function as an effective, safe haven during either crisis. The US dollar acts as a safe haven for all the countries except the US during the GFC, but a safe haven only for China and India during the COVID-19 pandemic. Interestingly, the Swiss Franc and both Treasuries, T-bills and T-bonds, act as a reliable safe haven during both crises. Finally, Bitcoin does not act as a safe haven, whereas Tether serves as an effective, safe haven during the COVID-19 pandemic for all ten countries.

This study makes three important contributions to the literature. First, by comparing the performance of the traditional safe-haven assets across stock markets of the world's largest ten economies, we uncover new evidence that gold is not reliable protection of investor wealth in all stressful markets or settings. Second, we show that investors from both developed and emerging markets make similar choices about safe haven assets during both crises. Third, we extend the existing literature on global safe assets (e.g. Brunnermeier et al., 2020) and propose that the Swiss Franc and Tether also acts as a global safe asset along with US treasuries in times of the crisis.

The remainder of the paper is organized as follows. Section 2 describes the data and methods, and Section 3 presents the results. Section 4 offers a potential explanation of why gold is not a safe haven during the COVID-19 pandemic, and Section 5 concludes the study.

2. Data and Methods

The analysis includes stock market indices of the ten largest economies in the world, namely, S&P500 US index, SSE composite index China, NIKKEI 225 Index Japan, MSCI Germany Index, FTSE100 Index UK, CAC 40 Index France, NIFTY 500 Index India, FTSE MIB Index Italy, MSCI Brazil Index, and TSX composite index Canada. The daily returns of stock market indices are denominated in US dollars, which is the preferred currency of international investors. Furthermore, returns denominated in the US dollar allow a direct comparison between stock market indices and safe haven assets.

Potential safe-haven assets include precious metals (gold and silver); currencies (US Dollar Index and Swiss Franc Index); Treasuries (S&P US Treasury bill index (T-bill) and S&P US Treasury bond index (T-bond)); and cryptocurrencies (Bitcoin and Tether). Bitcoin is the first and largest cryptocurrency; whereas, Tether is the first and largest stablecoin. According to the data obtained from coinmarketcap.com on June 27, 2020, the market capitalization of Bitcoin and Tether is over $167 billion and $9 billion, respectively. Any physical commodity or precious metals do not back Bitcoin tokens; whereas, Tether tokens are 100% backed by liquid reserves, including traditional currencies and other assets that make Tether a stable asset.[2] US dollar index and the Swiss Franc index represents the value of the US dollar and Swiss Franc relative to a basket of foreign currencies, respectively. DataStream International provides all data except data for the Swiss Franc index and the cryptocurrencies. The data of Swiss Franc index is collected from the online database of Swiss National Bank, while coinmarketcap.com

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[2] For details, please refer to Lipton et al. (2020) and Tether's Limited website, https://tether.to/

furnishes the data for Bitcoin and Tether. The sample period for all the assets except cryptocurrencies starts December 31, 2003; whereas the sample period for cryptocurrencies starts September 17, 2014. We restrict the start date to December 31, 2003, since the aim of this study is to examine the role of safe-haven assets during the 2008 GFC and COVID-19 pandemic. The sample period for all the assets ends May 19, 2020.

Following the literature (e.g. Baur and McDermott, 2010), we estimate the model,

$$RA_{i,t} = b_0 + b_1 \cdot RS_{j,t} + b_2 \cdot GFC \cdot RS_{j,t} + b_3 \cdot COVID \cdot RS_{j,t} + \varepsilon_t \qquad (1)$$

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (2)$$

where RA_i represents the log return of each given safe-haven asset i. RS_j denotes the daily log returns in US dollars of a stock market index j, with j equal to a given one of the ten countries in our sample. GFC is a dummy variable, which takes the value one from the designated start date (explained shortly) and the subsequent 20 trading days of the 2008 GFC, and zero otherwise. The dummy variable, $COVID$, is similarly constructed to the GFC variable. The residual term ε_t is modelled as a GJR-GARCH process introduced by Glosten et al. (1993) as defined in Equation (2). The γI_{t-1} is an indicator function that is equal to one if the corresponding lagged unconditional standard deviation is less than zero, and zero otherwise. The GJR-GARCH model accounts for the asymmetric effects when the stock market returns exhibit high volatility in response to bad news and low volatility to good news.

Following the literature (e.g. Baur and McDermott, 2010), we assume that the adverse effect of a stock market crisis occurs in the first 20 trading days since the start of the crisis. Figure 1 shows the stock market crises for both the GFC and COVID. It is evident from Figure 1 that the GFC stock market crisis intensified in September 2008 with the collapse of Lehman Brothers; whereas, the stock market crisis from COVID intensified in February 2020.
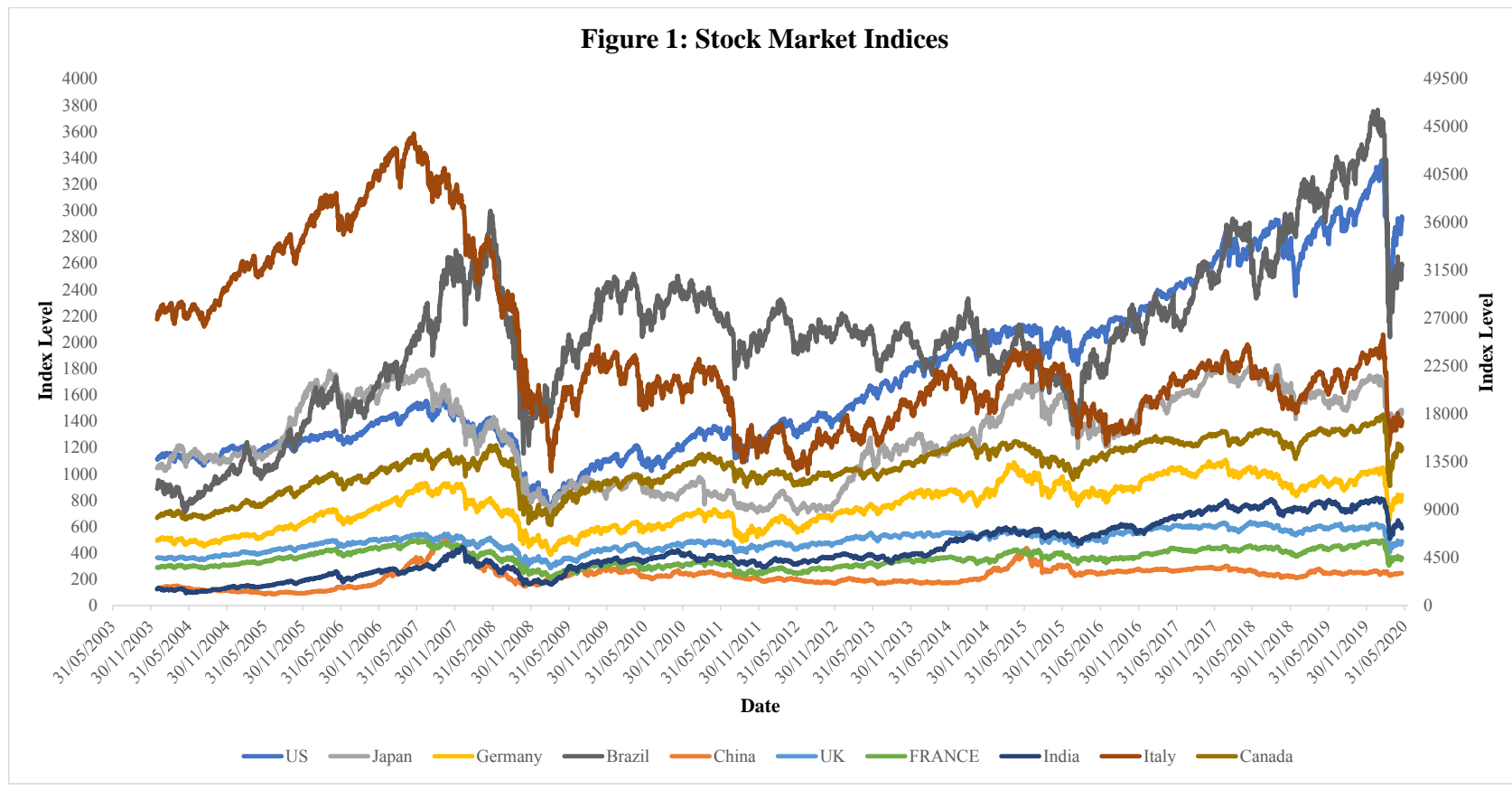
Figure 1: This figure displays the daily index level of the stock markets of all the ten largest economies in the world over the sample period. For the readers convenience, the index level of the US, Japan, Germany and Brazil is labelled on the left vertical axis, and the index level of other six countries is labelled on the right vertical axis

Therefore, we define the start date for GFC on September 12, 2008, and COVID on February 20, 2020.[3]

The interpretation of Equations (1) – (2) to see whether asset i serves as a safe haven during the GFC and COVID, is as follows. Parameter b_1 is the safe-haven asset's baseline (i.e. "normal" times, excluding GFC and COVID) beta with respect to the market in question. If parameter b_2 (including b_1) is non-positive and statistically significant (insignificant), then asset i serves as a strong (weak) safe haven from stock market losses during the GFC. Finally, if parameter $b3$ (including b_1) is non-positive and statistically significant (insignificant) then asset i serves as a strong (weak) safe haven from stock market losses during the COVID.

3. Results and Discussion

3.1. Descriptive statistics

Table 1, Panel A summarises the descriptive statistics of the daily log-returns of all assets in our study. The average returns (mean) of the safe haven assets except Bitcoin varies between 0.005% to 0.033% per day, while the average returns of Bitcoin are 0.177% per day. The T-bill shows the lowest standard deviation, whereas Bitcoin, silver and gold show the highest standard deviation. Furthermore, the negative skewness and high excess kurtosis of gold, silver and Bitcoin imply a significant crash risk that counters their effectiveness as a safe haven asset. The other safe haven assets show positive skewness and high excess kurtosis that indicates the possibility of having extreme positive returns instead of extreme negative returns. The descriptive statistics suggest that Bitcoin, silver and gold possess characteristics of risky assets rather than safe haven assets.

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[3] Low et al. (2016) use September 12, 2008 as a start date of the 2008 GFC. The 2020 stock market crash started in late February 2020 from the uncertainty and threat of COVID-19 (e.g. Baker et al., 2020).

Table 1: Descriptive Statistics

Panel A summarises the descriptive statistics for the daily returns (%) denominated in US dollars of all assets, while Panel B shows correlations between all assets with respective *p* values in the parenthesis. The sample period starts on December 31, 2003 and ends May 19, 2020.

Panel A: Descriptive Statistics								
Variable	N	Mean	Median	Minimum	Maximum	Std Dev	Skewness	Kurtosis
Safe Haven Assets								
Gold	4274	0.0330	0.0340	-10.1620	6.8650	1.1120	-0.4635	5.7784
Silver	4274	0.0220	0.0290	-19.4890	12.4700	2.0390	-0.9328	7.3540
US Dollar Index	4104	0.0030	0.0000	-2.7170	2.5240	0.4960	0.0052	1.8987
Swiss Franc Index	4261	0.0100	-0.0010	-7.8070	14.9720	0.4530	7.1365	306.0240
T-bill	4274	0.0050	0.0020	-0.2000	0.1270	0.0110	0.7648	43.8954
Tbond	4274	0.0140	0.0100	-1.6880	1.7880	0.2270	0.1040	5.5616
Bitcoin	1479	0.1770	0.1920	-46.4730	22.5120	4.2350	-1.0573	13.9434
Tether	1357	0.0010	0.0000	-5.2570	5.6610	0.5600	0.7356	29.9309
Stock Market Returns								
US	4274	0.0230	0.0380	-12.7650	10.9570	1.2030	-0.5420	15.4573
China	4260	0.0200	0.0140	-10.4660	9.1570	1.5750	-0.5614	5.3733
Japan	4230	0.0070	0.0410	-15.8610	17.6870	1.4120	-0.2980	18.4972
Germany	4230	0.0120	0.0500	-13.7630	24.3950	1.5840	0.5218	22.6394
UK	4243	0.0010	0.0310	-12.1420	11.0000	1.3270	-0.4076	10.6399
France	4230	0.0040	0.0370	-13.5220	25.6200	1.6160	0.5387	23.2506
India	4226	0.0270	0.1000	-14.2330	19.3620	1.5730	-0.3626	12.7007
Italy	4230	-0.0120	0.0380	-18.9380	24.3370	1.7740	-0.0179	17.2532
Brazil	3806	-0.0110	0.0000	-18.8250	19.7850	2.2670	-0.3420	9.2452
Canada	4246	0.0140	0.0820	-13.4360	11.1600	1.3740	-1.0627	14.3581

	Panel B: correlation matrix																	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Gold (1)	1																	
Silver (2)	0.6604 (0.0001)	1																
Dollar (3)	-0.3417 (0.0001)	-0.3854 (0.0001)	1															
Franc (4)	0.1092 (0.0001)	0.0370 (0.0158)	-0.0768 (0.0001)	1														
T-bill (5)	0.0612 (0.0001)	0.0007 (0.9627)	-0.0428 (0.0061)	0.0335 (0.0288)	1													
Tbond (6)	0.1072 (0.0001)	0.0195 (0.2023)	-0.1060 (0.0001)	0.0946 (0.0001)	0.2373 (0.0001)	1												
Bitcoin (7)	0.1120 (0.0001)	0.0783 (0.0026)	-0.0018 (0.9451)	0.0850 (0.0011)	-0.0388 (0.1361)	-0.0118 (0.6501)	1											
Tether (8)	-0.0436 (0.1088)	0.0374 (0.1687)	-0.0016 (0.9527)	0.0384 (0.159)	0.0236 (0.3844)	0.0106 (0.6965)	-0.0240 (0.3774)	1										
SP500 (9)	0.0020 (0.8977)	0.1334 (0.0001)	-0.1491 (0.0001)	-0.0959 (0.0001)	-0.1357 (0.0001)	-0.4018 (0.0001)	0.1379 (0.0001)	-0.0988 (0.0003)	1									
China (10)	0.0530 (0.0005)	0.0878 (0.0001)	-0.0445 (0.0044)	-0.0616 (0.0001)	-0.0282 (0.066)	-0.0538 (0.0004)	0.0215 (0.409)	0.0169 (0.5362)	0.0896 (0.0001)	1								
Japan (11)	0.0809 (0.0001)	0.1445 (0.0001)	-0.1089 (0.0001)	-0.1386 (0.0001)	-0.0380 (0.0135)	0.0164 (0.2855)	-0.0204 (0.4349)	0.0029 (0.9141)	0.0243 (0.1141)	0.2112 (0.0001)	1							
Germany (12)	0.1247 (0.0001)	0.2497 (0.0001)	-0.3044 (0.0001)	-0.1100 (0.0001)	-0.0903 (0.0001)	-0.2645 (0.0001)	0.0982 (0.0002)	-0.0731 (0.0072)	0.5790 (0.0001)	0.1576 (0.0001)	0.1435 (0.0001)	1						
UK (13)	0.1271 (0.0001)	0.2798 (0.0001)	-0.2909 (0.0001)	-0.1322 (0.0001)	-0.1436 (0.0001)	-0.2822 (0.0001)	0.0754 (0.0038)	-0.0825 (0.0024)	0.5744 (0.0001)	0.1722 (0.0001)	0.2436 (0.0001)	0.8041 (0.0001)	1					
France (14)	0.1151 (0.0001)	0.2512 (0.0001)	-0.3127 (0.0001)	-0.1196 (0.0001)	-0.1107 (0.0001)	-0.2765 (0.0001)	0.0933 (0.0003)	-0.0809 (0.0029)	0.5733 (0.0001)	0.1599 (0.0001)	0.1582 (0.0001)	0.9515 (0.0001)	0.8335 (0.0001)	1				
India (15)	0.0952 (0.0001)	0.1673 (0.0001)	-0.1048 (0.0001)	-0.1535 (0.0001)	-0.0653 (0.0001)	-0.1114 (0.0001)	0.0221 (0.3961)	-0.0838 (0.002)	0.2505 (0.0001)	0.2306 (0.0001)	0.2785 (0.0001)	0.3791 (0.0001)	0.4073 (0.0001)	0.3756 (0.0001)	1			
Italy (16)	0.0983 (0.0001)	0.2258 (0.0001)	-0.3179 (0.0001)	-0.1109 (0.0001)	-0.0969 (0.0001)	-0.2720 (0.0001)	0.1151 (0.0001)	-0.1130 (0.0001)	0.5398 (0.0001)	0.1380 (0.0001)	0.1416 (0.0001)	0.8845 (0.0001)	0.7645 (0.0001)	0.9193 (0.0001)	0.3445 (0.0001)	1		
Brazil (17)	0.1158 (0.0001)	0.2424 (0.0001)	-0.2245 (0.0001)	-0.1066 (0.0001)	-0.1291 (0.0001)	-0.2624 (0.0001)	0.1184 (0.0001)	-0.1302 (0.0001)	0.5718 (0.0001)	0.1813 (0.0001)	0.1811 (0.0001)	0.5300 (0.0001)	0.5868 (0.0001)	0.5462 (0.0001)	0.3638 (0.0001)	0.4949 (0.0001)	1	
Canada (18)	0.1984 (0.0001)	0.3359 (0.0001)	-0.2912 (0.0001)	-0.1008 (0.0001)	-0.1163 (0.0001)	-0.2962 (0.0001)	0.1382 (0.0001)	-0.0807 (0.003)	0.7289 (0.0001)	0.1512 (0.0001)	0.1537 (0.0001)	0.6210 (0.0001)	0.6625 (0.0001)	0.6335 (0.0001)	0.3334 (0.0001)	0.5867 (0.0001)	0.6394 (0.0001)	1

The average daily returns of stock market indices range between -0.012% (Italy) to 0.027 (India) per day. The standard deviation for each of the stock market indices is higher than all the safe-haven assets except Bitcoin and silver. Furthermore, all stock market indices exhibit negative skewness and high excess kurtosis, which indicates a significant crash risk. In sum, the descriptive statistics in Panel A suggest that the US Treasuries, US dollar, Swiss Franc and Tether could act as better safe havens than Bitcoin, gold and silver.

Table 1, Panel B, shows the correlations between the assets in our study. As expected, the correlation between gold and silver is positively correlated (0.66) and indicates that precious metals move in tandem. The correlation between gold and the US dollar is negatively correlated (-0.34) and indicates that these assets move in the opposite direction; thus, logically both assets cannot act as safe havens at the same time. The correlations between other safe haven assets are generally small, indicating that these assets do not have a tendency to move either in the same or in the opposite direction. Returns on the stock market indices for all ten countries are positively correlated to each other, with strong positive correlations between the US and Europe, and Canada and Brazil.

3.2. Maximum Losses during 2008 GFC and Covid-19 Pandemic

In this section, we examine the performance of safe haven assets during days of extreme stock market losses in the S&P500, during the 2008 GFC and COVID-19 pandemic. We use the S&P 500 stock market index since it is the proxy of the largest economy in the world, the US Nonetheless, we find similar results for the stock markets of other nine countries as well.[4]

We expect assets to earn positive or, at worst, close to zero returns on the days of large stock market losses if they possess qualities of safe-haven assets.

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[4] We do not report the results of the other nine countries for the sake of brevity. However, those results are available upon request from the authors.

Table 2: Extreme Losses during the 2008 GFC and COVID-19 Pandemic

Panels A and B list the ten largest daily losses of S&P 500 returns and the respective returns of safe haven assets during the 2008 GFC and COVID-19 pandemic, respectively.

Panel B: Extreme losses of SP500 Index during 2008 GFC						
Date	SP500	Gold	Silver	Dollar	Franc	T-bill	T-bond
15/10/2008	-9.4700	0.9800	-8.2920	0.8445	-0.0750	0.0286	0.1385
01/12/2008	-9.3540	-4.9180	-8.6740	1.2182	0.6250	0.0206	1.0559
29/09/2008	-9.2000	1.0180	-3.5920	0.6735	-0.0860	0.0383	1.0870
09/10/2008	-7.9220	-1.7390	0.8720	0.3085	0.0830	-0.0022	-0.5695
20/11/2008	-6.9480	0.1400	-3.1430	0.7531	0.2270	0.0220	0.9694
19/11/2008	-6.3110	1.3450	-2.5470	-0.0687	-0.5900	0.0149	0.5528
22/10/2008	-6.2950	-3.3520	-6.2930	1.6297	1.1680	0.0144	0.2707
07/10/2008	-5.9110	1.6080	0.8400	-0.8730	0.3810	-0.0311	-0.3689
20/01/2009	-5.4260	3.1880	-0.3580	2.3589	-0.2510	0.0024	-0.1339
05/11/2008	-5.4120	-1.3490	3.1590	-0.2007	-0.5410	0.0212	0.2961

Panel B: Extreme losses of SP500 Index during COVID-19 Pandemic								
Date	SP500	Gold	Silver	Dollar	Franc	T-bill	T-bond	Bitcoin	Tether
16/03/2020	-12.7650	-1.8930	-12.3410	-0.6706	0.6740	0.0182	1.5490	-7.2650	-0.4986
12/03/2020	-9.9940	-4.8790	-4.7040	0.9898	0.5230	0.0182	-0.2671	-46.4730	5.3393
09/03/2020	-7.9010	-0.1390	-1.2090	-1.1003	0.7900	0.0219	0.7507	-2.3010	-1.0680
18/03/2020	-5.3220	-3.2240	-5.9590	1.5742	0.0010	0.0309	-1.0611	0.2450	-0.1945
11/03/2020	-5.0100	-0.3120	-1.0590	0.1037	-0.2030	0.0129	-0.2964	0.0210	-0.2914
27/02/2020	-4.5170	0.5210	-0.9990	-0.5673	0.0780	0.0216	0.3753	-0.4090	-0.4327
01/04/2020	-4.5150	-1.5180	-1.2220	0.7250	0.1800	0.0035	0.3195	2.5780	0.1712
20/03/2020	-4.4330	0.7770	2.0490	0.0584	-0.8110	0.0037	1.7885	0.1220	-0.5635
05/03/2020	-3.4510	1.1760	0.8520	-0.5356	0.0460	0.0358	0.6556	3.6280	0.1897
27/03/2020	-3.4270	-0.2470	-0.9710	-1.0617	0.3530	-0.0037	0.6890	-3.7410	1.4748

Table 2, Panel A reports the results of safe-haven assets on the ten days of the largest losses in the S&P 500 during the period of the GFC from September 12, 2008, to June 30, 2009. The results show that gold returns are positive for six of the 10 days; silver shows positive returns for only three days, and the remaining safe haven assets, Treasuries and currencies, are positive for at least seven out of ten days. These results imply that, with the exception of silver, the chosen candidate assets generally exhibit the characteristics of a safe haven during days of large stock market losses during the GFC.

Table 2, Panel B reports a counterpart analysis for candidate safe-haven assets across the ten days of largest losses in the S&P 500 during COVID, covering February 20, 2020, to May 19, 2020, our current sample end date. The results show that gold returns generally move in tandem with the ten extreme stock market losses in the S&P 500 during COVID, with seven negative gold returns. For instance, gold lost 4.90% of its value on March 12, 2020, when the S&P500 index incurred a 10% loss. Silver also moved in tandem with extreme stock market losses during COVID, with eight out of 10 negative silver returns. Five out of the ten US dollar returns were negative, but only two Swiss Franc returns were negative on the days of the largest 10 losses in the S&P500. Notably, the T-bills recorded only one negative return, while the T-bond recorded two negative returns. Bitcoin and Tether have five and six negative returns, respectively, but the magnitude of Bitcoin's negative returns is much larger than Tether's negative returns. For example, Bitcoin dropped in value by 46.5% on March 12, 2020, while Tether recorded the maximum loss of just 1.07% on March 9, 2020. In sum, the results in Panel B imply that gold, silver and Bitcoin fail to protect the wealth of investors on those days when they needed it the most.

3.3. Estimation Results

In this section, we examine the relationship between safe haven assets and stock market returns using the regression model in Equations (1) and (2). Based on the preliminary analysis

shown in Section 3.2, we expect gold to act as a safe haven asset during the GFC but not during the COVID-19 pandemic. Furthermore, we expect Treasuries and currencies to act as safe haven assets for both the GFC and COVID. Finally, while Tether might act as a safe haven during the COVID; we do not expect Bitcoin to act as a safe haven asset since it can lose extreme value during days of extreme stock market losses.

Tables 3, 4, 5, and 6 present the estimation results for metals, currencies, Treasuries, and cryptocurrencies, respectively. The tables include the parameter estimates of b_0 (constant), $b1$ (hedge), the total effects during the 2008 GFC (sum of b_1 and b_2), and the total effect during the COVID-19 pandemic (sum of b_1 and b_3). All parameter estimates are multiplied by 100 for readability, while the t-statistics are provided in the parenthesis to determine the significance level of each coefficient.

3.3.1 Metals

Starting with gold, Panel A of Table 3 shows the parameter estimate, b_1 is positive for all ten countries and statistically significant for nine countries that indicates that gold does not serve as a hedge against the stock market indices except the US where it might act as a weak hedge. These results are generally consistent with Low et al. (2016) who show that gold is not a hedge for indices of several international markets. These results also partially corroborate Baur and McDermott (2010) who show that gold is not a hedge for most of the indices except North America using a sample between March 1979 and March 2009.

Most importantly, gold serves as a safe haven against the stock market losses for the ten countries during the GFC, strong safe haven against six, and weak safe haven against the other four countries that are generally consistent with the literature (e.g. Baur and McDermott, 2010; Low et al., 2016). Conforming to our expectations, gold fails to act as a safe haven against the stock market losses from all countries except Canada during COVID, where it serves as a weak

Table 3: Estimation results for Gold and Silver as safe haven assets during the 2008 GFC and Covid-19 pandemic

Table presents the estimation results of the role of gold and silver as a hedge and safe haven asset in the periods of stock market crises, such as the 2008 GFC and COVID-19 pandemic. The crisis duration is set to 20 trading days. The GFC starts on September 12, 2008, and ends October 10, 2008, while the COVID-19 pandemic starts on February 20, 2020, and ends March 18, 2020. The significant negative coefficients, b_1, in the hedge row indicates that the asset is a strong hedge, while insignificant coefficients, b_1, indicates a weak hedge. The significant negative coefficients, b_2 and b_3, in the GFC and COVID rows indicate that the asset is a strong safe haven during the 2008 GFC and COVID-19 pandemic, respectively, while insignificant coefficients, b_2 and b_3, indicate a weak safe haven during the 2008 GFC and COVID-19 pandemic, respectively. The t-statistics in the parenthesis refer to the marginal effect.

Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
	Panel A: Gold									
Const (b_0)	0.031	0.031	0.032	0.033	0.031	0.033	0.030	0.033	0.025	0.026
	(2.17)	(2.20)	(2.29)	(2.32)	(2.17)	(2.29)	(2.14)	(2.29)	(1.66)	(1.85)
Hedge (b_1)	1.170	3.660	5.880	6.760	10.080	5.930	5.620	3.960	6.550	19.170
	(0.92)	(4.29)	(5.94)	(7.14)	(9.15)	(6.3)	(5.67)	(4.82)	(9.45)	(16.09)
GFC (b_2)	-19.870	-18.240	-4.000	1.200	-15.430	-5.700	-26.310	-4.740	-14.330	-7.360
	(-2.78)	(-2.26)	(-1.06)	(-0.46)	(-1.8)	(-1.09)	(-2.08)	(-0.8)	(-5.13)	(-3.32)
COVID (b_3)	13.430	73.360	45.230	28.190	29.430	26.020	31.770	15.400	9.610	17.840
	(4.47)	(11.12)	(6.75)	(4.75)	(4.13)	(4.98)	(6.19)	(4.53)	(1.57)	(-0.47)

Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
	Panel B: Silver									
Const (b_0)	0.012	0.017	0.023	0.025	0.021	0.026	0.018	0.022	0.014	0.004
	(0.44)	(0.63)	(0.87)	(0.94)	(0.82)	(0.98)	(0.69)	(0.82)	(0.53)	(0.14)
Hedge (b_1)	23.060	8.750	14.510	26.740	36.590	25.640	16.520	19.020	21.410	56.550
	(9.75)	(5.53)	(7.43)	(16.60)	(20.60)	(16.67)	(9.39)	(14.21)	(17.32)	(27.15)
GFC (b_2)	-3.530	16.880	27.730	47.830	35.905	35.180	36.790	36.680	5.920	42.340
	(-1.99)	(0.52)	(1.35)	(1.61)	(-0.05)	(0.78)	(1.30)	(1.39)	(-2.41)	(-1.11)
COVID (b_3)	11.410	168.050	129.490	76.930	82.530	76.180	112.540	8.960	50.770	8.250
	(-3.37)	(17.76)	(13.76)	(11.86)	(9.72)	(11.86)	(17.30)	(-3.69)	(8.14)	(-16.13)

safe haven. However, the estimate of the total effect is positive, which indicates that the positive relationship between gold and Canada weakened during COVID.

Panel B shows that silver does not act as a hedge for the ten countries, consistent with the findings of Low et al. (2016). In fact, parameter estimate, b_1, shows that silver generally moves in tandem with stock market returns. Furthermore, silver serves as a strong, safe haven only for the US and Brazil during the GFC. However, the estimate of the total effect is positive for Brazil, which indicates that the positive relationship between silver and Brazil weakened during the GFC. Silver acted as a weak safe haven for the UK and Canada during the GFC; however, the total effect estimate is positive for both the UK and Canada, which implies that the positive relationship between silver and these countries weakened during the GFC. The total effects estimates are positive and relatively large for the other six countries implying that silver does not act as a safe haven despite the statistical insignificance. The non-significance of the positive coefficient estimates must be treated with care since it is based on observations of 20 trading days.

Silver does not act as a safe haven against stock market losses across all countries except the US, Italy and Brazil; however, the estimates of the total effect are also positive for these countries suggesting that the positive relationship between silver and stock market indices of the US, Italy and Brazil weakened during COVID. In sum, the results in Table 3 strongly refutes the use of gold and silver as safe havens during COVID and suggest that gold and silver could lose its safe haven status during pandemics. Section 4 provides further explanation of gold losing its status of a safe haven asset during COVID.

3.3.2 Currencies

Table 4, Panel A shows that the US dollar serves as a strong hedge for the ten countries except for China, where it serves as a weak hedge. Furthermore, it serves as a safe haven against the stock market losses for all the countries except the US and Brazil during the GFC; however,

Table 4: Estimation results for US Dollars and Swiss Francs as safe haven assets during the 2008 GFC and Covid-19 pandemic

Table presents the estimation results of the role of US Dollar and Swiss Franc as a hedge and safe haven asset in the periods of stock market crises, such as the 2008 GFC and COVID-19 pandemic. The crisis duration is set to 20 trading days between the start and end dates. The GFC starts on September 12, 2008, and ends October 10, 2008, while COVID-19 pandemic starts on February 20, 2020, and ends March 18, 2020. The significant negative coefficients, b_1, in the hedge row indicates that the asset is a strong hedge, while insignificant coefficients, b_1, indicates a weak hedge. The significant negative coefficients, b_2 and b_3, in the GFC and COVID rows indicate that the asset is a strong safe haven during the 2008 GFC and COVID-19 pandemic, respectively, while insignificant coefficients, b_2 and b_3, indicate a weak safe haven during the 2008 GFC and COVID-19 pandemic, respectively. The t-statistics in the parenthesis refer to the marginal effect.

Panel A: US Dollar Index									
Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	0.005	0.002	0.002	0.002	0.002	0.002	0.001	0.000	0.003	0.005
	(0.75)	(0.29)	(0.22)	(0.34)	(0.24)	(0.29)	(0.14)	(0.01)	(0.36)	(0.78)
Hedge (b_1)	-6.100	-0.663	-3.060	-8.630	-9.020	-8.840	-1.910	-8.300	-3.940	-11.380
	(-9.49)	(-1.51)	(-6.12)	(-18.99)	(-16.42)	(-20.19)	(-3.85)	(-21.21)	(-11.58)	(-20.05)
GFC (b_2)	5.210	-13.953	-9.360	-14.410	-13.070	-12.090	-9.020	-13.550	-1.420	-8.200
	(5.48)	(-4.55)	(-3.92)	(-2.45)	(-1.41)	(-1.25)	(-2.19)	(-2.51)	(2.00)	(1.11)
COVID (b_3)	4.480	-2.223	3.850	-0.380	-0.370	0.300	-3.870	0.980	1.460	2.260
	(10.67)	(-0.74)	(4.35)	(6.71)	(6.69)	(8.42)	(-1.14)	(11.22)	(8.07)	(14.56)

Panel B: Swiss Franc Index									
Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	-0.002	-0.001	0.002	0.002	0.001	0.002	0.001	0.003	0.036	0.005
	(-0.47)	(-0.17)	(0.34)	(0.51)	(0.17)	(0.44)	(0.21)	(0.65)	(7.09)	(1.07)
Hedge (b_1)	0.630	0.191	-2.610	-1.700	-6.260	-1.470	-0.847	-2.490	-1.520	-5.200
	(1.46)	(0.68)	(-7.15)	(-5.57)	(-17.51)	(-4.86)	(-2.92)	(-9.74)	(-5.20)	(-12.58)
GFC (b_2)	-1.290	-9.749	-8.440	-8.000	-10.310	-7.910	-12.227	-8.170	-3.460	-6.116
	(-0.58)	(-2.71)	(-2.49)	(-2.08)	(-1.66)	(-2.14)	(-1.64)	(-2.06)	(-1.56)	(-0.34)
COVID (b_3)	-5.240	-9.829	-8.400	-6.120	-7.027	-6.110	-7.517	-5.050	-3.460	-5.027
	(-5.60)	(-3.94)	(-3.60)	(-4.30)	(-0.73)	(-4.67)	(-4.25)	(-3.70)	(-2.34)	(0.19)

the total effect estimate is negative for Brazil indicating that the negative relationship between US dollar and Brazilian stock market is weakened during the GFC. The US dollar does not act as a safe haven from the stock market losses for the countries except China and India where it serves as a weak safe haven; however, the estimate of the total effect is negative for UK and Germany indicating a weakness in the negative relationship during COVID.

Table 4, Panel B shows that the Swiss Franc serves as a strong hedge for the ten countries except for China and the US, where it serves as a weak hedge. Furthermore, it serves as a safe haven against the stock market losses for all the countries during the GFC and COVID. In sum, the results in Table 4 indicate that the Swiss Franc has maintained its role as a safe haven asset during COVID. On the other hand, the US dollar is less effective as a safe haven for the majority of the stock markets during COVID.

3.3.3 Treasuries

Table 5, Panel A, shows that the T-bill is a strong hedge for the US, Germany, UK, France, Italy, and Canada; whereas, a weak hedge for the other four countries. Furthermore, the T-bill serves as a strong safe haven during the GFC for all the countries except the US and China, where it serves a weak safe haven. Moreover, the T-bill has maintained its safe haven status during COVID and serves as a strong safe haven for all the countries except Italy and Brazil, where it serves a weak safe haven.

Table 5, Panel B, shows that the T-bond is a strong hedge for all the countries except Japan, where it serves as a weak hedge. Similar to the results in Panel A for the T-bill, the T-bond also serves as a strong safe haven for all the countries except Japan during the GFC, where it serves as a weak safe haven. Although T-bond also serves as a safe haven for all the countries during COVID, it is a weak safe haven except for Japan, China and Brazil where it serves as a strong safe haven. In sum, the results in Table 5 suggest that Treasuries acts as a safe haven asset cross

Table 5: Estimation results for T-bill and T-bond as safe haven assets during the 2008 GFC and Covid-19 pandemic

Table presents the estimation results of the role of T-bill and T-bond as a hedge and safe haven asset in the periods of stock market crises, such as the 2008 GFC and COVID-19 pandemic. The crisis duration is set to 20 trading days from the start and end dates The GFC starts on September 12, 2008, and ends October 10, 2008, while the COVID-19 pandemic starts on February 20, 2020, and ends March 18, 2020. The significant negative coefficients, b_1, in the hedge row indicates that the asset is a strong hedge, while insignificant coefficients, b_1, indicates a weak hedge. The significant negative coefficients, b_2 and b_3, in the GFC and COVID rows indicate that the asset is a strong safe haven during the 2008 GFC and COVID-19 pandemic, respectively, while insignificant coefficients, b_2 and b_3, indicate a weak safe haven during the 2008 GFC and COVID-19 pandemic, respectively. The t-statistics in the parenthesis refer to the marginal effect.

Panel A: US Treasury Bills Index									
Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001
	(16.10)	(13.03)	(12.84)	(14.57)	(12.89)	(12.97)	(12.74)	(13.16)	(12.25)	(12.93)
Hedge (b_1)	-0.014	0.001	0.007	-0.010	-0.015	-0.013	-0.007	-0.009	-0.005	-0.013
	(-3.49)	(0.12)	(0.97)	(-2.42)	(-2.31)	(-2.13)	(-1.15)	(-1.84)	(-1.23)	(-2.00)
GFC (b_2)	-0.126	0.052	-0.237	-0.295	-0.493	-0.352	-0.600	-0.302	0.038	-0.315
	(-1.62)	(0.37)	(-5.81)	(-3.31)	(-9.14)	(-3.85)	(-25.34)	(-3.55)	(1.75)	(-7.04)
COVID (b_3)	-0.094	-0.494	-0.261	-0.215	-0.215	-0.185	-0.327	-0.122	-0.048	-0.104
	(-2.14)	(-4.06)	(-5.40)	(-2.95)	(-2.95)	(-2.13)	(-5.96)	(-1.36)	(-1.54)	(-3.24)

Panel B: US Treasury Bonds Index									
Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	0.015	0.012	0.011	0.012	0.012	0.012	0.012	0.012	0.011	0.012
	(5.36)	(4.14)	(3.85)	(4.40)	(4.24)	(4.34)	(4.16)	(4.17)	(3.74)	(4.30)
Hedge (b_1)	-8.120	-0.633	-0.082	-3.780	-4.220	-3.870	-1.250	-3.210	-1.870	-4.410
	(-30.27)	(-3.32)	(-0.38)	(-19.49)	(-18.06)	(-20.50)	(-5.76)	(-18.96)	(-12.61)	(-17.77)
GFC (b_2)	-10.460	-9.703	1.548	-6.930	-8.490	-7.370	-9.800	-6.810	-5.540	-10.280
	(-3.08)	(-6.74)	(1.65)	(-4.63)	(-6.52)	(-6.07)	(-8.06)	(-5.93)	(-11.05)	(-8.54)
COVID (b_3)	-8.186	-9.133	-11.472	-2.760	-4.438	-3.144	-2.560	-2.735	-2.960	-4.192
	(-0.08)	(-4.14)	(-7.73)	(1.04)	(-0.22)	(0.83)	(-1.07)	(0.66)	(-1.72)	(0.24)

all countries during both crises which provides strong empirical support to Brunnermeier et al. (2020) who propose US Treasuries as a global safe asset in times of the crisis.

3.3.4 Cryptocurrencies

Table 6, Panel A shows that the parameter estimate, b_1, is positive for all countries except Japan and India which indicates that Bitcoin does not serve as an effective hedge for the majority of the countries in our study.[5]

Most importantly, the total effect estimates for COVID are all positive and statistically significant, implying that Bitcoin moves in tandem with the stock market losses and does not serve as a safe haven during the COVID.

Table 6, Panel B, shows that Tether is a weak hedge for all the countries except Germany. Furthermore, Tether serves as a strong safe haven against stock market losses for all the countries during COVID. Therefore, it is evident that Tether, the largest stablecoin, exhibits strong safe haven properties during a market turmoil because it is backed by traditional currencies and other assets. On the other hand, the largest traditional cryptocurrency, Bitcoin, suffers huge losses instead of serving as a safe haven asset.

3.3.5 Summary

Gold has acted as a safe haven asset during the GFC but loses its safe haven status during the COVID. Silver fails to exhibit safe haven characteristics during both crises. For currencies, the Swiss Franc has acted as a safe haven during both the crises; whereas, US dollar has served as a safe haven during the GFC but not for the majority of the countries during COVID. The Treasuries have exhibited safe haven characteristics during both the crisis. For cryptocurrencies, only Tether, a stablecoin, has acted as a safe haven asset during COVID.

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[5] The sample period for cryptocurrencies starts September 17, 2014. Therefore, we estimate Equations (1) and (2) without the 2008 GFC dummy.

Table 6: Estimation results for Bitcoin and Tether as a safe haven asset during Covid-19 pandemic

Table presents the estimation results of the role of Bitcoin and Tether as a hedge and safe haven assets during the COVID-19 pandemic. The crisis duration is set to 20 trading days starting on February 20, 2020, and ending March 18, 2020. The significant negative coefficients, b_1, in the hedge row indicates that the asset is a strong hedge, while insignificant coefficients, b_1, indicates a weak hedge. Significant negative coefficients, b_2, in the COVID row indicate that the asset is a strong safe haven during the COVID-19 pandemic, while an insignificant b_2 indicates a weak safe haven. The t-statistics in the parenthesis refer to the marginal effect. The t-statistics in the parenthesis refer to the marginal effect.

Panel A: Bitcoin										
Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	0.194	0.202	0.204	0.205	0.202	0.204	0.208	0.207	0.210	0.201
	(1.96)	(2.04)	(2.03)	(2.06)	(2.04)	(2.04)	(2.1)	(2.07)	(2.13)	(2.03)
Hedge (b_1)	12.230	8.090	-16.170	3.900	0.627	2.890	-0.492	4.680	3.450	11.100
	(1.44)	(2.09)	(-1.99)	(0.59)	(0.08)	(0.43)	(-0.06)	(0.82)	(0.72)	(1.43)
COVID (b_2)	181.920	482.560	352.910	219.580	224.677	211.660	287.158	165.660	121.710	150.990
	(14.04)	(32.12)	(19.51)	(19.1)	(17.49)	(18.19)	(23.95)	(15.5)	(16.25)	(14.45)

Panel B: Tether										
Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	0.001	-0.004	-0.008	0.010	-0.003	-0.002	-0.003	-0.003	-0.004	-0.005
	(0.05)	(-0.50)	(-1.17)	(7.53)	(-0.49)	(-0.25)	(-0.37)	(-0.45)	(-0.51)	(-0.85)
Hedge (b_1)	0.404	-0.118	-0.528	1.980	-0.186	0.141	-0.011	-0.050	-0.206	-0.410
	(0.51)	(-0.21)	(-0.79)	(29.4)	(-0.31)	(0.26)	(-0.02)	(-0.09)	(-0.69)	(-0.64)
COVID (b_2)	-14.056	-21.778	-21.728	-6.410	-11.826	-11.009	-20.031	-9.660	-9.286	-6.560
	(-7.45)	(-9.25)	(-8.21)	(-10.19)	(-8.44)	(-9.46)	(-10.07)	(-8.81)	(-6.31)	(-7.31)

4. Potential Explanations

The most surprising finding from Section 3 is that the gold has lost its safe haven status during the COVID-19 pandemic. Traditionally, gold is considered as one of the most effective safe haven assets, and it has exhibited safe haven characteristics during the previous crises such as the 1987 stock market crash and the GFC (e.g. Baur and McDermott, 2010).

Figure 2 plots the gold price from January 1, 1990, to May 19, 2020. It is evident from Figure 2 that gold attained the maximum price of \$1898.25 on September 5, 2011 and lost its peak value by 45% by December 17, 2015. Therefore, investors might have lost their trust in the gold as a safe haven asset since a loss of 45% over four years indicates instability in gold prices. Therefore, we examine the performance of gold as a safe haven asset during extreme stock market movements after September 5, 2011. As in Baur and Lucey (2010), we define extreme stock market movements where stock market return at time t are in a low quantile, such as the 10%, 5%, and 1% quantile. To the extent, gold has lost its status of a safe haven among investors due to the extreme losses between 2011 and 2015; we hypothesize that gold does not act as a safe haven during extreme stock market movements. We estimate the following regression model first proposed and utilized by Baur and Lucey (2010):

$$RGold_t = b_0 + b_1 \cdot RS_{j,t} + b_2 \cdot D_{q10} \cdot RS_{j,t} + b_3 \cdot D_{q5} \cdot RS_{j,t} + b_4 \cdot D_{q1} \cdot RS_{j,t} + \varepsilon_t \quad (3)$$

Equation (3) models the relation of gold and stock market returns. The dummy variables, D, capture extreme stock market movements, taking a value of one if stock market return at time t is in the low quantile, such as 10%, 5% and 1%, and zero otherwise. The residual term ε_t is modelled as a GJR-GARCH process introduced by Glosten et al. (1993) as defined in Equation (2).

The gold is a hedge for the stock market j if the parameter b_1 is zero (weak hedge) and negative and significant (strong hedge), and the sum of parameters from b_2 to b_4 are not jointly

Figure 2: Gold Prices
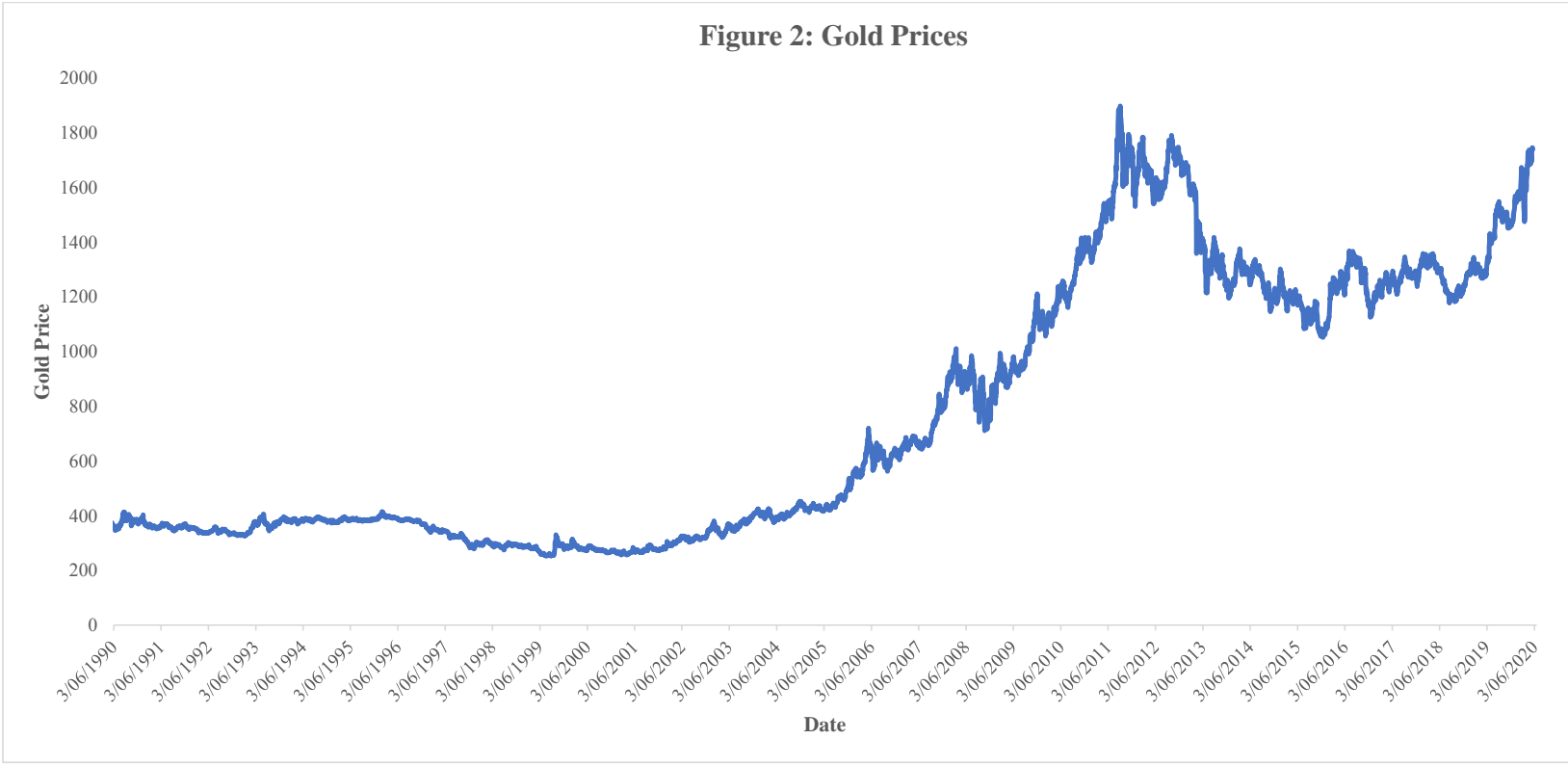
Figure 1: This figure displays the daily gold prices in US dollars from 1990 to 2020. The gold prices are labelled on the vertical axis, and date on the horizontal axis.

Table 7: Estimation results for gold as a safe haven in extreme market conditions

Table presents the estimation results of the role of gold as a hedge and safe haven asset during the periods of extreme market conditions namely, quantile 10% (b_2), 5% (b_3), and 1% (b_4). A significant negative coefficient, b_1, in the hedge row indicates that an asset is a strong hedge, while an insignificant coefficient, b_1, indicates a weak hedge. The significant negative coefficients b_2, b_3, and b_4 indicate that asset is a strong safe haven; whereas, insignificant coefficients indicates that asset is a weak safe haven. The t-statistics in the parenthesis refer to the marginal effect.

Coefficients	US	China	Japan	Germany	UK	France	India	Italy	Brazil	Canada
Const (b_0)	-0.018	-0.011	-0.013	-0.001	-0.009	-0.011	-0.017	0.007	0.001	-0.019
	(-0.95)	(-0.54)	(-0.63)	(-0.05)	(-0.47)	(-0.57)	(-0.89)	(0.37)	(0.08)	(-0.99)
Hedge (b_1)	3.390	4.130	2.370	-2.650	2.540	-1.190	1.220	-2.870	3.230	14.530
	(1.51)	(2.06)	(1.29)	(-1.70)	(1.23)	(-0.72)	(0.62)	(-2.15)	(2.75)	(6.39)
Quantile 10% (b_2)	1.110	4.101	-0.180	-7.030	-6.690	-12.390	-14.980	3.970	10.870	5.040
	(-0.38)	(-0.01)	(-0.49)	(-0.91)	(-1.66)	(-2.24)	(-3.26)	(1.65)	(2.16)	(-1.65)
Quantile 5% (b_3)	-16.140	1.491	-4.570	0.320	0.350	-3.460	-4.830	1.720	-2.210	-6.920
	(-2.75)	(-0.52)	(-0.80)	(1.57)	(1.31)	(1.87)	(2.05)	(-0.53)	(-3.41)	(-2.04)
Quantile 1% (b_4)	6.670	-3.949	-3.270	4.600	8.190	4.440	9.360	-4.570	11.810	21.480
	(5.32)	(-1.80)	(0.35)	(1.70)	(2.36)	(3.25)	(3.66)	(-2.89)	(4.98)	(7.21)

positive exceeding the value of b_1. If parameter b_2, b_3 and b_4 (including b_1) are non-positive and statistically significant (insignificant), then gold serves as a strong (weak) safe haven.

For extreme negative stock market returns, half of the parameter estimates are positive for the 10% quantile; whereas four of the coefficient estimates are positive for 5% quantile. Most importantly, eight out of ten parameter estimates are positive for the most extreme quantile, 1%, which indicates that gold does not serve as a safe haven for adverse market returns. Therefore, gold has lost its status as a safe haven for extreme adverse market conditions since 2011. As previously mentioned, it could be that gold attained its peak value on September 5, 2011, and lost it by 45% over the next four years, and consequently, investors lost trust in gold as a stable asset.

5. Conclusion

This paper examines the performance of gold, silver, US Treasuries, US dollar, Swiss Franc, Bitcoin and Tether as safe haven assets from stock market losses of the world's largest ten economies during the 2008 GFC and COVID-19 pandemic. Our findings show that US Treasuries and Swiss Franc protect investors from stock market losses during both crises, which indicate that investors trust US Treasuries and Swiss Franc during both the GFC and the COVIDc. For the US dollar, our results show that it acts as a safe haven during the GFC, but it does not act as an effective safe haven during COVID. The most surprising finding comes from the gold that has acted as a safe haven during the GFC but not during the COVID1. Silver does not exhibit safe haven characteristics during both crises. Our results show that Bitcoin does not protect investors wealth during COVID, but the largest stablecoin, Tether that acts as an effective safe haven for the ten largest economies.

Our findings also show that investors from both developed and emerging markets not only seek the shelter of a safe haven asset in the same way during both crises but also choose the same safe haven assets. For instance, investors from the ten largest economies including the

emerging markets of China, India and Brazil choose gold as a haven asset during the GFC, but investors from those ten countries might have stayed away from gold as a safe haven during COVID.

We also explain why gold loses its value as a safe haven asset during COVID when, traditionally, it acted as a safe haven asset during the previous stock market crises of 1987 and the GFC. We suggest that investors might have lost trust in gold as a stable asset after losing 45% of its value between 2011 to 2015. Furthermore, investors now have access to more safe haven assets for shelter during crises, such as derivatives and stablecoins.

The findings are useful for investors and fund managers searching for the best safe haven, such as gold, silver, Treasuries, currencies and cryptocurrencies to offset large stock market losses. Furthermore, the results suggest that investors should prefer liquid and stable assets such as Tether and Treasuries during a pandemic rather than gold. Therefore, central banks, financial institutions and regulatory authorities should consider supporting financial assets that remain liquid during stock market crises. Future research endeavours should identify other safe haven assets during COVID.

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Delays in death reports and their implications for tracking the evolution of COVID-19[1]

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Understanding the determinants and implications of delays in reporting COVID-19 deaths is important for managing the epidemic. Contrasting England and Mexico, we document that reporting delays in Mexico are larger on average, exhibit higher geographic heterogeneity, and are more responsive to the total number of occurred deaths in a given location-date. We then estimate simple SIR models for each country to illustrate the implications of not accounting for reporting delays. Our results highlight the fact that low and middle-income countries are likely to face additional challenges during the pandemic due to lower quality of real-time information.

1 Introduction

Tracking the spread of the SARs-CoV-2 virus and subsequently the evolution of the COVID-19 epidemic is important for managing the outbreak (Shea et al., 2020), evaluating the effectiveness of different policy tools to contain it (Kraemer et al., 2020; Chinazzi et al., 2020; Hartl et al., 2020), and for effectively communicating risks and undertaking different policy actions (WHO, 2005; Saliou, 1994), such as enforcing or lifting social distancing measures (WHO, 2020; Greenstone and Nigam, 2020). The effectiveness of surveillance systems is thus critical for the management of pandemics (Olson et al., 2020; Carey et al., 2020; Woolhouse et al., 2015; Brookmeyer, 1991; Krause, 1992). Low surveillance capacity represents not only a threat to the prompt identification of outbreaks in low and middle-income countries, but also for assessing their evolution comparatively across countries (Halliday et al., 2017).

Reporting delays for deaths, defined as the time difference between when a death occurs and when it is registered in the system, have been long recognized in various settings (AbouZahr et al., 2015; Bird, 2015). Nevertheless, in the context of COVID-19, many academics, policy-makers, and media outlets are tracking the pandemic's evolution within and across countries by focusing on death counts (Weinberger et al., 2020), arguing that they are more easily identified and consistently reported than cases (Roser et al., 2020). However, data on death counts may exhibit shortcomings similar to case counts due to reporting delays, and the extent of these issues may also vary across and within countries. This, in turn, may limit policy-makers' ability to effectively communicate the risks associated with individuals' behavior in the midst of the pandemic (Avery et al., 2020).

This paper seeks to characterize reporting delays of COVID-19 deaths across two distinct settings, contrasting the various determinants of these delays and illustrating the implications of these reporting delays for modeling the epidemic. We focus on England and Mexico to contrast delays between a developed and developing country, and since both governments publicly release detailed data that allow us to construct measures of reporting delays.

We document that death counts due to COVID-19 are reported with different delays in England and Mexico. Reporting delays in Mexico are larger, more heterogeneous across space, and most importantly, are more affected to the total number of actual occurred deaths in a particular location on a given day. We then illustrate the implications of not accounting for delays in reporting by

estimating simple SIR models for both countries accounting and not accounting for reporting delays, showing very different predictions for Mexico, consistent with the larger and more heterogeneous delays.

There is a rapidly growing literature touching on various topics related to the COVID-19 pandemic. In particular, our paper speaks directly to two strands of this work. First, recent papers explore how persuasive and/or informative messages correlate with or affect compliance with social distancing measures, which are important for both the economic costs associated with the pandemic and for the evolution of the epidemiological curve (Ajzenman et al., 2020; Allcott et al., 2020; Barrios and Hochberg, 2020; Bursztyn et al., 2020; Grossman et al., 2020; Kushner Gadarian et al., 2020; Painter and Qiu, 2020).

Second, a large literature is attempting to identify the additional restrictions and challenges that low and middle-income countries face in the management of and economic recovery from this pandemic, such as the capacity of the healthcare system, poverty, inequality, and corruption (Gallego et al., 2020; Gottlieb et al., 2020; Loayza, 2020; Monroy-Gómez-Franco, 2020; Ribeiro and Leist, 2020; Walker et al., 2020). By identifying a potential difference in information quality in a middle-income country, we shed light on an additional challenge that policy-makers may face when managing epidemics.

Our main contribution consists in contrasting reporting delays for deaths in two very different settings. We argue (and show supporting evidence in the online appendix) that the difference between Mexico and England in terms of reporting delays is consistent with lower state capacity. To the extent that this is a widespread problem across the developing world, our insights imply that successfully managing the epidemic in these regions will be further complicated by lower quality real-time information.

The rest of the paper is organized as follows. Section 2 presents the data and some descriptives of the evolution of deaths during the COVID-19 epidemic in England and Mexico, as well as the average delays in reporting these deaths. Section 3 decomposes delays into location shifters, date shifters, and the effect of total deaths. Section 4 then illustrates the implications of these reporting delays when modeling the evolution of the epidemic. Lastly, Section 5 concludes.

2 Data and Descriptive Evidence

2.1 Death reports in England and Mexico

We obtain publicly-available data with daily COVID-19 death counts from the England NHS, available from April 1 to June 7, 2020.[1] Each file contains the deaths from the corresponding reporting period, and indicates the date at which these reported deaths occurred. These counts are further disaggregated by NHS trust, which correspond to groups of hospitals and healthcare providers in the public system. Our data covers 198 NHS trusts across seven regions.[2] It should be noted that these counts do not include deaths that occur outside the hospital system.

For Mexico, we obtain publicly-available data from the Ministry of Health that tracks all patients that were ever suspected of having COVID-19 over time.[3] The government uses this database to announce cumulative counts and deaths in a nightly press conference, allowing us to identify each of the newly reported cases and deaths on each date and the deaths' date of occurrence. We observe a few characteristics for each patient, including their municipality of residence. Unfortunately, we cannot observe which healthcare facility they visit and thus reports them to the database. We use these data to construct counts of deaths that are reported each day, as well as the actual date of death for each municipality. Our data includes 593 municipalities.[4]

2.2 Reporting delays in England and Mexico

We present the evolution of death counts over time for each country in Figure 1, distinguishing between aggregates based on the actual date of death and those based on the date of reporting. Figure 1a shows the daily number of total deaths in England by date, while Figure 1b shows the corresponding cumulative deaths. Figures 1c and 1d show analogous plots for Mexico. Over all, we observe that the evolution of death counts over time differs significantly between aggregates by

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[1]Data are available at https://www.england.nhs.uk/statistics/statistical-work-areas/covid-19-daily-deaths/. We were unable to find similar data for other countries in the United Kingdom.

[2]These regions are East England, London, Midlands, North East and Yorkshire, North West, South East, and South West.

[3]Data are available at https://www.gob.mx/salud/documentos/datos-abiertos-bases-historicas-direccion_general-de-epidemiologia.
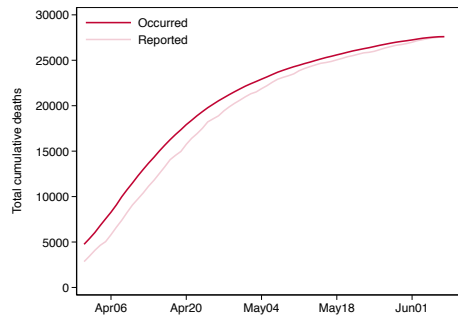
[4]Although Mexico has 2,448 municipalities in total, the remaining 1,855 are those that have not reported any COVID-19 cases. These are mostly rural areas.

date of occurrence and date of reporting, especially for Mexico, where delays also appear to be larger.
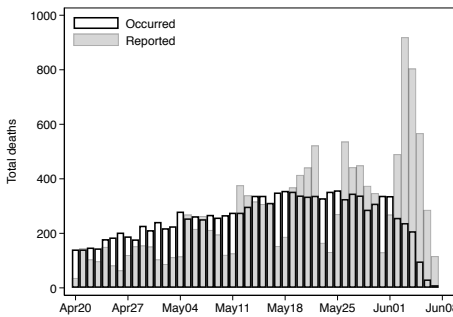
Figure 1:
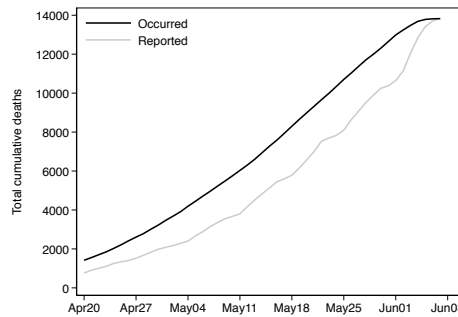COVID-19 Deaths Over Time by Country
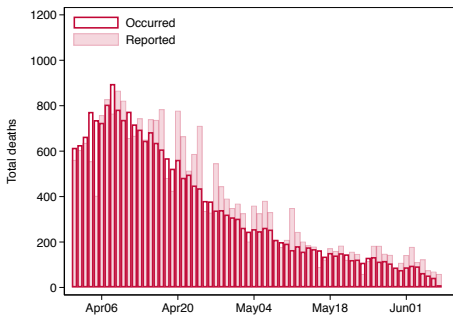
(a) England - Daily deaths

(b) England - Cumulative deaths

(c) Mexico - Daily deaths

(d) Mexico - Cumulative deaths

Notes: These graphs show the distribution of deaths over time for each country using the full available data (starting April 1 for England and April 20, 2020 for Mexico). We distinguish between deaths that actually occurred on a given date, and deaths that were reported on that date. Figures 1a and 1c show counts of total deaths per day, while Figures 1b and 1d show total cumulative deaths for England and Mexico, respectively.

From these datasets, we construct measures of the delays with which deaths are reported by each location in each period, conditional on having at least one observed occurred death. Specifically, we compute the average delay with which deaths that occurred in each location-date pair were reported, conditional on having being reported within k days after their occurrence. Since the data are naturally censored, we drop all deaths reported in the last k days of available reports for each country, regardless of their date of occurrence. The implicit assumption is that the probability of

observing all deaths that occurred on a given date is one (or close to one) when relying on reports up to k days after that date. We focus on $k = 14$, but present results for $k = 21$ also.
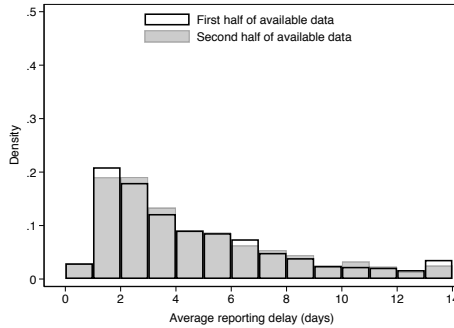
We show the distribution of average reporting delays in Figure 2, where we have restricted the data by setting $k = 14$.[5] We present a direct comparison between England and Mexico in Figure 2a, and then restrict to data for England in Figure 2b and Mexico in Figure 2c. These last two graphs further split the sample based on the median date of death.

Figure 2:
Average Reporting Delay Over Time by Country
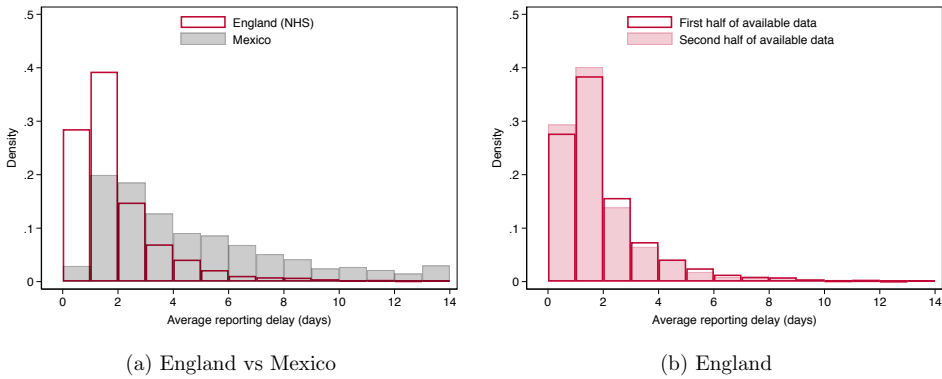
(a) England vs Mexico

(b) England

(c) Mexico

Notes: These graphs show the distribution of the average reporting delay measured in days for each country. In Figures 2b and 2c, the data are further stratified by median date of death for the available span of data. We drop the most recent 14 days of data reports, and delays that are over 14 days. In Figure 2a, the mean for England is 1.74, and 4.29 for Mexico, implying a difference of 2.56, with a 95% CI [2.45,2.66]. The mean for the first half of the data for England in Figure 2b is 1.84, and 1.64 for the second half, implying a difference of 0.20, 95% CI [0.10,0.29]. Lastly, the mean for the first half of the data in Figure 2c is 4.31, 4.28 for the second half, and a difference of 0.03, 95% CI [-0.19,0.25].

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[5]See Figure A1 in the online appendix for analogous graphs with $k = 21$.

Figure 2a documents that the average reporting delay is larger in Mexico, with a distribution that is not only mean-shifted but also has a heavier right tail. Figures 2b and 2c further show that the average delay in England decreased over time, while it did not for Mexico. Given the differential timing of the epidemic, one must be cautious when interpreting these differences. Nevertheless, these plots do suggest that trends in delays are not the same between England and Mexico.

There are many potential reasons for why Mexico, a middle-income country, has significantly larger reporting delays than a developed country like England. Although we cannot fully discard alternative explanations, we posit that larger delays are correlated with state capacity, which is lower in Mexico. We present suggestive evidence consistent with this explanation in Figure A2 in the online appendix. We show that the municipalities in Mexico with larger reporting delays are those that have fewer healthcare units per capita, slightly fewer medical staff per capita, and higher patient volumes per healthcare unit. Furthermore, municipalities where a larger share of the population is covered by the public healthcare system, which would indicate a larger presence of the state, are those with significantly lower reporting delays. Over all, this suggests that state capacity plays a key role in decreasing reporting delays.

3 Determinants of reporting delays

There are at least three different determinants of reporting delays for deaths that matter for tracking the evolution of a pandemic. First, there may be spatial differences in delays. Different reporting units may face different staffing and infrastructure constraints that can lead to variation in their reporting capabilities. If this is the case, as the disease spreads geographically, the average delay with which deaths are reported may change, affecting the shape of the curve of reported deaths independently of the pandemic.

Second, there may be system-wide changes in delays over time. If countries improve their reporting systems in real time as the pandemic progresses, then death reports could misrepresent the evolution of the pandemic in different ways over time.

Lastly, there may be decreasing returns in reporting. Hence, as more deaths occur, it may be less likely that these deaths are reported in a timely manner. This too would imply a different shape for the curve from reported deaths when making comparisons.

The data and statistical tools needed to account for the reporting delays implied by these three factors are different and difficult to develop in real time as the pandemic progresses. For geographic differences, large amounts of data are necessary for each location to correctly model location-specific delays and correct for them. Time-specific delays and delays related to the total deaths imply that the corrections should be updated over time. While correcting reports for these factors requires data from which estimates of delays may be inferred, correcting for delays due to changes in death counts also requires information on the total deaths that *actually* occurred in a given moment in addition to those that were reported.

3.1 Framework

In order to characterize and illustrate the differences in the determinants of the delays in death reports in Mexico and England, we assume that reports are a series of Bernoulli trials, so that the number of days it takes for a death to be reported by location l in period t (plus one) follows a geometric distribution with success probability p_{lt}. We further assume that p_{lt} can be parametrized as follows:

$$p_{lt} = p_0 \cdot exp^{\left(\sum_{q=1}^{Q} \alpha_q \mathbb{I}(deaths_{lt}=q) + \pi_l + \xi_t + \varepsilon_{lt}\right)}$$

simply stating that there is a baseline probability p_0 that deaths are reported, which may then be shifted by certain variables as outlined below. This implies then that:

$$\mathbb{E}\left(delay_{lt} + 1\right) = \frac{1}{p_0 \cdot exp^{\left(\sum_{q=1}^{Q} \alpha_q \mathbb{I}(deaths_{lt}=q) + \pi_l + \xi_t + \varepsilon_{lt}\right)}}$$

where we have only used the fact that the mean of a geometric distribution with parameter p is equal to $\frac{1-p}{p}$.

We proceed by log-linearizing this expression. This allows us to decompose the reporting delays into location-specific shifters, period-specific shifters, and parameters that measure the response to the number of occurred deaths through the following ordinary least squares regression:

$$\ln\left(\overline{delay}_{lt} + 1\right) = \sum_{q=1}^{Q} \alpha_q \mathbb{I}(deaths_{lt} = q) + \pi_l + \xi_t + \varepsilon_{lt} \tag{1}$$

where $\overline{delay}_{lt}$ denotes the average delay in reporting deaths that occurred in location l on date t, $\mathbb{I}(deaths_{lt} = q)$ are indicators equal to one if total occurred deaths in a given location and time fall in a category q, the coefficients α_q measure how log delays respond to total deaths that occurred in a particular location-date, π_l denotes reporting unit fixed effects corresponding to the location-specific shifters (hence, the estimates of these parameters $\hat{\pi}_l$ for each location l recover the estimates of $p_0 + p_l$), ξ_t are the date-specific shifters, and lastly ε_{lt} is an error term that captures any time-varying location-specific shocks to average delays other than the total occurred deaths. We run regressions separately for each country, cluster our standard errors by reporting unit to allow for serial correlation in the error term, and present our results graphically.

3.2 Results

Figure 3 plots the estimated coefficients $\hat{\alpha}_q$ from estimating equation 1 for each country, with Figure 3a using reported data up to 14 days to identify total occurred deaths ($k = 14$) and Figure 3b considering 21 days instead ($k = 21$).[6] The vertical bars indicate 95% confidence intervals. We use integers of total deaths as our categories, with the last category considering 5 or more deaths.[7] We take one death as the excluded category, so that our estimated effects are relative to the average delay for reporting units with one death.

Our point estimates are larger for Mexico across specifications. In Figure 3a, we interpret this to mean that, accounting for location and date effects, the occurrence of two deaths significantly increases the average delay by 0.056 log points in England, which can be approximated as 5.6%, and by 0.129 log points in Mexico on average, or around 12.9%, relative to when there is only one death. For five or more deaths, we find that average delays significantly increase by 0.125 and 0.136 log points for England and Mexico, respectively, relative to the average delay when there is one death only. Importantly, the estimates of how changes in the death toll affect delays are calculated from variation within each reporting unit over time, accounting for system-wide trends in delays. Hence, our results in Figure 3 are not conflating occurred deaths with the general progression or regional variation of death counts and delays.

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[6]Table A1 in the online appendix shows the corresponding point estimates.

[7]Figure A3 in the online appendix presents similar results for Mexico using deciles of deaths per capita, by matching population at the municipality level from the 2010 census. We were unable to find a consistent mapping between population and NHS trusts.

Over all, these results show that total death counts matter for average delays, regardless of any spatial and temporal differences, and that they matter much more in Mexico than in England. This relationship is in line with reporting units becoming overwhelmed by higher death tolls, which is exacerbated by settings with low state capacity. Alternatively, a higher death toll may increase the likelihood that at least some deaths require further testing and scrutiny before being reported, which would lead to larger average delays.

Figure 3:
Relationship between Total Deaths and Reporting Delays

(a) $k = 14$ (b) $k = 21$
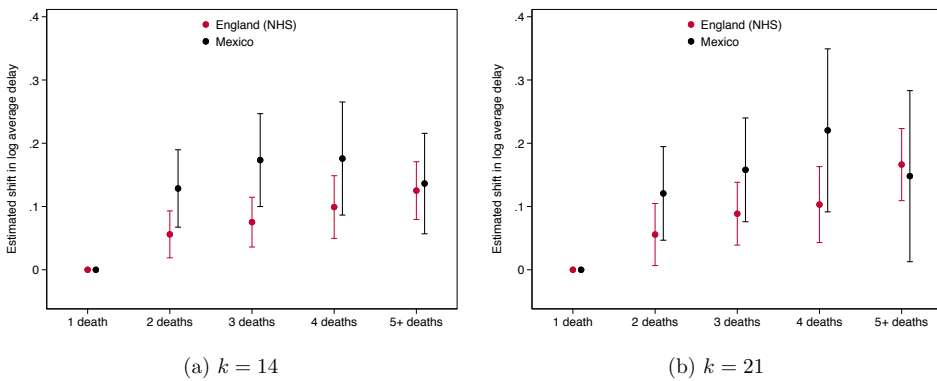
Notes: These graphs show the estimated shift in the log average delay in relation to quartiles of total deaths per reporting unit from estimating equation 1. All effects are calculated relative to the mean shift for the first quartile (one death). Figure 3a corresponds to data that exclude the last 14 days of available reports, as well as delays over 14 days (N=5991 for England, N=3660 for Mexico). Figure 3b uses 21 days instead (N=5531 for England, N=2875 for Mexico). The vertical lines indicate 95% confidence intervals from robust standard errors clustered by reporting unit.

Figure 4 shows the estimates of the reporting unit fixed effects. Each coefficient indicates the average shift in delays relative to the excluded location, net of general time trends and accounting for variation in total deaths.[8] Since there is no commonality in reporting units between England and Mexico, we normalize the median reporting unit for each country in terms of its estimate to zero and order them by size to allow comparability. Figure 4a considers $k = 14$ and 4b $k = 21$.

The results show that the predicted shift in log average delays is more homogenous for England than Mexico, as noted by the larger slope in the coefficients for Mexico. Given that for Mexico each estimate is obtained from a smaller number of observations,[9] it should not be surprising that these

[8]We arbitrarily exclude East Coast Community Healthcare, Beccles Hospital for England, and Aguascalientes municipality in the state of Aguascalientes for Mexico.
[9]For example, for $k = 14$, each reporting unit has on average 27.5 and 6.2 days with occurred deaths in England and Mexico, respectively.

estimates exhibit a higher variance. However, the confidence intervals for Mexico and England do not overlap for a large share of the estimates in both tails of the distribution. This indicates that, indeed, geographic variation in delays is significantly higher in Mexico.

We argue that the larger spatial heterogeneity in Mexico is related to the lower state capacity of this middle-income country, relative to England. Figure A4 in the online appendix shows the correlation between the estimated municipality shifters and various measures of healthcare infrastructure. These plots show that the locations with larger reporting delays, net of time effects and the actual death toll, are those with fewer healthcare units per capita, higher patient loads per healthcare unit, and a smaller share of the population covered by the public healthcare system. Hence, this is consistent with state capacity playing an important role in delays.

Figure 4:
Relationship between Reporting Units and Reporting Delays

(a) $k = 14$ (b) $k = 21$
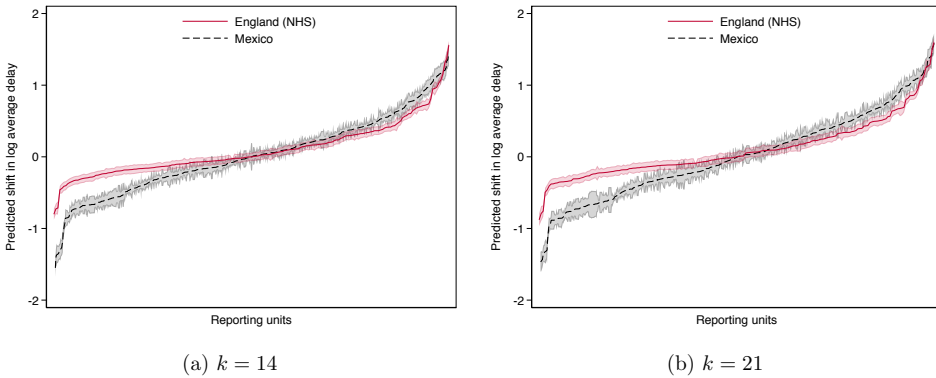
Notes: These graphs show the predicted shift in the log average delay across reporting units from estimating equation 1. The median shift in each series has been normalized to zero to allow comparability. Figure 4a corresponds to data that exclude the last 14 days of available reports, as well as delays over 14 days (N=5991 for England, N=3660 for Mexico). Figure 4b uses 21 days instead (N=5531 for England, N=2875 for Mexico). The shaded areas indicate 95% confidence intervals from robust standard errors clustered by reporting unit. Reporting units correspond to 198 NHS trusts in England and 749 municipalities in Mexico in Figure 4a, and 198 trusts and 668 municipalities in Figure 4b.

Finally, we show our estimates of the date effects in Figure 5. The excluded category here is the first calendar day with available data for both countries, April 20. Once again, each plot considers alternative values of k. The point estimates show a decreasing effect over time for England up to April 20. This suggests that NHS trusts improved their reporting over time. For the dates in which we observe data for both countries, the point estimates are mostly flat for both England

and Mexico.[10] Over all, the estimates of the date fixed effects show that England decreased its delays over time, and that, contrary to what the raw data may suggest, there is not much of a relationship between average delays and time for Mexico, once we account for location effects and occurred deaths.

Figure 5:
Relationship between Date and Reporting Delays

(a) $k = 14$ (b) $k = 21$
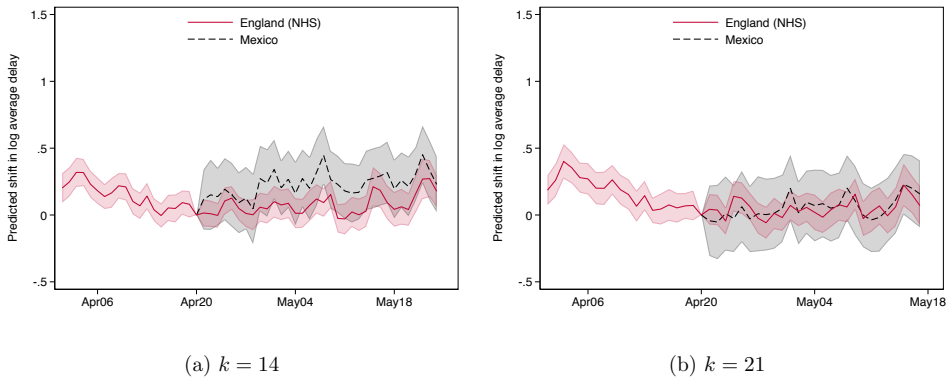
Notes: These graphs show the predicted shift in the log average delay over time from estimating equation 1. All date estimates are calculated relative to the mean shift on April 20. Figure 5a corresponds to data that exclude the last 14 days of available reports, as well as delays over 14 days (N=5991 for England, N=3660 for Mexico). Figure 5b uses 21 days instead (N=5531 for England, N=2875 for Mexico). The shaded areas indicate 95% confidence intervals from robust standard errors clustered by reporting unit. Our sample includes 54 days for England and 35 for Mexico in Figure 5a, and 47 days for England and 28 for Mexico in Figure 5b.

Taken together, the results in Figures 3 - 5 suggest than correcting for reporting delays may not be a straight-forward task, since detailed information by location is needed and a single correction factor is unlikely to capture the heterogeneity we document. Moreover, tracking the evolution of COVID-19 from death reports may deliver a biased representation of the epidemic curve that is not comparable across locations.

4   Implications for epidemiological modeling

The results presented in section 3 suggest important challenges for the development of algorithms that can systematically correct for reporting delays, given the heterogeneity we document. We now emphasize the importance of taking delays into account by highlighting how they may affect model

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[10]Note that there is perhaps a slight increasing trend in the point estimates for Mexico, although the evidence is not strong. This trend is most obvious in Figure 5a.

estimates that are commonly used to support predictions and policy interventions (Zhang et al., 2020; Dehning et al., 2020).

We proceed by contrasting estimates based on reported deaths relative to two alternative ways of counting deaths. First, we consider actual occurred deaths, as reported up to k days after the fact. Second, we consider a hypothetical scenario in which reporting delays are fourteen days shorter than observed, by taking the difference between cumulative occurred deaths at time t and at time $t-1$ as reported at time $t+14$ and $t+13$, respectively. It is important to stress that our objective is not to provide accurate forecasts about the dynamics of the infection in England and Mexico. Instead, we simply illustrate how reporting delays directly impact short-run analyses in modeling the evolution of the COVID-19 pandemic.

To this end, we use a simple homogeneous mixing agent version of the SIR model (Kermack and McKendrick, 1927).[11] SIR models are relatively tractable and remain an important tool in epidemiological analysis (Hethcote, 2000), including the current epidemic (Verity et al., 2020; Fox et al., 2020; Kucharski et al., 2020; Giordano et al., 2020). In our model, we allow for time-dependent frequency of contacts to capture the effect of individual behavioral changes or containment policies (Maier and Brockmann, 2020), as this improves fit (Fernández-Villaverde and Jones, 2020). We then evaluate how the main predictions change when the model is estimated using different death counts as outlined above.

4.1 Model setup

Our model is based on Fernández-Villaverde and Jones (2020).[12] The model considers an initial uniform population of mass P_0.[13] Assume the time period to be one day. After the outbreak of the epidemic, each individual of the population can be in either one of the following five states at date t: susceptible S_t, infected I_t, resolving R_t, recovered C_t, or dead D_t. Since the dead individuals are

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[11]In the classic SIR model, population is compartmentalized into three states: susceptible, infected, and recovered (also called resistant or removed).

[12]We model behavioral responses exogenously, as in Fernández-Villaverde and Jones (2020). Other recent studies have attempted to endogenize behavior in an optimizing environment where adjustment occurs directly at the contact level (Greenwood et al., 2019; Dasaratha, 2020), or indirectly through decisions of consumption and production (Eichenbaum et al., 2020; Krueger et al., 2020; Acemoglu et al., 2020). For simplicity, we abstract from endogeneizing behavior, although our model could be extended accordingly.

[13]Acemoglu et al. (2020) considers heterogeneity of the population across age groups. It would be straight-forward to extend our model in this way as well.

removed from the population, at every point in time the total population P_t equals:

$$P_t = S_t + R_t + I_t + C_t$$

We assume that an infection occurs when a susceptible person enters in contact with an infected person at a rate of $\beta_t I_t / P_t$, where β_t represents the number of random contacts a susceptible person has with the rest of the population and is assumed to change with t to capture behavioral responses to the disease.

The system evolves according to:

$$
\begin{aligned}
S_{t+1} &= S_t - \beta_t S_t I_t / P_t + C_t \\
I_{t+1} &= I_t - \beta_t S_t I_t / P_t - \gamma I_t \\
R_{t+1} &= R_t - \gamma I_t - \theta R_t \\
D_{t+1} &= D_t + \delta \theta R_t \\
C_{t+1} &= C_t + (1 - \delta)\theta R_t
\end{aligned}
$$

where the parameter γ captures the rate at which infected agents start recovering and cease to be infectious, and θ is the rate at which recovering agents resolve the disease, where a fraction δ dies while the remaining $(1 - \delta)$ recovers and acquires immunity. The epidemic begins with an initial (exogenous) mass of infections I_0. Once contagion starts spreading, we allow for time-dependent frequency of contacts, either due to individual behavior changes or public containment policies, according to:

$$\beta_t = \beta^{final} + (\beta^{init} - \beta^{final})e^{-\lambda t}$$

where β^{init} is the initial contact rate across agents that converges at a period rate of λ to a β^{final} rate of contact. Note that the model implies a basic reproduction number of $R^{init} = \beta^{init}/\gamma$ when $t = 0$, which converges to $R^{final} = \beta^{final}/\gamma$ as $t \to \infty$.

The model is then characterized by seven parameters: $\{\gamma, \theta, \delta, \lambda, \beta^{init}, \beta^{final}, I_0\}$. We take the first three parameters from epidemiological estimates in the literature and estimate the remaining four parameters which we denote by $\Phi \equiv \{\lambda, \beta^{init}, \beta^{final}, I_0\}$. We take $\gamma = 0.2$, meaning individuals

are infectious on average for 5 days; $\theta = 0.1$, meaning that it takes on average 15 days for the infection to resolve; and $\delta = 0.008$, which is the case fatality rate (Bar-On et al., 2020).[14] We fix P_0 to be the initial population of each country and assume that $C_0 = D_0 = R_0 = 0$, that is, at the start of the outbreak there are no fully recovered, dead, or recovering agents. Period $t = 0$ is assumed to be the first day when the official total case count of SARs-CoV-2 reaches more than 150 individuals.

Estimates for Φ are then generated by solving

$$\widehat{\Phi} = \arg \min_{\Phi} \left\{ \frac{1}{T} \sum_{t=\underline{t}}^{\bar{t}} \left(\log D_t - \log D_t \left(\Phi \right) \right)^2 \right\} \tag{2}$$

using a global minimizer where the death series $D_t \left(\Phi \right)$ is generated by solving numerically the system of equations outlined above for a parameter choice of Φ.

We define D_t^k as the deaths that occurred at time t and were reported up to k days afterward, in line with the data setup used above. With a slight abuse of notation, we define D_t^0 as the deaths that were reported on date t, regardless of when they occurred. Hence, since $D_t^0 \neq D_t^k, \quad \forall k > 0$ due to reporting delays, the model estimates $\widehat{\Phi}$ may change whether one uses deaths by reporting date D_t^0 (to $\widehat{\Phi}^0$) or deaths by date of occurrence D_t^k (to $\widehat{\Phi}^k$). We additionally present estimates of the model in a hypothetical scenario in which delays are fourteen days shorter than observed, by taking the difference between cumulative occurred deaths at time t and at time $t - 1$ as reported at time $t + 14$ and $t + 13$, respectively.
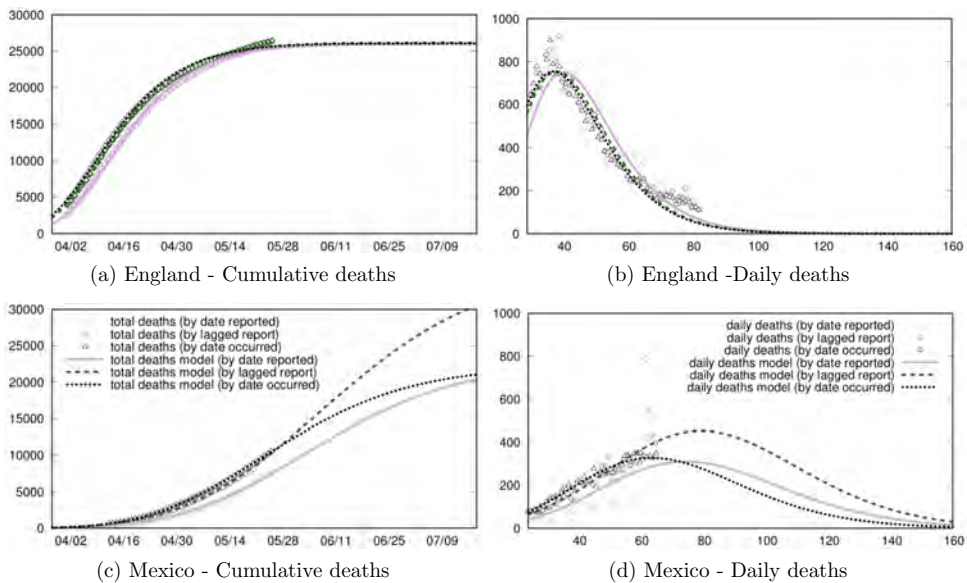
4.2 Model estimates

We estimate the model by solving equation 2 using the data for England and Mexico, considering $k = 14$ as before. The dynamics corresponding to the estimation results of this procedure are shown graphically in Figure 6, with the parameter estimates presented in Table 1.

We find that, for England, the differences in predictions when using deaths when reported, when reported with a shorter delay, and when they actually occurred are small, consistent with

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[14]This estimate is close to evidence presented in a recent sero-epidemiological national survey undertaken by the Spanish government from April 27 to May 11 to measure the incidence of SARs-CoV-2 in Spain. The report is available at https://www.ciencia.gob.es/stfls/MICINN/Ministerio/FICHEROS/ENECOVID_Informe_preliminar_cierre_primera_ronda_13Mayo2020.pdf.

the smaller average delays documented above. In contrast, the differences are striking for Mexico, where we previously found large average delays and considerable heterogeneity. Early estimates for Mexico based on reported deaths would predict a total number of deaths of about 20 thousand (after 120 days from the onset) with a peak in daily deaths of 310. However, if the delay were fourteen days shorter, these estimates change to around 31 thousand total deaths, with a peak of 453 daily deaths (occurring four days later), which implies an increase of about 50%. When using deaths by date of occurrence, the total number of deaths is not that different from the estimates from deaths by date reported, but the shape of the epidemic curve changes: the maximum number of cases is reached eleven days earlier.

Figure 6:
Model Predictions of Deaths Based on Reported vs Occurred Deaths

(a) England - Cumulative deaths

(b) England - Daily deaths

(c) Mexico - Cumulative deaths

(d) Mexico - Daily deaths

Notes: These graphs show model predictions of total (Figures 6a and 6b) and daily deaths (Figures 6c and 6d) as a result of estimating equation 2 Figures 6a and 6c correspond to England, while 6b and 6d are for Mexico. Each plot shows the model predictions from using reported deaths (not accounting for delays), the hypothetical scenario with delays that are 14 days shorter, and from using deaths by date of occurrence. To identify occurred deaths, the data exclude the last 14 days of available reports. Markers represent actual data, while lines show model predictions.

Table 1 further shows that the estimation results show a very reasonable fit of the model with respect to the data, with mean sum of square errors ranging from 0.023% to 0.031% for England, and 0.011% to 0.158% for Mexico. The superior fit when using revised data, particularly for Mexico,

accrues from the fact that daily new deaths become less lumpy when considering occurred deaths, as seen for instance in Figure 6d. Moreover, our estimates of the initial number of infected I_0 in Table 1 imply severe under-reporting of total SARs-CoV-2 cases, possibly reflecting a sluggish identification or testing of the first people who contracted the new disease (Li et al., 2020).

Table 1:
Estimates of SIR Model for England and Mexico Accounting vs Not
Accounting for Reporting Delays

	I_0	R^{init}	R^{final}	λ	Mean Sum of Square Errors	Total deaths after 120 days	Maximum daily deaths	Days until maximum daily deaths
England								
By date reported	5.9	9.71	0.517	0.095	0.00031	25,985	750	40
By date occurred	340.0	5.95	0.467	0.083	0.00024	26,053	754	37
By date reported (14 days later)	194.3	6.25	0.467	0.082	0.00023	26,158	754	38
Mexico								
By date reported	4015.1	1.77	0.627	0.017	0.00158	20,361	310	75
By date occurred	8344.3	1.77	0.627	0.021	0.00011	21,024	328	64
By date reported (14 days later)	9622.9	1.57	0.470	0.010	0.00030	30,510	453	79

Notes: This table presents the model estimates for England and Mexico corresponding to estimating equation 2. We distinguish between model predictions that use deaths by the date on which they were reported, deaths as they would have been reported if delays were fourteen days shorter, and deaths by the date on which they occurred. The first four columns correspond to the choice parameters defined by Φ. The last three columns show predictions in terms of total deaths after 120 days and the peak of the predicted epidemiological curve (number of daily deaths and days until reached).

Lastly, our results also reveal the importance of taking into consideration behavioral or containment policies when modeling epidemics, as this affects the basic reproduction number. In our estimates for Mexico, for example, the initial magnitudes of this parameter R^{init} range from 1.6 to 1.8, implying an explosive behavior of contagion, but it then swiftly converges to magnitudes that are much smaller, with R^{final} ranging from 0.5 to 0.6.

Over all, our model estimates show that, particularly for Mexico, there are large differences between predictions based on reported deaths and those based on alternative death counts that incorporate the delays. These large differences seem relevant for authorities that use these predic-

tions to manage the epidemics, especially if we believe that information on model predictions and subsequent policies affect individual behavior, which in turn impacts the spread of the disease.

5   Conclusion

This paper analyzes delays in death reports in two distinct settings. Our data analysis for England and Mexico suggests ample heterogeneity in reporting delays, particularly for Mexico, which we argue is related to lower state capacity. This heterogeneity may then complicate applying systematic corrections to the data, since a single correcting factor is unlikely to adequately capture the full variability of delays. However, failing to accurately account for delays yields drastically different model predictions, which in turn may impact policy-making and policy implementation in undesirable ways.

Ignoring reporting delays and their determinants may lead to biased estimates of demand for healthcare, such as intensive care units (Kissler et al., 2020; Li et al., 2020). Additionally, not considering these delays may give a wrong perception of the severity of the disease to the general public, potentially reducing support for containment policies or a lower adoption rate of individual protective measures. It seems thus imperious that policy-makers recognize early on the role of reporting delays as well as understanding their determinants when formulating policy and communication strategies to fight epidemics.

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Appendix for Online Publication

Supplementary Tables and Figures

Figure A1:
Average Reporting Delay Over Time by Country
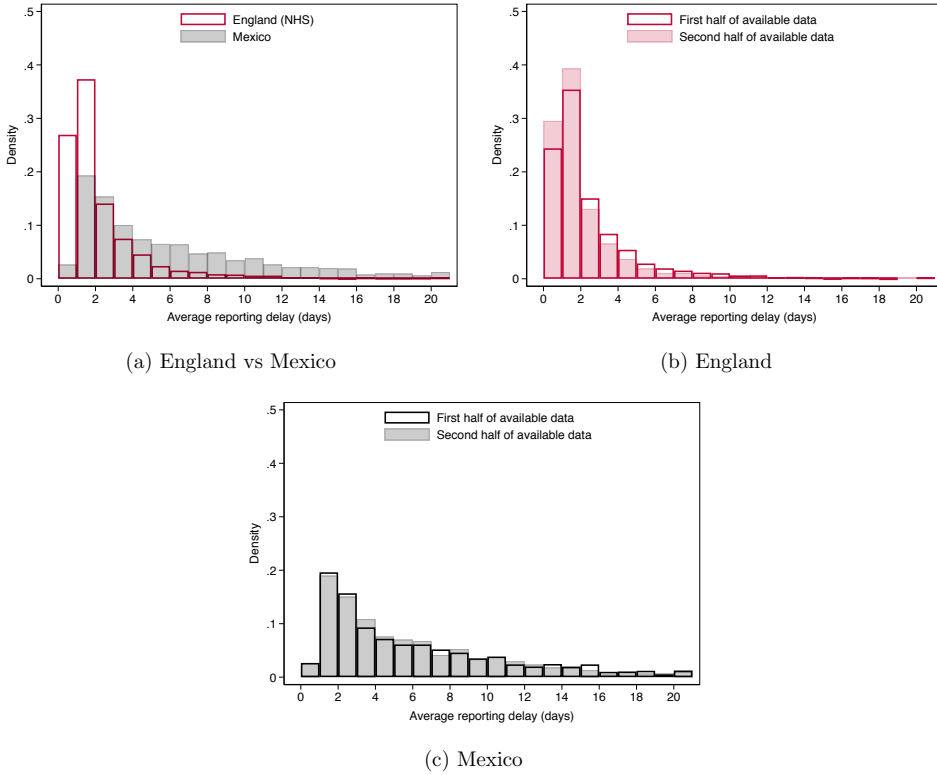
(a) England vs Mexico

(b) England

(c) Mexico

Notes: These graphs show the distribution of the average reporting delay measured in days for each country. In Figures A1b and A1c, the data are further stratified by median date of death for the available span of data. We drop the most recent 21 days of data reports, and delays that are over 21 days. In Figure A1a, the mean for England is 2.10, and 5.56 for Mexico, implying a difference of 3.46, with a 95% CI [3.30,3.62]. The mean for the first half of the data for England in Figure A1b is 2.35, and 1.86 for the second half, implying a difference of 0.49, 95% CI [0.35,0.63]. Lastly, the mean for the first half of the data in Figure A1c is 5.66, 5.47 for the second half, and a difference of 0.19, 95% CI [-0.16,0.54].

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Figure A2:
Average Reporting Delays and Healthcare Infrastructure in Mexico

(a) Healthcare units per capita

(b) Medical staff per capita

(c) Consultations per healthcare unit

(d) Share with healthcare

(e) Share without healthcare
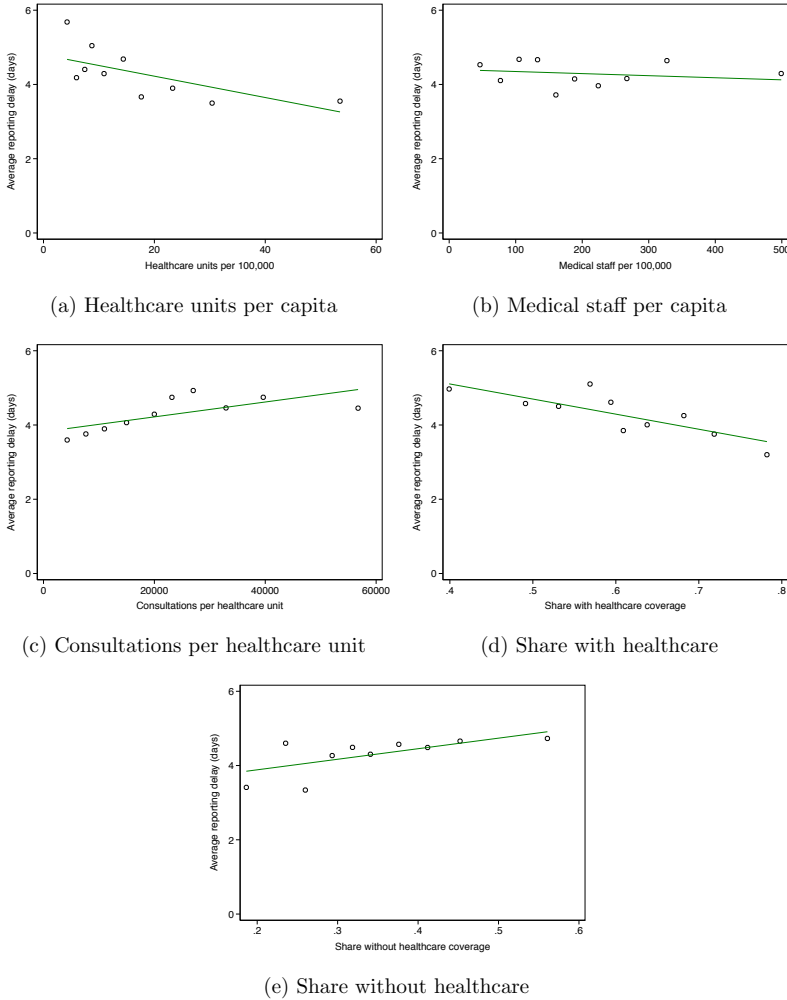
Notes: These graphs show the correlation between average reporting delays measured in days and various measures of healthcare infrastructure in Mexico. Figure A2a shows the number of healthcare units per 100,000 individuals in a municipality as measured in 2016, Figure A2b shows the number of healthcare workers per 100,000 individuals in 2016, Figure A2c shows the number of medical consultations per healthcare unit in 2016, and Figures A2d and A2e show the share of the population in a municipality with public healthcare coverage and without any coverage according to the 2010 census. Each plot shows the average over 10 bins, as well as a line of best fit. To calculate delays, we drop the most recent 14 days of data reports, and delays that are over 14 days.

Figure A3:
Relationship between Total Deaths per Capita and Reporting Delays
in Mexico

(a) $k = 14$

(b) $k = 21$
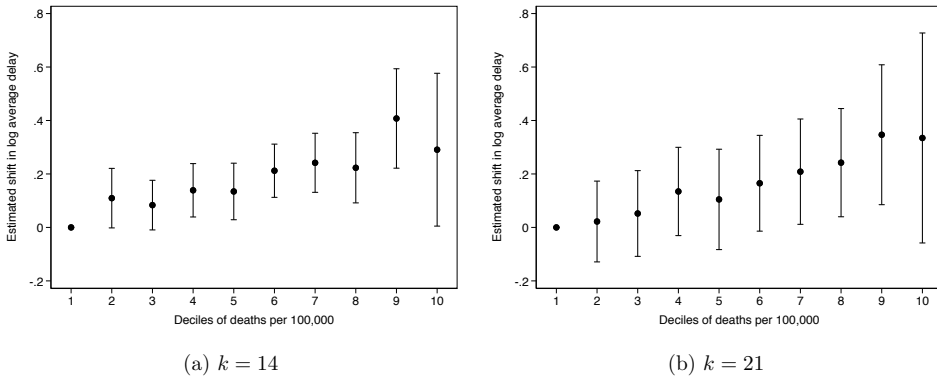
Notes: These graphs show the estimated shift in the log average delay in relation to deciles of total deaths per 100,00 people per municipality from estimating equation 1. All effects are calculated relative to the mean shift for the first decile. Figure A3a corresponds to data that exclude the last 14 days of available reports, as well as delays over 14 days (N=5991 for England, N=3660 for Mexico). Figure A3b uses 21 days instead (N=5531 for England, N=2875 for Mexico). The vertical lines indicate 95% confidence intervals from robust standard errors clustered by municipality.

Figure A4:
Location Fixed Effects and Healthcare Infrastructure in Mexico

(a) Healthcare units per capita

(b) Medical staff per capita

(c) Consultations per healthcare unit

(d) Share with healthcare

(e) Share without healthcare
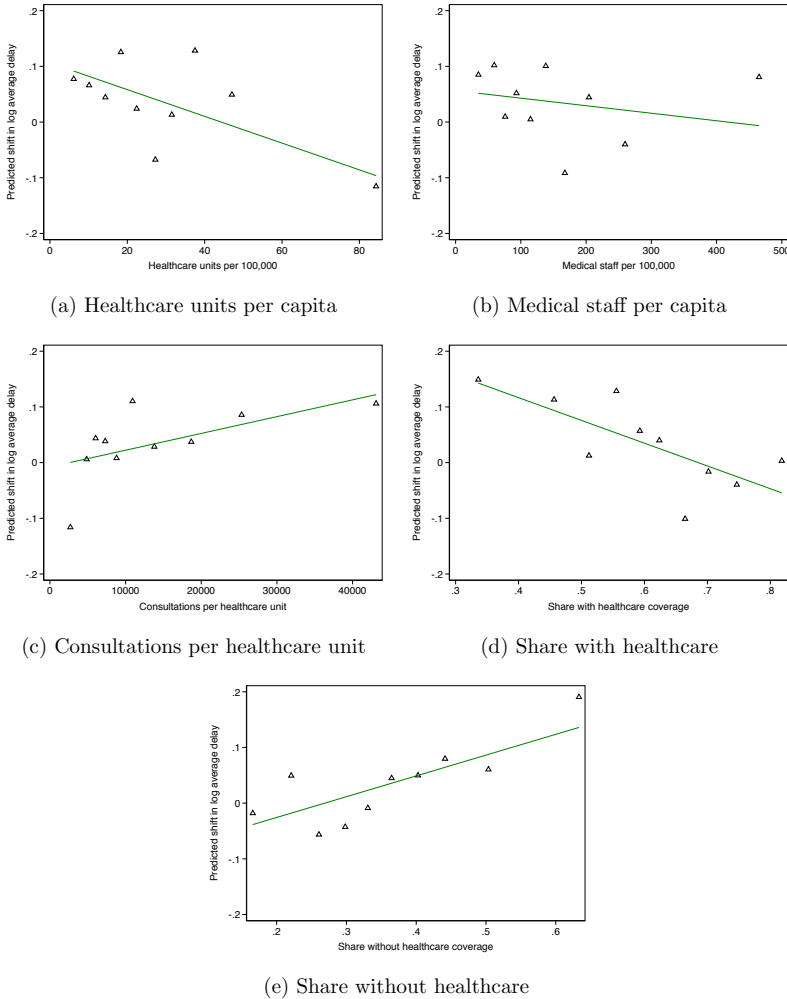
Notes: These graphs show the correlation between our estimated location (municipality) fixed effects from estimating equation 1 and various measures of healthcare infrastructure in Mexico. Figure A4a shows the number of healthcare units per 100,000 individuals in a municipality as measured in 2016, Figure A4b shows the number of healthcare workers per 100,000 individuals in 2016, Figure A4c shows the number of medical consultations per healthcare unit in 2016, and Figures A4d and A4e show the share of the population in a municipality with public healthcare coverage and without any coverage according to the 2010 census. Each plot shows the average over 10 bins, as well as a line of best fit. To calculate delays, we drop the most recent 14 days of data reports, and delays that are over 14 days.

Figure A5:
Determinants of Delays using the Inverse Hyperbolic Sine
Transformation

(a) Total deaths

(b) Location effects

(c) Time effects
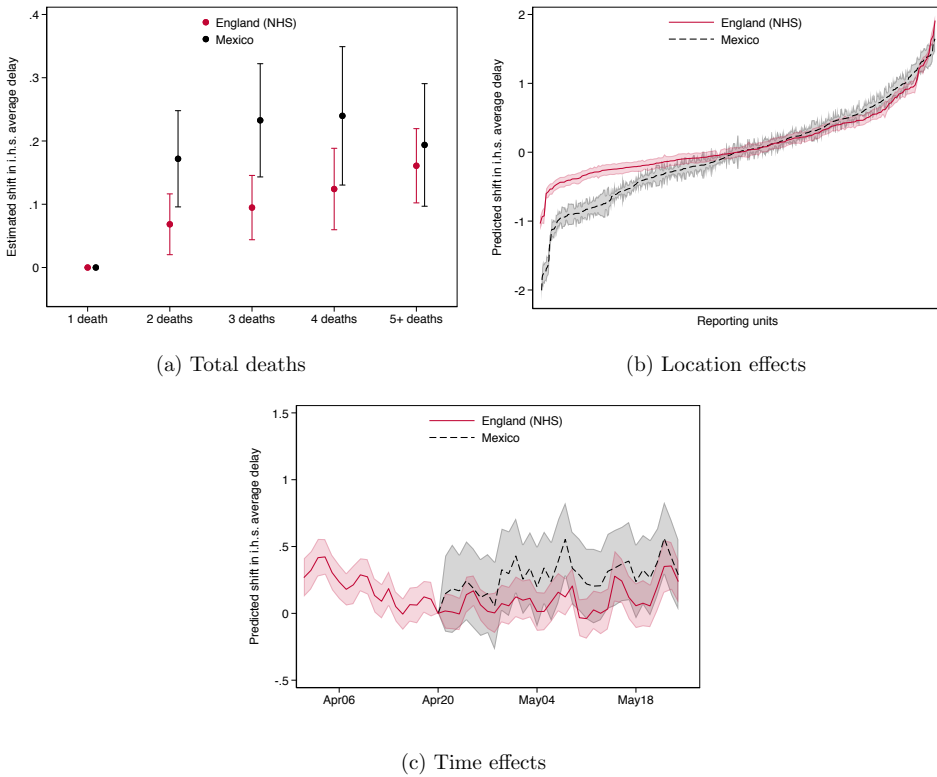
Notes: These graphs show estimates from regressions similar to equation 1, using the inverse hyperbolic sine of average delays instead of the log as in Figures 3-5. The vertical lines and shaded areas indicate 95% confidence intervals from robust standard errors clustered by reporting unit. We drop the most recent 14 days of data reports, and delays that are over 14 days.

A-5

Table A1:

Point Estimates of Relationship between Total Deaths and Average Delays

	Data: $k = 14$		Data: $k = 21$	
	(1)	(2)	(3)	(4)
Two deaths	0.056***	0.129***	0.056**	0.121***
	(0.019)	(0.031)	(0.025)	(0.038)
Three deaths	0.075***	0.173***	0.089***	0.158***
	(0.020)	(0.037)	(0.025)	(0.042)
Four deaths	0.099***	0.176***	0.103***	0.220***
	(0.025)	(0.046)	(0.030)	(0.066)
Five or more deaths	0.125***	0.136***	0.166***	0.148**
	(0.023)	(0.040)	(0.029)	(0.069)
Observations	5,991	3,660	5,531	2,875
R-squared	0.394	0.421	0.371	0.483
Sample	England	Mexico	England	Mexico
Mean dep. var.	1.74	4.29	2.10	5.56

Notes: This table presents the point estimates corresponding to categories of total deaths from estimating equation 1, as shown in Figure 3. Robust standard errors clustered by reporting unit are shown in parentheses. We report the mean average reporting delay for each sample. *** p<0.01, ** p<0.05, * p<0.1

Consumer spending responses to the Covid-19 pandemic: An assessment of Great Britain[1]

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John O.S. Wilson[4]

Since the first death in China in early January 2020, the coronavirus (Covid-19) has spread across the globe and dominated the news headlines leading to fundamental changes in the health, social and political landscape, and an unprecedented negative impact on the current and future prospects of households, businesses and the macro-economy. In this paper, we examine consumer spending responses to the onset and spread of Covid-19, and subsequent government imposed lockdown in Great Britain, GB (England, Scotland, Wales). Our sample period spans January 1st 2020 to 7th April 2020. This allows us to observe consumer spending behavior from the initial incubation phase of the crisis. We partition the sample period into incubation (1st-17th January), outbreak (January 18th-February 21st), fever (February 22nd-March 22nd), lockdown (March 23rd–May 10th 2020) and stay alert (May 11th- June 18th) phases. Using a high frequency transaction level proprietary dataset comprising 101,059 consumers and 23 million transactions made available by a financial technology company, we find that discretionary spending declines during the fever period as the government imposed lockdown becomes imminent, and continues to decline throughout the lockdown period. Shortly after the May 10th 'stay alert' announcement by Prime Minister Johnson, a short-term decline in spending across all nations occurs. However, a week later, spending is at the same level as that observed prior to the announcement. There is a strong increase

in groceries spending consistent with panic buying and stockpiling behaviour in the two weeks following the World Health Organisation (WHO) announcement describing Covid-19 as a pandemic. Variations in the level and composition of consumer spending across nations and regions (particularly during the early stages of the outbreak period), and by age, gender and income level are also observed. Our results are of particular relevance to government agencies tasked with the design, execution and monitoring economic impacts arising from the spread of the virus and the public health measures imposed to mitigate the health costs of the crisis.

1. Introduction

This study investigates the impact of the coronavirus (Covid-19) on consumer spending in Great Britain (GB). Since the first death in Wuhan, Hubei, China in early January 2020, the Covid-19 virus has spread across the globe and dominated the news headlines. The outbreak and initial spread of the virus was confined to China, but then spread through Asia, Europe and the rest of the world.[1] On March 11th 2020, the World Health Organization (WHO) declared Covid-19 as a global pandemic. By June 29th 2020, the total number of official cases exceeded 10.2 million and deaths exceeded 502,000.[2] Beyond the health and social costs, the economic damage to households, firms and the wider economy resulting from the outbreak of Covid-19 are likely to be enormous.

In this paper, we present estimates of consumer spending responses to the onset and spread of Covid-19 in Great Britain, where the first documented cases were reported in the city of York in late January 2020. The virus evolved quickly from a few isolated cases, to incidence across the country, and leading to the UK becoming one of the worst affected countries in the world. By 29th June, the number of official cases in the UK exceeded 313,000 and deaths exceeded

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[1] Unchecked the spread of Covid-19 (and indeed any virus) depends crucially on the rate of transmission across individuals, which is driven by the relative levels of: those open to contracting the virus; those currently infected by the virus; and those have contracted the virus and have either recovered or passed away. However, active public health intervention measures (non-pharmaceutical interventions, NPIs) can affect the evolution of the virus, and mitigate the negative impacts of the crisis on public health, public services and the wider economy. The public health interventions used to slow virus transmission vary across countries, and continue to evolve at the time of writing. These responses have ranged from compulsory quarantining of known cases; voluntary quarantining of households (where a member of the household) is exhibiting symptoms; social distancing and shielding of vulnerable individuals and those exceeding 70 years of age; social distancing across all age groups; and the closure of schools, universities and non-essential workplaces (Ferguson, 2020). The effectiveness of such measures in slowing the spread of the virus is still to be determined with any certainty (Agosto et al, 2020; Anderson et al, 2020; Atkenson, 2020; Ferguson, 2020; McKibbon & Fernando, 2020). However, the more extensive the public health intervention measures aimed at slowing the rate of infection are, the less significant the macroeconomic costs are likely to be (Gourinchas, 2020; Greenstone & Nigam, 2020). Koren & Peto (2020) present theory-based measures by industry and location of the extent to which US businesses rely on close human interaction human interaction, and thus which are most likely to be significantly affected by social distancing measures. In a cross-country analysis, Dingel & Neiman (2020) find that lower-income economies have a lower proportion of jobs that can be performed from home. See Cheng et al (2020) and Elgin et al (2020) for a list and an early analysis of cross country economic policy responses. A resource base of international policy response produced by the International Monetary Fund can be found at: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

[2] Officially recorded Covid-19 global cases are updated daily by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University https://coronavirus.jhu.edu/map.html.

43,500.[3] As the virus spread, the UK government and devolved administrations introduced successive public health measures aimed at curbing the spread of the virus. This culminated in late March 2020 with: enforced closures of non-essential businesses; prohibition on large gatherings; cancellations of sporting events; extensive restrictions on freedom of movement; social distancing; and isolation of vulnerable individuals. Alongside, these health measures, the UK government introduced an extensive set of fiscal support measures for households and businesses in order to mitigate lost income and ensure stability in employment for millions of workers.[4] In the medium term this is likely to have significant implications for public sector borrowing and debt (OBR, 2020). On May 10th Prime Minister Johnson announced a relaxation in lockdown measures in England (designed to begin to re-start much of the economic and social activity stalled during the lockdown period), thus shifting from a '*stay at home*' to '*stay alert*' policy stance. This change happened unexpectedly and did not apply to Scotland (Northern Ireland and Wales) where more stringent restrictions remained in place, and did not begin to ease significantly until the end of June 2020.

Observing the impact of Covid-19 and public policy interventions on consumer spending presents significant challenges given that official statistics produced by government agencies come with a lag, and as such do not provide an accurate picture of current spending.[5] For example, the *Family Spending in the UK Report* for April 2018 – March 2019 produced by the UK Office of National Statistics was published in March 2020.[6] Fortunately, recent advances in information technology and financial applications that allow consumers to manage money more efficiently have allowed the real time collection of transaction level data via supermarkets, financial institutions and technology platforms. This enables researchers to conduct more granular analysis of patterns in consumer spending and saving as they occur (Gelman et al, 2014; Pistaferri,

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[3] Year-on-year excess deaths were estimated on 2nd June at 62,000 (see for example: 'UK excess deaths during pandemic reach 62,000', Financial Times, June 2nd 2020, https://www.ft.com/content/3c53ab12-d859-4ceb-b262-f6a0221ca129). By the 23rd June this figures had increased to 65000.

[4] These measures included: short-term funding to non-financial firms (Covid Corporate Financing Facility; Coronavirus Business Interruption Loan Scheme); tax deferrals and rates holidays; employer grants (Coronavirus Job Retention Scheme) and the self-employed.

[5] Coronavirus outbreak will harm UK data collection and statistics, *Financial Times*, 2nd April 2020.

[6] In March 2020, the UK Office for National Statistics (ONS) commenced collecting new experimental indicators on the UK economy and society. These indicators are constructed from novel data sources (including small scale surveys of approximately 4000 UK businesses and 1500 individuals) and experimental methods (such as scraping on-line prices data from supermarkets and other large shops), and include information regarding Covid-19.

2015; Aladangady et al, 2019; Kolsrud, 2019). Thus improving the accuracy of empirical testing and reducing potential problems inherent in using survey or experimental data (De Nicola & Gine, 2014; Karlan & Zinman, 2008)[7] as well as providing up to date information to policymakers.

In order to assess the impact of the Covid-19 pandemic on consumer spending, we collect data from Money Dashboard. Money Dashboard is a popular personal finance application, which aggregates all transactions from linked bank accounts and credit or debit cards for users located throughout Great Britain (GB). Our sample contains 23 million transactions carried out by 101,059 individuals over the period January 1st, 2020 to June 18, 2020. This allows us to observe consumer spending responses during the period from the incubation of Covid-19 in the UK. We partition our sample period into five phases or sub-periods, which are labelled *incubation*, *outbreak*, *fever, lockdown* and *stay alert*. The *incubation* phase covers the period 1st to 17th January. *Outbreak* covers the period January 18th to February 21st. The *Fever* phase spans February 22nd to March 22nd. *Lockdown* covers the period March 23rd to May 10th when Prime Minister Johnson declared that every individual (barring non-essential workers) should stay at home (unless taking necessary exercise or trips to purchase essential food and medical items) and that non-compliance would be subject to police intervention and enforcement. *Stay Alert* covers the period since May 10th when Prime Minister Johnson announced a relaxation in lockdown measures in England (designed to begin to re-start much of the economic and social activity stalled during the lockdown period), thus shifting from a 'stay at home' to 'stay alert' policy stance. This change happened unexpectedly and did not apply to Scotland (and Northern Ireland and Wales). Consequently, there was a sudden and unexpected divergence in public policy between Westminster and other UK nations with potential implications for consumer spending behaviour.

Our analysis proceeds as follows. First, we examine total discretionary spending (defined as the sum of spending in categories such as groceries, dining and drinking, alcohol, gambling, games and gaming, and other related items, which individuals can influence directly) at: GB level; nation level (England, Scotland and Wales); and regional level (East Midlands, East of England, London, North East, North West, Scotland, South East, South West, Wales). Second, we analyse specific spending categories such as groceries spending and going-out (dining and drinking)

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[7] Data is produced by financial service providers such as mint.com (US), Money Dashboard (UK) or Meniga (Iceland). Notable examples of recent papers using this type of data include Baker (2014), Gelman et al. (2014), Kueng (2015), Baker et al (2018), Carlin et al. (2017), Olafsson & Pagel (2018), Gelman et al (2020).

related expenses by nation and region to better understand heterogeneities in consumer spending responses across different locations.

By way of preview, our findings suggest at GB level, discretionary spending remains relatively stable throughout the *incubation, outbreak* and most of the *fever* phases of our sample period. As the government imposed lockdown becomes imminent, discretionary spending declines markedly. This decline continues throughout the *lockdown* period. Shortly after the May 10th 'stay alert' announcement by Prime Minister Johnson, a short-term decline in spending across all nations occurs. However, a week later, spending is on the same level as before the announcement. By spending category, there is a strong increase in groceries spending for the two weeks following the announcement of Covid-19 as a pandemic by WHO. This is consistent with panic-buying and stockpiling behaviour reported widely by UK media outlets.[8] Grocery spending declines considerably at the onset of the *lockdown* period. Spending on dining and drinking increases during the *outbreak* and early weeks of the *fever* period before declining (with the exception of a slight increase around the time of the government lockdown announcement). Moreover, we observe some variation in consumer spending responses across nations. For example, consumers based in Scotland appear to adjust spending more markedly during the early stages of the *outbreak* period. Spending on groceries remains significantly higher throughout the *lockdown* and remains so even after the *stay alert* announcement. These consumers also appear to reduce spending on dining and drinking before counterparts located in England and Wales. Interestingly, the week before *lockdown* shows the lowest values of dining and drinking expenses. Throughout the *lockdown* and *stay alert* period spending remains stable at around £50 in England and around £45 per week in Scotland and Wales. At regional level, we observe stark differences in discretionary spending between the *incubation* and *fever* period, with consumers based in the South East, South West, and especially London reducing discretionary spending faster than counterparts located in other regions. We also observe differences in groceries spending growth with individuals located in Scotland and the East Midlands appearing to spend more between the *incubation* and *fever* period, which could be indicative of early stockpiling. Utilising additional information regarding gender, age and income levels of the individuals in our sample, we find that males spend significantly more than females. Younger individuals spend more than older counterparts. High income individuals spend more that low income counterparts. A key

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[8] See for example: 'Coronavirus: Supermarkets ask shoppers to be 'considerate' and stop stockpiling', BBC News, 15th March 2020, https://www.bbc.co.uk/news/business-51883440; 'Supermarkets take measures to control panic buying', Financial Times, 18th March 2020, https://www.ft.com/content/737a9a24-68ea-11ea-a3c9-1fe6fedcca75; and 'How panic buying is affecting supermarkets', Economist, 21st March 2020, https://www.economist.com/britain/2020/03/21/how-panic-buying-is-affecting-supermarkets.

difference when considering spending reactions is the observation that older individuals appear to keep increasing dining and drinking expenditure until week nine of our sample period, while younger individuals exhibit declines in this form of spending in week seven. Females increase spending on dining and drinking related items up to week nine, while males show little increase during the first weeks of the *fever* period.

Overall, our results suggest that consumer spending has declined since the onset of the Covid-19 outbreak. As such our results offer real-time insights on consumer responses to the onset and spread of Covid-19, and on the impacts of the compulsory *Lockdown* policy introduced by the UK government in late March 2020 (which imposed significant restrictions on the movement and activities of individuals) and later *Stay Alert* policy introduced in mid May 2020 (which commenced a partial relaxation of the mobility and activity restrictions introduced at the time of *Lockdown*). Consequently, we augment and complement recent studies utilising official UK government data, where estimates suggest that the outbreak and spread of Covid-19 is having significant (albeit uneven) economic and social impacts on UK households, businesses and the wider economy (ONS, 2020a, 2020b; OBR, 2020).

Our study contributes to the general literature on consumer spending. This literature suggests that consumers respond to negative shocks by reducing spending. Prior evidence suggest that such declines occur due to the onset of increased uncertainty, financial constraints or declining expectations regarding future income prospects (Baker & Yannelis, 2017; Baker, 2018; Gelman et al., 2020; Garmaise et al., 2020). The structure of our dataset and our study is closest in spirit to several recent studies (reviewed in further detail in section 2 below) that take advantage of large transaction level datasets to examine the impacts of Covid 19 on consumer spending behaviour. These include: Andersen et al (2020a) who find significant declines in Danish consumer spending that varies across product categories and correlates with government imposed restrictions on consumer mobility; and Baker et al (2020a) who find that significant changes in US consumer spending across a broad change of product categories, which differs by age, gender and family structure. In contrast to the dataset used in the present study and (by Andersen et al, 2020a; Baker et al, 2020b), Chen et al (2020), Carvalho, Garcia et al (2020) and Carvalho (2020) rely on merchants' transactions and do not have access to the detailed demographic information on individuals executing transactions. Using these datasets, Chen et al (2020), Carvalho, Garcia et al (2020) and Carvalho et al (2020) find significant changes in Chinese, Spanish and Portuguese consumer spending following a government imposed lockdown limiting individual movement.

The results of our study are broadly in line with the aforementioned studies and suggest that the onset and spread of Covid-19 led to overall declines in consumer spending, but this masks differences across product category. Spending declines across many product categories is undoubtedly impacted by impending and actual restrictions on consumer mobility. Dining and drinking being very notable examples. However, in other product categories such as groceries spending we observe very strong increases in spending as the incidence of Covid-19 cases increases and a government imposed lockdown becomes imminent. By utilising our granular regional data, we also find that strong differences seem to appear between rural and urban areas within GB. Our data covering London suggests that in some categories individuals were quick to change their spending patterns.

We also contribute to the established literature on the economic impacts of pandemics as well as the emergent literature on the economic impacts of Covid-19. This rapidly growing literature (which is reviewed in Section 2) suggests that epidemics impose substantial costs to the real economy, which vary substantially across households, firms, industries and countries. The results produced in this study suggest that Covid-19 has negatively impacted average consumer spending. However, this decline masks variations across product categories, as well as the location, gender, age and income levels of consumers.

The rest of the paper is structured as follows. Section 2 provide a review of relevant literature which explores the impact of pandemics (with a specific focus on Covid-19) on stock markets, businesses, households as well as the wider macro-economy. In section 3 we discuss our sample period (and constituent sub-periods or phases) and data sources. We also present summary information on consumer spending by month and by demographic (income, age, gender) attributes. We also present the results of a descriptive empirical analysis of discretionary consumer spending at aggregate and product level at GB, nation and regional level as well as by gender, income and age. Section 4 provides concluding remarks where we provide a summary of key findings, caveats regarding the composition of the dataset and avenues where further research is urgently required.

2. Literature

In this section we provide a brief overview of literature regarding the impact of epidemics on economics outcomes. We also provide a selective review of recent studies that provide useful evidence regarding the initial impacts of the Covid-19 pandemic on businesses, stock markets, households and the macroeconomy.

Prior Epidemics

Prior literature suggests that epidemics such as the Spanish Flu (Almond, 2006; Garret, 2008; Karlsson et al., 2014; Guimbeau et al, 2020), avian influenza (Bruns et al, 2006), SARS (Chou et al, 2004; Hiu et al, 2004; Lee & McKibbin, 2005; Liu et al, 2005; Brahmbhatt & Dutta, 2008; Keogh-Brown et al, 2008), swine flu (Rassy & Smith, 2013) and Ebola (Kostova et al, 2004) impose substantial costs on the real economy.[9] The extent of these costs varies considerably, and depends upon the extent and timing of public health interventions (Meltzer et al., 1999; Brainerd & Siegler, 2003; Bootsma, & Ferguson 2007; Karlsson et al., 2014; Correia et al., 2020).[10]

Macroeconomic Evidence

Early evidence suggests that Covid-19 is likely to transfer significant costs to the global economy due to disruptions to global supply chains, and temporary and permanent closures of businesses with resultant negative consequences for output and employment (Fornaro & Wolfe. 2020; OECD, 2020).[11] The overall negative impact on the economy is likely to depend on the extent of government investments in healthcare, particularly in less developed countries (McKibbon & Fernando, 2020a, 2020b). Barro et al (2020) utilise data from the Spanish Flu pandemic to estimate the potential impacts of the Covid-19 virus on economic activity. Based upon the two percent death rate observed during the Spanish Flu pandemic, the authors suggest that this would equate to 150 million deaths arising from Covid-19. If realised, such a death rate would result in global GDP and consumption declines of six and eight percent respectively. Fernandes (2020) contends the economic structure and industry composition will lead to a differential impact across countries, with more service-oriented economies likely to be most affected. Stock market volatility, newspaper-based coverage of economic uncertainty, and subjective uncertainty in business expectation surveys have all increased markedly following the onset of Covid-19 (Baker et al., 2020b; Leduc & Liu, 2020). Using these aforementioned measures of uncertainty, Baker et al (2020b) estimate the likely impact of Covid-19 on the macro-economy. The authors estimate a decline in real US GDP of approximately 11 percent by the final quarter of 2020.

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[9] Jorda et al (2020) provide a useful discussion of the long-run economic consequences of pandemics from the Black Death of 1347 to the present day.

[10] Bloom & Canning (2006, 2014), Bloom et al (2018) and Fan et al (2017, 2018) provide useful overviews of the links between population health and economic outcomes.

[11] Baldwin & Weder di Mauro (2020a, 2020b) and Baldwin & Evenett (2020) provide a collection of essay from leading economists regarding the likely impacts of Covid-19 on trade, finance, travel and monetary policy among others.

Impact on Businesses

Recent surveys suggest that business uncertainty has increased dramatically since the onset and spread of Covid-19 (Altig et al, 2020). Hassan et al (2020) develop text-based measures of the costs, benefits, and risks to listed firms in over 80 countries affected by Covid-19. The authors find that as Covid-19 spreads across countries during the first quarter of 2020, firms expressed significant concerns regarding a collapse in demand, heightened uncertainty and disruptions to supply chains and detriment to employee welfare. Firms operating in locations impacted previously by SARS or H1N1 (swine flu) expressed greater confidence in their likely ability to absorb the negative impacts of Covid-19. De Vito and Gomez (2020) investigate via a series of scenarios, the likely impact of Covid-19 on the liquidity of listed firms across 26 countries. The authors assess the extent to which firms' liquidity can withstand a decline in sales of 25%, 50% and 75%. They find that in the most extreme case (where sales decline by 75%), the average firm would exhaust liquidity in approximately 12 months - with around a third of firms becoming illiquid in less than six months.[12] Bartik et al (2020) in a survey of 5800 US small and medium sized enterprises (SMEs) find that 43 percent were temporarily closed with a resultant decline in employment of 40 percent. Campello et al (2020) find that Covid-19 had a negative and varied impact on new hiring across firms, industries and locations. Reductions were most pronounced for: high skilled jobs; unionized and service sectors; and areas where low-incomes and income inequality were more prevalent. Bloom et al (2020) contend that Covid-19 will cause many industries to shrink as businesses cease trading. The authors also point out that Covid-19 will also lead to an intra- and inter-industry re-allocation of demand and employment. Landier and Thesmar (2020) find that earnings analysts expect the Covid-19 virus outbreak to have a significant and long-lasting impact on firm earnings.

In the UK, an ONS survey of businesses suggests that 24% had temporarily ceased trading (for the period 6 to 19 April 2020). Of businesses continuing to trade, 24% of all businesses continuing to trade reported that turnover had decreased by more than 50%, while 30% reported that their financial performance had been unaffected (ONS, 2020a). A study by the British Chamber of Commerce (2020) suggests that 66% of firms have furloughed staff. Prasher et al (2020) compare business incorporations and dissolutions in the early part of 2020, with the same period in 2019, in order to provide initial insights as to the possible impacts of Covid-19. The authors find a 70% increase in the dissolutions in March 2020 relative to March 2019. Younger

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[12] Li et al (2020) note that upon the onset of COVID-19, liquidity pressures led US firms to drawdown pre-existing credit lines and loan commitments on an unprecedented scale.

businesses as well as businesses in the wholesale and retail, professional services, transport and construction are particularly affected. Joyce and Xu (2020) find that the impact of lockdown measures and enforced closures of non-essential business are likely to disproportionately affect employees under 25; low earners; and women.[13] Lenoël & Young (2020) find that public policy interventions to limit the spread of Covid-19 are causing a severe contraction in the UK economy, with forecasts suggesting a GDP decline of seven per cent in 2020. Ogden and Phillips (2020) note that demographic and structural differences within the UK make some geographic areas more vulnerable than other to the economic, health and social impacts of the Covid-19 crisis.

Stock market Responses

Stock markets have responded to the spread of Covid-19 as investors have adjusted expectations regarding future corporate earnings. Baker et al (2020c) note that news coverage of Covid-19 is the most significant driver of large daily US stock market movements since the end of February 2020. Ramelli & Wagner (2020a, 2020b) assess stock market reactions to Covid-19. The authors partition their sample period into *incubation* (1st-17th January), *outbreak* (20th January - February 21st), and *fever* (February 24th - March 20th) sub-periods. They find that the overall stock price reaction varies by the extent of international trade exposure; firms with global value chains experiencing larger declines in value. Firms with high levels of debt also experience marked declines in value. Industry factors also played an important role, with firms located in telecommunications and food retailing experiencing increases in value for much of the sample period. However, the authors note that during the *fever* period most stocks decline as investors anticipated an economic recession. For the US, Albuquerque et al (2020) compare the returns of firms with higher environmental and social (ES) ratings compared to other firms. The authors show that the stocks of firms with higher ES ratings have significantly higher returns, lower return volatilities and higher trading volumes than stocks of firms with lower ES ratings. Gormsen & Koijen (2020) examine aggregate movements in the US S&P500 and the EU Euro Stoxx 50 index since the outbreak of Covid-19. The authors find that stock markets declined sharply as the virus spread to Italy, South Korea, and Iran around February 20th, and later in March upon announcements of travels restrictions by the US and successive EU member states. Alfaro et al (2020) find that day-to-day changes in forecasts of infectious disease during the SARS epidemic (in Hong Kong) and the Covid-19 pandemic (in the US) lead to significant changes in aggregate

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[13] Similarly, for the US, Alon et al (2020) suggest that employment losses arising from social distancing interventions has a larger impact on sectors with higher female employment shares.

stock returns. For the UK covering the period 2nd January to 20th March, Griffith et al (2020) examine changes in share prices of listed firms (relative to the FTSE All-Share index). They find that firms located in tourism and leisure, fossil fuels production and distribution, insurance, non-food and non-drug retailers and several large manufacturing industries saw the largest declines in value, while food and drug manufacturers, food retailers, utilities, high tech manufacturing and tobacco firms outperformed the market. Ding et al (2020) use a large cross-country, cross-industry dataset to investigate the relationship between corporate balance sheet characteristics and stock prices following the spread of Covid-19 cases. The authors find that while the spread of Covid-19 resulted in an overall decline in stock prices, the decline was less severe for firms with: stronger balance sheets; less globalised supply chains and international trade; and more CSR engagement in the pre-crisis period. Fahlenbrach et al (2020) stock price and credit risk reactions to Covid-19. The authors find that firms with less cash and more short and long-term debt perform experience larger stock price declines and large increases in credit default swap premiums. Finally, Capelle-Blancard and Desroziers (2020) provide an extensive international assessment of stock market reactions to the Covid-19 crisis. Using stock market data covering the period January to April 2020 for a sample of 74 countries (to trace investor reactions to the onset and evolution of the Covid-19 crisis) - the authors find that investor reactions to the onset of Covid-19 were initially subdued before reacting negatively as the virus spread. These negative responses were relatively short lived before prices recovered.

Impacts on Households

Evidence of household level responses to the onset of Covid-19 is emerging. Much of the evidence presented to date relies upon online surveys of consumer expectations. However, a number of important studies have emerged where researchers have used transaction level datasets made available by commercial banks, credit card companies and FinTech platforms to examine consumer spending behaviour in real time.

China

Chen, He et al (2020) assess the impact of the Wuhan, Hubei lockdown on the monthly sales of various products for sale on a major online platform in China. The authors find a significant decline in the sales of digital and electronic goods, and a significant increase in sales of groceries. Chen et al (2020) use daily transaction data in 214 cities over a 12 week period to study the impact of Covid-19 on consumption after China's outbreak in late January 2020. The authors utilise consumer spending transaction level data at offline merchants using bank cards and QR codes (captured by a large payment provider Point of Sale machines and QR scanners) to find that consumption declined by an average of 32% across Chinese cities. Spatial variation is

observed with heavily exposed cities such as Wuhan experiencing more significant declines (70%) in consumer spending.

United States

Dietrich et al (2020) assess the response of household expectations to the Covid-19 outbreak using an online survey of US consumers. From a sample of 1,600 responses, the authors find that consumers expect GDP to decline by six percent over a 12-month period and two per cent over 36 months. Binder (2020) conducts an online survey on US consumers on 5th and 6th March 2020, to solicit information regarding concerns and responses to the Covid-19 virus. The results of the survey suggest that consumers are *somewhat* or *very concerned* regarding the effects of coronavirus on their financial and personal well-being as well as the wider economy. Of the consumers surveyed, 28% postponed travel, while 40% had purchased additional food supplies. Armantier et al (2020a, b) utilise the March and April 2020 *Survey of Consumer Expectations (SCE)* to find that between February and April 2020, the median expected year-ahead forecast of growth in income and spending declined dramatically across all genders, age groups, income level, race, and education level. Using US survey data collected on March 24th 2020, Adams-Prassl et al (2020a) find that 65% of workers engaged in less paid work, and expected to earn 39% less in the next four months. 11% of workers had lost employment, with a 40% chance of job loss within the next four months for those remaining employed. 56% of those surveyed reported likely problems in facing future bills. Variations are observed across both the age and income distribution with younger and lower income individuals most affected. Baker et al (2020a) use transaction-level household financial data from a personal financial website to examine US consumer spending responses to the onset of the Covid-19. The authors observe a substantial increase in consumer spending (transactions increasing by 15%; average transaction value by 50%) as the rate of increases in Covid-19 cases increases, followed by a significant decline in general spending. Spending on grocery items remains at a higher level over a longer time period before declining. The authors also observe heterogeneity in spending responses across states (depending on the severity of the virus outbreak) the age distribution and structure of the family unit. Building upon this Baker et al (2020d) investigate consumer spending responses to US government direct cash payments to households which form part of the fiscal stimulus measures set out in the 2020 CARES Act. They find that households respond to the receipt of direct payments; those on lower incomes and experiencing larger income declines responding most strongly. Consumers with higher bank account balances do not appear to adjust consumption following the receipt of a direct payment. Coibion et al (2020) investigate how the varied timing of local lockdowns affects households' spending using several waves of a survey exceeding 10,000 respondents. The authors find significant declines in aggregate consumer spending. Very large

declines are observed in travel and clothing sectors. They also observe that households under lockdown spend less than other households due to mobility restrictions and expectations regarding future economic conditions. Finally, Chetty et al (2020) examine weekly consumer spending disaggregated by geographic area, industry, and income group. The authors find that following the spread of Covid-19, high-income individuals reduced spending. These declines were particularly marked in geographic areas with high numbers of reported Covid-19 cases and in industry sectors where physical proximity is required. The authors also find a positive impact of government stimulus payments on consumer spending of low-income households.

Denmark

For Denmark, Andersen et al (2020a) use transaction-level bank account data from a large Danish bank to find a decline in spending following the onset of the Covid-19 virus, which varies across expenditure categories and correlates with government restrictions. Specifically, the authors find that that aggregate card spending declined by approximately 25% following the government shutdown. Moreover, the observed decline in spending is more concentrated on product categories where trading is restricted under the terms of the government shutdown. Andersen et al (2020b) utilise transaction-level bank account data from a large Scandinavian bank to study the effect of government social distancing laws on consumer spending. In order to disentangle the possible effects on consumer spending due to fears regarding the virus from the impact of the lockdown measures, the authors design a quasi-natural experiment. Specifically, they compare consumer spending patterns in Denmark where the government mandated social distancing (in order to reduce the spread of Covid-19) and Sweden where a lockdown was not imposed. The authors find that at the time of the lockdown announcement in Denmark, there is a large decline in consumer spending across both countries. The overall decline in consumer spending comprised a common 25 percent to both countries, and an additional decline of 4 percentage points in Denmark. The observed declines were most significant across younger consumers (below 29 years of age). The authors conclude that the most significant declines in consumer spending arise not from government imposed interventions, but rather the virus spread impacting consumer choices on discretionary spending.

France

For France, Bounie et al (2020) utilise data on five billion payment card transactions from 70 million cards issued by all banks in France. The sample period is split into two sub-periods covering the time before and during the containment measures imposed by the French government. The authors find that consumers used their cards in less locations and across a small number of retailers following the imposition of containment. Both off- and on-line consumer spending declined, with the former experiencing twice the decline of the latter.

Portugal

For Portugal, Carvalho, Gaercia et al (2020) use a large point of sale terminal and on-line payments dataset, in order to investigate the impact of a government imposed lockdown on consumer purchases. Using a difference-in-differences event study approach (which compares purchases from January to April 2020 with purchases for the same period of 2018 and 2019), the authors observe a significant overall decline in spending. However, changes in the patterns of purchases varies across product types with groceries spending increasing, while spending on products and services most affected by the lockdown (leisure, bars, restaurants) declined.

Spain

For Spain, Carvalho et al (2020) utilise a large high-frequency transaction data from a large commercial bank to investigate consumer expenditure during the Covid-19 pandemic. The authors find no significant change in consumer spending patterns prior to the lockdown measures. However, following the lockdown, large overall spending declines are observed, albeit significant variation exists across product categories with expenditures on drinking and dining, clothing and personal services exhibiting large declines, while food expenditure increased.

United Kingdom

For the UK, Crawford et al (2020) use the *ONS Living Costs and Food Survey, 2017* in order to predict which types of spending are likely to be most affected by the spread of Covid-19 and social distancing measures. The authors assert lower-income households find it more difficult to absorb income shocks and adjust relative to higher-income counterparts, given that these households spend a greater proportion of their income on essential items. Spending in higher income households are likely to decline more for areas (such as restaurant dining and drinking) prohibited or discouraged as a consequence of public health interventions. An ONS survey of UK households suggests that the well-being (82%) and household finances (22.9%) was negatively affected by the Covid-19 virus (ONS, 2020b). Using UK survey data collected on March 25th 2020, Adams-Prassl et al (2020b) find that 57% of workers engaged in less paid work, and expected to earn 35% less in the next four months. 8% of workers had lost employment, with a 33% chance of job loss within the next four months for those remaining employed. 49% of those surveyed reported likely problems in facing future bills. Variations are observed across both the age and income distribution with younger and lower income individuals most affected. In the remainder of this paper, we augment substantially these insights to produce the most granular and comprehensive assessment of consumer spending responses over the duration of the Covid-19 crisis and public policy interventions to date.

3. Data & Results

The empirical analysis in the present study is based on data provided by Money Dashboard, a popular personal financial technology company founded in 2010 and based in Edinburgh. Money Dashboard's application aggregates all transactions from linked bank accounts and credit or debit cards to provide users with a detailed view of how, when and where money is being spent. The service is aimed at individuals who have more than one bank account or several different credit cards. Once users sign up, Money Dashboard collects all available information from an individuals' online account. In the next step, Money Dashboard uses a machine learning algorithm to identify the type of transaction and automatically assigns each transaction to one of 270 expense and income tags. All data is anonymised prior to sharing with the authors of this study. A timestamp of the transaction and a merchant tag are also included. The user interface for the mobile and web based versions of the application are shown in Figure 1.

Figure 1: Money Dashboard Interface

Note: This figure illustrates the iOS and web interface of Money Dashboard. The example for the mobile phone interface shows the current balance across accounts and a chart summarising expenditures per category and the current status of three active budgets.

We focus our analysis on consumer spending behaviour from January 1st to April 7th 2020. We separate our analysis into fiver sub-periods comprising: *incubation* (1st-17th January), *outbreak* (20th January-February 21st), *fever* (February 24th-March 22nd), *lockdown (*March 23rd to 7th April) and *stay alert* (May 11th- June 18th). In total, there are 101,059 individual users in our sample, which can be matched to postcode level. For 98,939 of these information regarding age is available. For our analysis, we use those users where location can be identified. We are also

able to identify, the income of a large number of users (45,858). Panel A, Table 1 provides summary statistics. Panels B to D present summary statistics for spending categories including discretionary, groceries and dining and drinking for each full month covered in our analysis.

Moreover, we also separate our analyses into nine distinct regions as defined by the UK Office for National Statistics. This serves the purpose of shedding light on possible heterogeneous responses to the pandemic in terms of spending patterns across different regions of GB. Table 2 reports the regional distribution of the consumers in our sample.

Table 1: Summary Statistics

	mean	median	sd	N
Panel A: Demographics				
Income	3149.55	2339	2941.79	45,858
Age	37.33	35	11.033	98,939
Male	.6037	1	.4891	103,856
Panel B: Monthly Sums January				
Total Discretionary	867.58	594.37	1035.55	96,467
Cash	280.99	100	606.41	57,083
Dining & Drinking	129.55	81.96	150.78	79,439
Home Improvement	157.28	46.65	344.75	43,897
Fuel	105.80	79.11	94.47	51,122
Gambling	71.76	20	252.61	19,221
Groceries	267.94	186.69	261.27	83,711
Panel C: Monthly Sums February				
Total Discretionary	792.15	515.77	1037.92	87,662
Cash	271.32	100	632.44	49,049
Dining & Drinking	134.67	81.69	161.40	69,943
Home Improvement	154.56	43.50	346.09	34,950
Fuel	102.09	73.89	92.15	43,032
Gambling	70.87	20	258.31	15,784
Groceries	253.30	167.30	259.78	74,519
Panel D: Monthly Sums March				
Total Discretionary	626.41	360.84	840.49	73,510
Cash	213.15	82	444.50	33,786
Dining & Drinking	85.986	50.57	107.08	54,815
Home Improvement	147.73	45.89	308.61	25,839
Fuel	79.179	58.46	72.17	31,509
Gambling	74.070	20	287.91	11,344
Groceries	240.42	134.66	285.13	61,485
Panel E: Monthly Sums April				
Total Discretionary	620.76	395.94	750.31	41,186
Cash	243.74	70	600.47	7,323
Dining & Drinking	72.062	43	87.15	16,089
Home Improvement	163.85	64.04	296.14	11,884
Fuel	57.72	40.01	61.96	9,707
Gambling	52.09	20	188.02	8,436
Groceries	325.12	229.91	313.70	29,473
Panel F: Monthly Sums May				
Total Discretionary	638.36	411.425	754.03	36,554
Cash	237.76	80	502.52	8,694
Dining & Drinking	75.849	43.975	97.04	16,828
Home Improvement	161.81	66.65	277.12	12,281
Fuel	59.38	43.2	58.25	10,711
Gambling	60.08	20	238.13	7,197
Groceries	321.41	223.935	314.88	26,216

Note: This table provides summary statistics for a sample of 103,856 consumers. Panel A of the table summarises key demographic indicators for the 2020 sample and income levels (winsorised at the 1% of the distribution). Panel B to F provide the monthly sums by spending category in the months covering *incubation, outbreak, fever, lockdown* and *stay alert.* The complete data for June 2020 was not available at the time of writing and is therefore excluded in this version.

Table 2: Regional Sample Distribution

Region	Frequency	Percentage (%)	Cum. (%)
East Midlands	5,742	5.68	5.68
East of England	9,194	9.10	14.78
London	25,189	24.93	39.70
North East	2,497	2.47	42.18
North West	8,775	8.68	50.86
Scotland	8,233	8.15	59.01
South East	17,178	17.00	76.00
South West	8,874	8.78	84.78
Wales	3,099	3.07	87.85
West Midlands	6,225	6.16	94.01
Yorkshire and The Humber	6,053	5.99	100.00

Note: This table presents the number of users included in our sample distributed across Scotland, Wales and different regions of England as defined by the Office for National Statistics.

Discretionary spending

Figure 2 shows the evolution of total discretionary spending (measured as the sum of spending in a wide range of categories including groceries, dining and drinking, clothing, games and gambling, entertainment and other related items); groceries spending; and spending on dining and drinking at GB level over the sample period, which is partitioned into *incubation, outbreak, fever, lockdown* and *stay alert* sub-periods. Figure 3, Figures 4a – 4c and Figures 5a-5c present this information at a disaggregated national level, demographic and regional level respectively. While the general trends are similar between the GB and the individual nations, some differences occur at key points during the sample period, especially at the regional level. The following sections summarise the key trends in the total discretionary, groceries and dining and drinking spending categories at GB, individual nation and regional level.

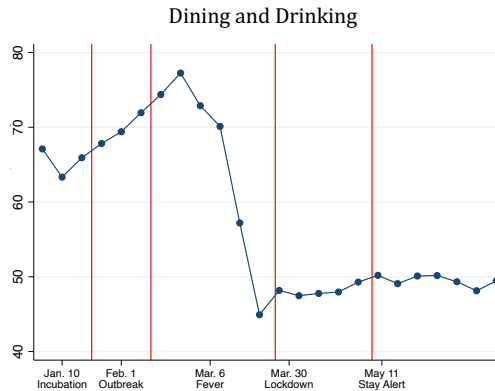**Figure 2. Average Weekly spending per category for Great Britain**

Panel A: Discretionary
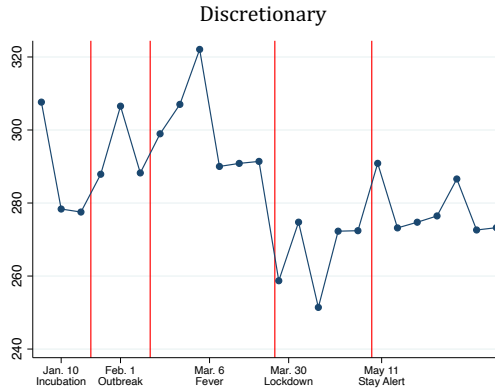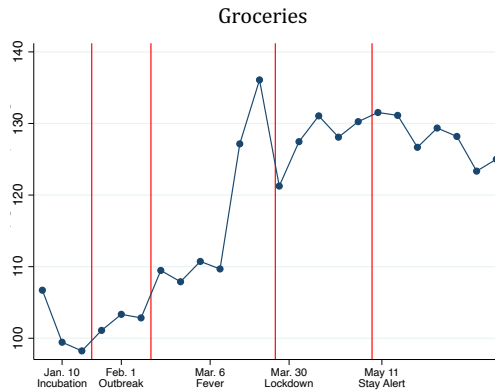
Panel B: Groceries

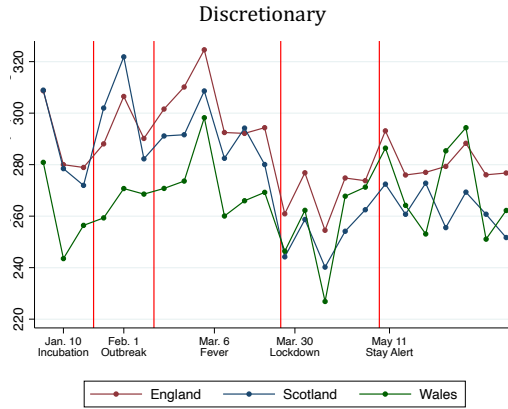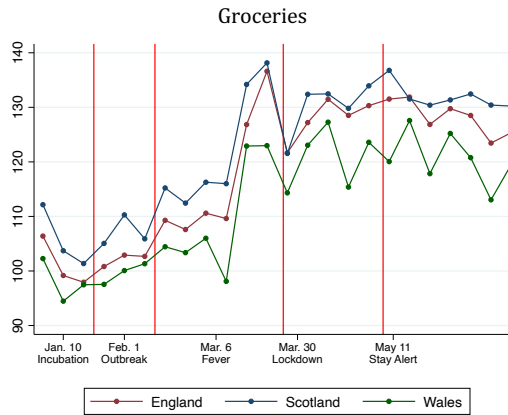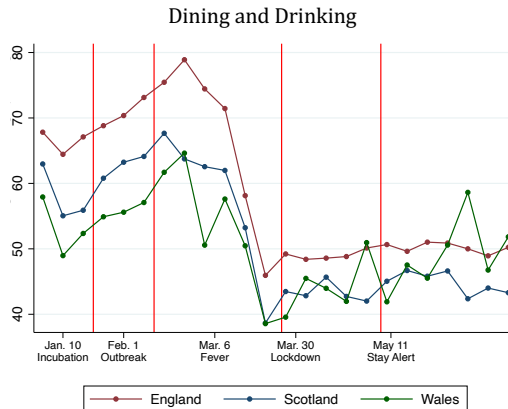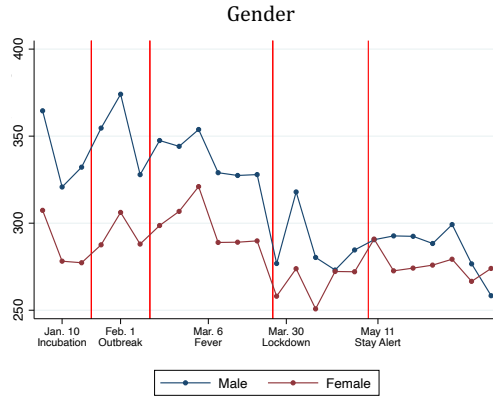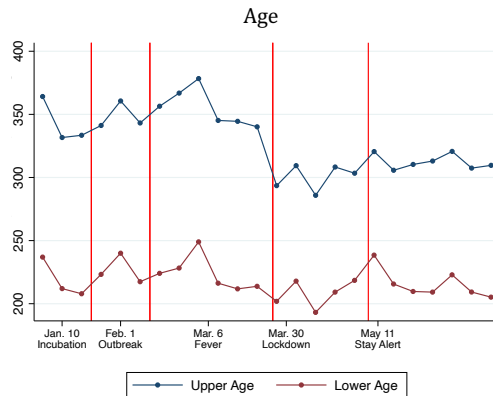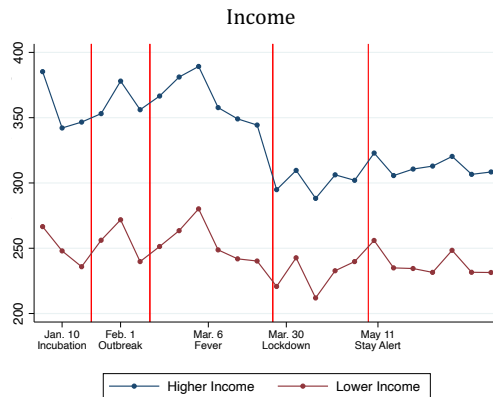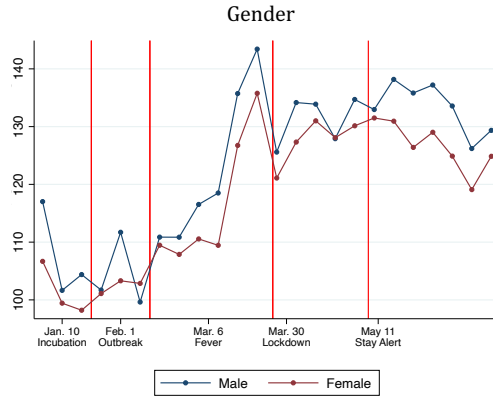Panel C: Dining and Drinking

Note: Each panel shows the weekly average spending in pounds sterling (£) per average individual for the respective expense category on the y-axis. The x-axis shows the week of the year, starting on Wednesday 1st of January. The period of analysis is separated in four phases: *incubation, outbreak*, *fever*, *lockdown* and *stay alert*.

Figure 3. Average Weekly Spending per category: Nation Level

Panel A: Discretionary

England — Scotland — Wales

Panel B: Groceries

England — Scotland — Wales

Panel C: Dining and Drinking
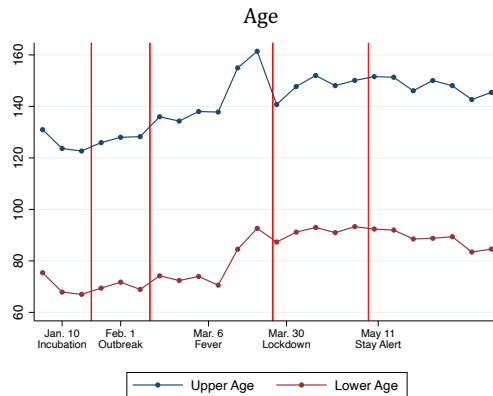

England — Scotland — Wales

Note: Each panel shows the weekly average spending in pounds sterling (£) per average individual for the respective expense category on the y-axis. Spending is separated by country - England, Scotland and Wales. The x-axis shows the week of the year, starting on Wednesday 1st of January. The period of analysis is separated in four phases: *incubation, outbreak, fever, lockdown* and *stay alert*.

Figure 4a. Average Weekly discretionary spending by gender, age and income

Panel A: Gender

Panel B: Age

Panel C: Income

Note: Each panel shows the weekly average spending in pounds sterling (£) per average individual for the respective expense category on the y-axis. Spending is separated by demographic characteristic – gender, age, income. The x-axis shows the week of the year, starting on Wednesday 1st of January. The period of analysis is separated in five phases: *incubation, outbreak, fever, lockdown* and *stay alert.* All individuals with identifiable postcodes or monthly income in Great Britain are included.

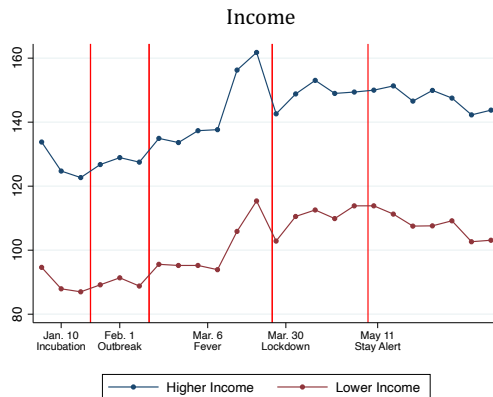**Figure 4b. Average Weekly groceries spending by gender, age and income**

Panel A: Gender

Panel B: Age
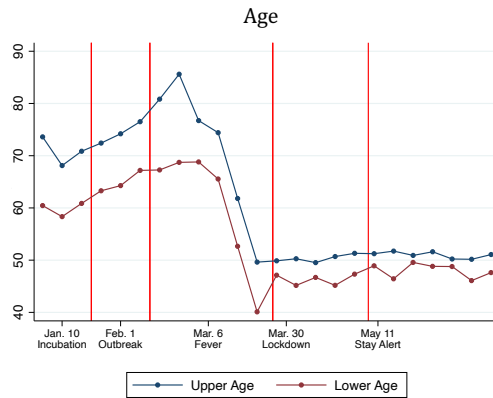
Panel C: Income

Note: Each panel shows the weekly average spending in pounds sterling (£) per average individual for the respective expense category on the y-axis. Spending is separated by demographic characteristic – gender, age, income. The x-axis shows the week of the year, starting on Wednesday 1st of January. The period of analysis is separated in five phases: *incubation, outbreak, fever*, *lockdown* and *stay alert.* All individuals with identifiable postcodes or monthly income in Great Britain are included.

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Figure 4c. Average Weekly dining and drinking spending by gender, age and income
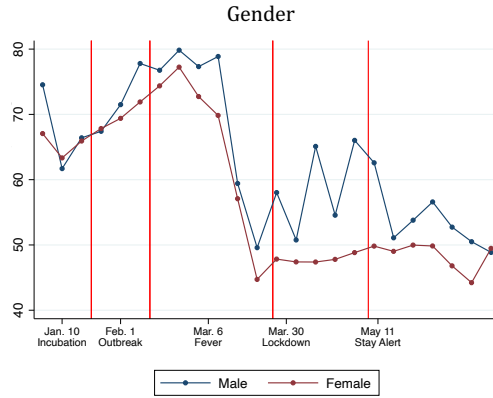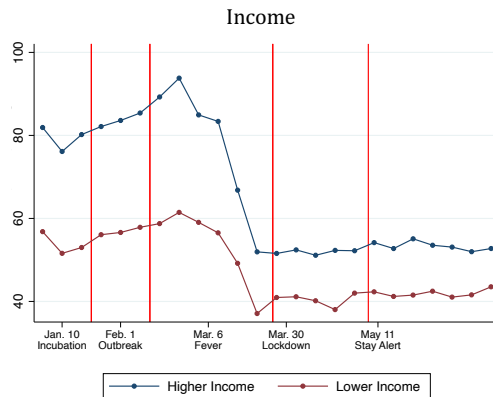
Panel A: Gender

Panel B: Age

Panel C: Income

Note: Each panel shows the weekly average spending in pounds sterling (£) per average individual for the respective expense category on the y-axis. Spending is separated by demographic characteristic – gender, age, income. The x-axis shows the week of the year, starting on Wednesday 1st of January. The period of analysis is separated in five phases: *incubation, outbreak, fever, lockdown* and *stay alert.* All individuals with identifiable postcodes or monthly income in Great Britain are included.

Panel A of Figure 2 suggests that at GB level, discretionary spending is largely flat throughout the first three (*incubation, outbreak,* fever) phases of the pandemic. The first significant change in overall discretionary spending occurs around week nine of the sample period. Here, a trend-change occurs, with average discretionary spending declining by 10.4% on a week-to-week basis (from an average of £307 to £275). This downward trend continues with declines of similar magnitudes throughout the remainder of the *fever* phase. The largest decline occurs during the first weeks of the *lockdown* phase. In the first week after *lockdown*, discretionary spending is at an all-year low average spend of £258 (a decline of 11% compared to spending in the *incubation* period) before declining further to an average spend of £251 per week in week 15. Shortly after the 'stay alert' message, average discretionary spending increases again with a high of £290 in week 18 which is nearly on the same level as pre-lockdown spending.

Discretionary spending differs significantly between demographic groups. Figure 4a illustrates differences in discretionary spending between males and females by applying a median split analysis for age (35), and monthly net income (£2,333). We find that females spend less than males in all phases. The average gap in weekly spending between males and females during the *incubation* and *outbreak* period is around £50. This spending gap decreases after female users start spending slightly more after week 9. One week before *lockdown*, spending differs by around £30. The spending gap is insignificant during *lockdown*. The spending gap is larger across younger and older individuals, ranging between £120 and £130 until the commencement of *lockdown*, after which the gap closes. In terms of changes in spending patterns, we observe very similar increases and decreases in weekly spending for both age groups. We also find very similar results, when assessing differences across income groups. The gap between age and income remains on a similar level in the *stay alert* phase. However, it appears that male and female individuals reacted differently to the announcement. While we find nearly identical levels of discretionary spending in week 18, it appears that female users reduce their spending after the announcement whereas male individuals keep spending on similarly high levels.

There are some apparent differences in the way individuals located in England, Scotland and Wales react to the Covid-19 crisis. Panel A of Figure 3 suggests that while individuals from England and Wales exhibit relatively stable spending patterns throughout the first nine weeks of the crisis, Scottish consumers appear to react more dramatically to the announcements of the first Covid-19 cases in the UK. We observe a strong significant increase in the first two weeks of the outbreak period. In week five, individuals located in Scotland spent around 10% (£323 versus £291) more than English, and 18.9% more than Welsh (GBP 262) counterparts. However, after this week, spending in Scotland is at a similar level to the other two nations. Finally, while we see

a disparity in the level of spending in the early weeks between Scotland and England on the one hand and Wales on the other hand, this difference disappears during lockdown where spending on discretionary spending is almost identical across the three nations. In terms of discretionary spending behaviour after the 'stay alert' message, we find that English residents seem to keep spending on similar levels while Scottish individuals marginally reduce their spending. Welsh individuals reduced their spending for two weeks but returned to high levels around week 22.

While the discretionary spending patterns are relatively similar at national level, larger differences occur at the regional level. Figure 5a summarises change in average weekly spending across regions between the different phases of the Covid-19 pandemic. Changes from the *incubation* to the *outbreak* phase are largely similar for all regions. All regions experience single-digit growth in discretionary spending, albeit this growth is at low levels in the South East England, South West England and Wales (of between 2% and 3%). However, when comparing the figures for changes between the *incubation* and *fever* period, stark differences occur. It appears that the South East, South West, and especially London react more quickly in terms of discretionary spending reductions than other regions (with between 2.5% and 3.2% declines in spending). Increases in discretionary spending during this phase of the pandemic are observed for East-Midlands (plus 0.8%) and Scotland (plus 1.3%) only. Figure 6 further details the differences in spending between the lockdown and stay alert phases (Panel: (a) total discretionary spending; (b) groceries; (c) dining & drinking). The results suggest, that total discretionary spending (panel (a)) increases in nearly all regions. This is also true for Scotland, which should not be affected by the stay alert announcement, which only applied to England. Nevertheless, spending on discretionary items increased by around 2.3% after this announcement.

Figure 5a. Change in weekly discretionary spending across sub-periods (*incubation* to *outbreak; incubation* to *fever*; *incubation* to *lockdown, incubation to stay alert*) by region
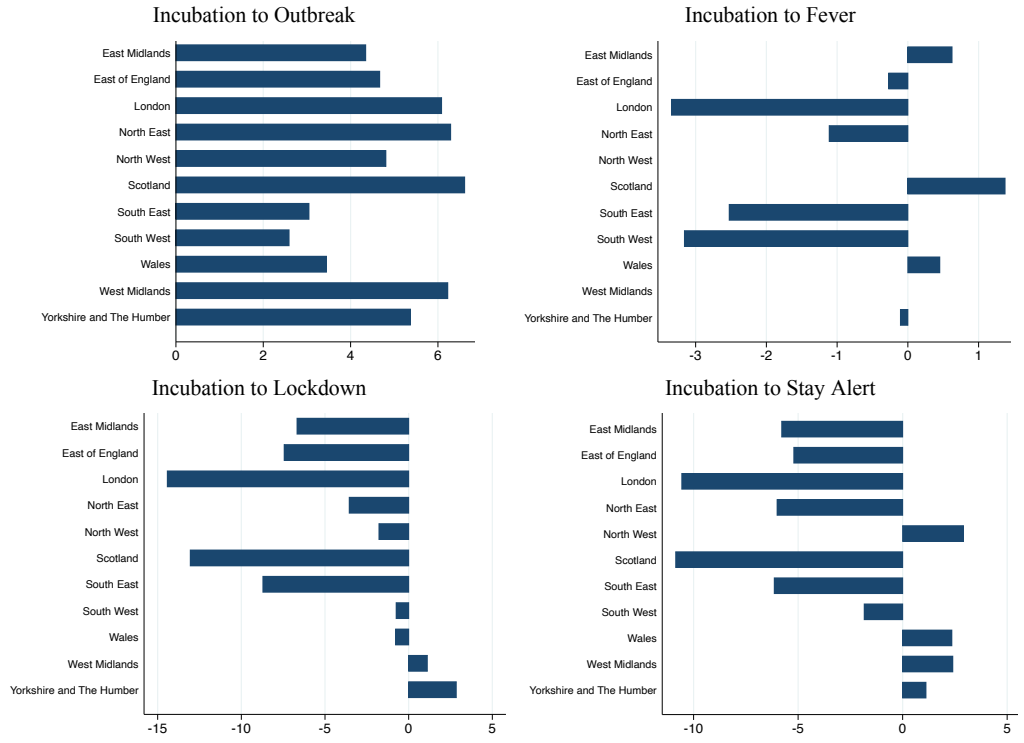
Note: Each sub-figure shows the median relative change in average weekly discretionary spending between the five time periods: incubation, outbreak, fever, lockdown and stay alert. The change is measured in comparison to the average weekly spending in the incubation phase. The y-axis is separated into the main nine regions of Great Britain as defined by the Office for National Statistics. The x-axis depicts the phase-to-phase change of weekly spending in percent. Included are all individuals who spent on discretionary items and whose postcode could be identified (as summarised in Table 2).

These recorded differences in the week-to-week spending appear to be driven by changes in groceries and dining and drinking spending. While we observe very strong increases in spending on grocery items, a strong decline in spending on dining and drinking and other discretionary items occurs. We explore these patterns in further detail below.

Groceries spending

According to Panel B of Figure 2, with the exception of seasonal spending in the first week of January, groceries spending remains relatively flat throughout the *incubation* period, and continues in this manner until the last week of the *outbreak* period. This is followed by elevated spending in the first part of the *fever* period. There is a strong increase in groceries spending for the two weeks following the WHO announcement on March 11, 2020, which designated Covid-19 as a pandemic. This is consistent with panic buying behaviour and stockpiling behaviour, which was widely reported by UK news media outlets. However, groceries spending declines considerably as the UK enters the *lockdown* phase, albeit this effect is only short lived. One week after *lockdown* total grocery spending increases again to around £30 more per week than in the *incubation* period. Only in the *stay alert* period grocery spending decreases slightly towards £123 per week.

As with discretionary spending, differences between the three nations in terms of groceries spending is also apparent. The results in Panel B of Figure 3 indicate that individuals in Scotland began to stockpile on grocery items much earlier than individuals located in Wales and England. Specifically, we can see that spending on groceries accelerates by 13.23% during the outbreak phase (from an average of £98.95 in week three to £112.05 in week seven). Individuals based in Scotland continue spending more on groceries than counterparts located elsewhere in GB until week 12, at which point individuals located in England exhibit the same average weekly spending patterns. This points to a stark increase in spending by individuals located in England in the two weeks prior to the announcement of a lockdown by the UK government. During this time, individuals located in England increased average weekly grocery spending by 18.5% (relative to spending in week three). Shortly after the announcement of the lockdown, groceries spending declines significantly to a level lower than that observed prior to the onset of the crisis. As in the case of discretionary spending, grocery spending shows considerable convergence across the three nations during the *lockdown* period.

In a similar manner to the analysis of overall discretionary spending, Figure 4b presents the differences in grocery spending by demographic indicators. As before, we see a trend of

absolute differences in spending with male, older and wealthier individuals spending more than female, younger and lower income individuals.

Figure 5b summarises the results for changes in grocery spending at the regional level. As indicated previously, most regions show strong increase in week-to-week grocery spending between the *incubation* and *outbreak* period. In particular, the spending growth in grocery shopping of individuals located in Scotland (plus 4.8%) and the East Midlands (plus 5%) is indicative of early stockpiling. The effect becomes even stronger when comparing i*ncubation* to the *fever* period. In this case, individuals located in Scottish increased spending on groceries by more than 7%, which is nearly twice the increase observed for individuals located in other regions of GB. Individuals located in London and the North East only marginally increased spending between the *incubation* and *fever* periods. The figures comparing spending in the *incubation* to *lockdown* period suggest a rather strong divide between regions such as London (minus 5.2%) or the North West (minus 5.1%) and Wales (plus 4%) or the West Midlands (plus 6%). However Figure 6 panel (b) shows that the *stay alert* announcement reduces groceries spending. Only the North East exhibits an increases in grocery spending when comparing spending between the *lockdown* and *stay alert* periods.

Figure 5b. Change in weekly groceries spending across sub-periods (*incubation* to *outbreak; incubation* to *fever; incubation* to *lockdown, incubation to stay alert*) by region

Incubation to Outbreak

Incubation to Fever

Incubation to Lockdown

Incubation to Stay Alert
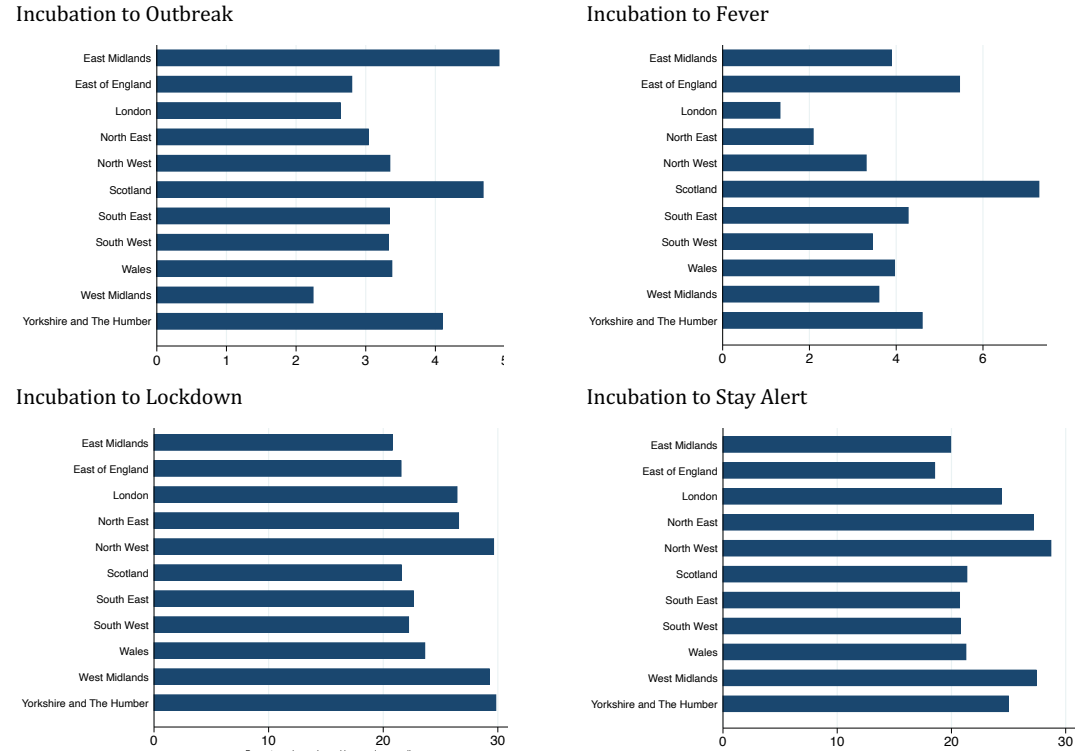
Note: Each sub-figure shows the mean relative change in average weekly grocery spending between the five time periods: *incubation, outbreak, fever, lockdown* and *stay alert*. The change is measured in comparison to the average weekly spending in the incubation phase. The y-axis is separated into the main nine regions of Great Britain as defined by the Office for National Statistics. The x-axis depicts the phase-to-phase change of weekly spending in percent. Included are all individuals who spent on grocery items and whose postcode could be identified (as summarised in Table 2).

Dining and Drinking

Similar to the patterns observed for overall discretionary and groceries spending, Panel C of Figure 2 shows a steady increase in spending on dining and drinking related items in the first eight weeks of the crisis. We observe an increase of more than 11% in spending between the first week and up to two weeks into the *fever* period. However, shortly after week 13, spending on these items declines by 47.1% within four weeks. Contrary to the advice of UK government and counterparts in devolved administrations to refrain from going out for non-essential activities, it appears that individuals actually spend slightly more around the time of the lockdown announcement than they did in the days leading up to it. It appears that there is a marginal increase in related spending during the five weeks of lockdown (from £48 to £49.70). The change of policy towards a *stay alert* approach does not seem to influence the overall spending within Great Britain. However, further analysis shows heterogeneity between the nations.

Three interesting patterns emerge when analysing the spending trends between the individual nations in Panel C of Figure 3. First, it appears that while all nations show an increasing trend in dining and drinking spending, Scottish individuals appear to reduce spending in this category in week nine, one week earlier than counterparts located in England and Wales. Secondly, the relative change in spending between the beginning and end of the *fever* period is very similar between the nations. England experiences a 42% reduction, Scotland a reduction of 45.2% and Wales of 46%. Thirdly, it appears that especially dining and drinking expenses seem to rise in Scotland after the 'stay alert' message. Hence, even though the stay alert announcement was only directed at English residents, the consumer spending behaviour of Scottish residents changed as well.
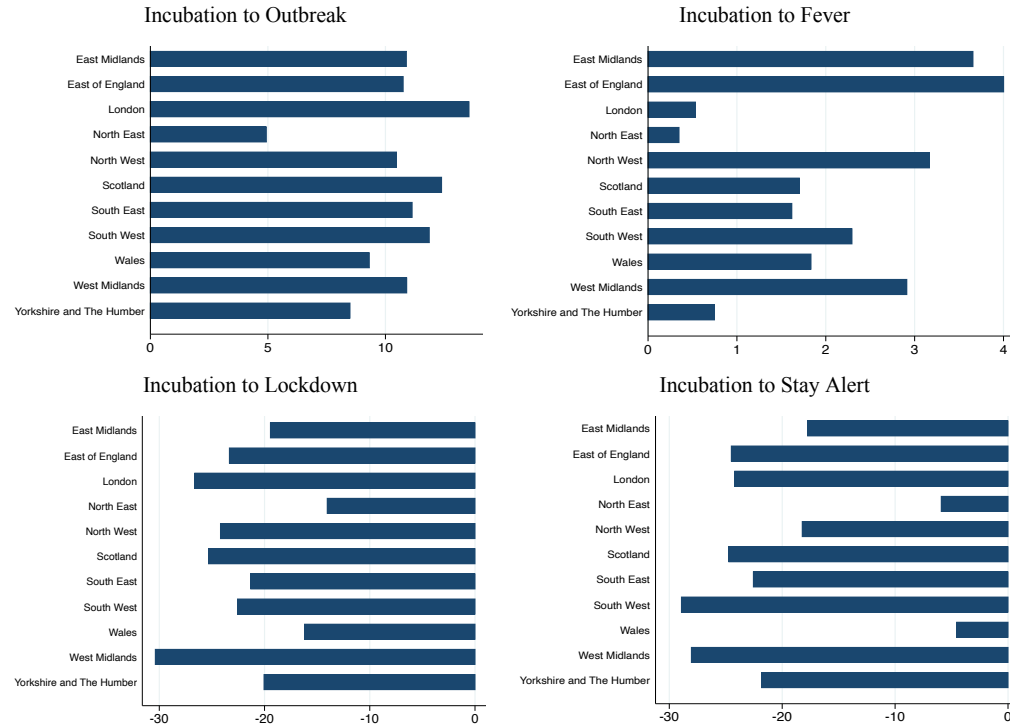
Another pattern appears when considering the differences in spending for dining and drinking in different age groups. We find that younger individuals start to spend less on dining and drinking than older users. Specifically, young individuals (below 35 years of age) exhibit their highest spending in week six of the sample period, while the upper age group continues to increase spending until week eight. This appears to suggest that younger individuals were quicker to react to news and public health announcements to avoid non-essential journeys and public gatherings. However, as before the gap between absolute spending figures diminishes over time, with older users exhibiting a significant change in spending in week nine.

Figure 5c provides additional insights for dining and drinking spending patterns across the regions. Unsurprisingly, this category shows the strongest differences between the different phases. As before, we observe a strong increase in spending between the *incubation* and *outbreak*

phase of around 9% to 12%. Only the North East exhibits slower growth of around 5% during this period. Larger differences are observable when comparing the *incubation* and *fever* phases. As in the groceries category, we see that especially London and the North East show slower growth rates (around 0.7%) compared to the East of England (with an increase of 4%). The largest declines in spending occur when comparing the *incubation* to the *lockdown* periods. Almost all regions exhibit a reduction exceeding 30% in dining and drinking spending. Only individuals based in Wales show slightly lower decreases, albeit spending declines in this category exceed 20%. As in the previous analysis, Figure 6, panel (c) shows that there is strong heterogeneity in terms of the impact of the stay alert message on dining and drinking spending between the regions. It appears that especially individuals in Wales significantly increased relevant spending (+14.5%) whereas spending in the South West dropped further by around 8%.

Overall, the results of our analysis suggest that discretionary spending of consumers in GB declines as the incidence of Covid-19 increases. This confirms findings for recent studies carried out using transaction level data for consumers located in China, Denmark, France, Spain, Portugal and the United States. Unsurprisingly, and also in line with recent evidence presented for Denmark and the United States, government interventions to mitigate the spread of Covid-19 cases (such as lockdown) impact negatively on spending, albeit these declines are uneven across product type, and the age, gender and income of consumers.

Figure 5c. Change in weekly dining and drinking spending across sub-periods (*incubation* to *outbreak; incubation* to *fever*; *incubation* to *lockdown, incubation to stay alert*) by region

Incubation to Outbreak

Incubation to Fever

Incubation to Lockdown

Incubation to Stay Alert

Note: Each sub-figure shows the mean relative change in average weekly dining and drinking spending between the five time periods: *incubation, outbreak, fever, lockdown* and *stay alert.* The change is measured in comparison to the average weekly spending in the incubation phase. The y-axis is separated into the main nine regions of Great Britain as defined by the Office for National Statistics. The x-axis depicts the phase-to-phase change of weekly spending in percent. Included are all individuals who spent on dining and drinking items and whose postcode could be identified (as summarised in Table 2).

Figure 6. Change in weekly spending across sub-periods between lockdown and the 'stay alert' message for all categories by region

Panel (a) Lockdown to Stay Alert Discretionary

Panel (b) Lockdown to Stay Alert Grocieries

Panel (c) Lockdown to Stay Alert Dining and Drinking

Note: Each sub-figure shows the mean relative change in average weekly spending between the *lockdown* and *stay alert period.* The y-axis is separated into the main nine regions of Great Britain as defined by the Office for National Statistics. The x-axis depicts the phase-to-phase change of weekly spending in percent. Included are all individuals who spent on the relevant items and whose postcode could be identified (as summarised in Table 2).

4. Concluding Remarks

In the first quarter of 2020, the Covid-19 virus spread around the world to become a global pandemic. The virus has wreaked havoc on the health and well-being of individuals, and stretched health and social care systems to breaking point as governments scrambled to dampen its spread (via closures of non-essential businesses; prohibitions on large gatherings; and severe restrictions on freedom of mobility) and short term economic impacts (via short-term funding to non-financial firms, tax and rates deferrals and employer grants). Early evidence assembled in a variety of settings using: historical comparisons with prior epidemics; computer-based simulations; stock market event studies; surveys of businesses and households; and econometric analyses of large transaction level datasets suggest that the spread of Covid-19 is having an unprecedented negative impact on the current and future prospects of households, businesses and the macro-economy.

In this study, we use Great Britain (England, Scotland, Wales) as a setting to examine initial consumer spending responses to the onset, and spread of Covid-19, and accompanying public health interventions (including social distancing and lockdown). Using proprietary data on 103,856 consumers and 23 million transactions collected from a popular personal finance application (which aggregates transactions from linked bank accounts and credit and debit cards), we find that consumer spending remains relatively stable in the early stages (*incubation* and *outbreak* periods) of the Covid-19 crisis. During the latter stages of the *fever* period when a government imposed lockdown becomes imminent, discretionary spending declines significantly, and continues to do so after the *lockdown* is announced. Since the *stay alert* announcement by Prime Minister Johnson, a temporary decline in consumer spending across all nations occurs before returning to the same level as that observed prior to the announcement.

Consumer spending responses vary across product categories, especially for groceries, where we observe large increases in spending (associated with panic-buying and stockpiling behaviour) prior to the onset of the *lockdown* period. Spending responses also vary by location (across nations and regions) and demographic characteristics (age, gender and income level). These findings suggest that the Covid-19 virus and public health interventions instituted by the UK government (and devolved administrations) are having significant impacts on the level and composition of consumer spending patterns across Great Britain. However, these impacts are not uniform with differential impacts observed across different nations, regions and demographic groups.

Our results augment a growing international evidence base regarding the impacts of Covid-19 on the economic behaviour of consumer. The real time, high frequency aspects of our

dataset allow for insights regarding changes in the level and composition of consumer spending in response to changes in the incidence of Covid-19 and adjustments to public policy by the UK government and the devolved administrations based in Scotland and Wales. However, our findings are preliminary and come with the caveat that our sample is skewed toward younger individuals. Nevertheless, our results do provide a starting point for academics, policymakers and practitioners in understanding the real-time impacts of Covid-19 on consumer spending, and basis for further in-depth investigations of consumer spending behaviour as the Covid-19 crisis evolves. Future research will extend to a formal regression-based analysis in order to observe the extent to which patterns observed represent transitory or more permanent changes in consumer spending across consumer locations and demographic characteristics. The insights from such research will provide a basis for a nuanced analysis of the impacts of changes in government policies regarding social distancing, lockdown and differential easing of mobility restrictions on consumer spending patterns.

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