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FATALISM, BELIEFS, AND BEHAVIORS DURING THE COVID-19 PANDEMIC

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ABSTRACT

Little is known about individual beliefs concerning the Coronavirus Disease 2019 (COVID-19). Still less is known about how these beliefs influence the spread of the virus by determining social distancing behaviors. To shed light on these questions, we conduct an online experiment (n = 3,610) with participants in the US and UK. Participants are randomly allocated to a control group, or one of two treatment groups. The treatment groups are shown upper- or lower-bound expert estimates of the infectiousness of the virus. We present three main empirical findings. First, individuals dramatically overestimate the infectiousness of COVID-19 relative to expert opinion. Second, providing people with expert information partially corrects their beliefs about the virus. Third, the more infectious people believe that COVID-19 is, the less willing they are to take social distancing measures, a finding we dub the "fatalism effect". We estimate that small changes in people's beliefs can generate billions of dollars in mortality benefits. Finally, we develop a theoretical model that can explain the fatalism effect.

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A randomized controlled trials registry entry is available at
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1 Introduction

The Coronavirus Disease 2019 (COVID-19) has already exacted a considerable toll, with impacts measurable in lives lost, freedoms curtailed, and reductions in economic welfare (Baker et al., 2020; Guerrieri et al., 2020; Gormsen and Koijen, 2020; Reis, 2020).[1] In the absence of an effective treatment or vaccine, governmental efforts to contain the outbreak have relied heavily on behavioral restrictions, including lockdowns where people are largely confined to their homes, limitations on business operations, and requirements for social distancing. These measures could remain in place for more than a year (Ferguson et al., 2020).

The mortality benefits of social distancing are estimated to be worth around $60,000 per US household (Greenstone and Nigam, 2020). Improving compliance with such behavioral restrictions could, thus, have large social payoffs. We do not yet know, however, the determinants of individual compliance and how they might change over time (Anderson et al., 2020; Avery et al., 2020; Briscese et al., 2020; Hsiang et al., 2020; Lewnard and Lo, 2020). In particular, we do not understand the role of individual beliefs, and whether these beliefs can be revised in ways that generate greater compliance.

To shed light on these questions, we conducted an online experiment in the US and UK with 3,610 participants in late March 2020. Participants are randomly assigned to a control condition or one of two treatment groups. Those in the first group (i.e., the 'lower-bound' condition) are told that those who contract the virus are likely to infect two other people.[2] Those in the second group (i.e., the 'upper-bound' condition) are told that those who contract the virus are likely to infect five other people. This estimated range comes from experts and reflects uncertainties regarding both the characteristics of the virus and people's behavior (Liu et al., 2020).

Our analysis yields three main empirical findings. First, we find that participants overestimate the infectiousness and deadliness of COVID-19. For example, participants believe, on average, that one person will infect 28 others; whereas experts estimate that the figure is between one and six (Liu et al., 2020). This result is consistent with previous studies that suggest individuals are likely to overestimate risks that are unfamiliar, outside of their control, inspire feelings of dread, and receive extensive media coverage (see, e.g., Slovic (2000)).

Second, we show that people update their posterior beliefs about COVID-19 in response to expert information—at least in the short-run. The modal belief is that one person will

[1] Over 290,000 deaths have been attributed to COVID-19 worldwide as of 13 May 2020 (Roser et al., 2020).

[2] In other words, they are told that R_0 is two. R_0—the number of people that one infected person is likely to infect—is a central parameter that determines the evolution of the virus over time. As a result, it is frequently covered in the media and brought up in public statements by government officials (see, for example, Gallagher (2020)).

infect two others in the lower-bound group, while the modal belief is that one person will infect five others in the upper-bound group. However, not all participants fully believe or understand the information conveyed in the treatments, with 46% and 61% of participants believing that one person will infect more than six others in the upper- and lower-bound groups respectively.

Third, we examine how beliefs causally affect behavior. In general, this is a difficult task. Randomly providing certain individuals with information can both influence their beliefs and the confidence with which these beliefs are held, making it difficult to obtain an unbiased estimate of the causal impact of beliefs. We are able to overcome this issue by exploiting variability in expert estimates. While assigning participants to the upper-bound group (i.e., showing them a high estimate) increases participant assessments of the virus' infectiousness (relative to the lower-bound group), it should not increase their confidence in these assessments because participants in both groups are shown an expert estimate. We can, thus, estimate the causal impact of beliefs on behavior by using the random assignment of individuals to the upper- or lower-bound groups as an instrument for their beliefs.

This approach yields our third central finding: exaggerated posterior beliefs about the infectiousness of COVID-19 actually make individuals less likely to comply with best practice behaviors, a phenomenon we call the "fatalism effect". On average, for every additional person that participants believe someone with COVID-19 will typically infect, they become 0.5 percentage points less likely to say that they would avoid meeting people in high-risk groups. They also become 0.26 percentage points less likely to say that they would wash their hands frequently.[3]

While others have observed the existence of a fatalism effect (see, e.g., Ferrer and Klein (2015) or Shapiro and Wu (2011)), we are among the first to demonstrate the existence of such effects using experimental methods.[4] We also develop a basic model that is capable of explaining the fatalism effect. The model applies not just to this pandemic, but also to more general situations where people must choose whether to change their behavior to reduce personal or societal risks.

The intuition of our model is straightforward. Increasing individual estimates of the infectiousness of COVID-19 raises their perception of the probability that they will contract the disease even if they socially distance. This, in turn, reduces the perceived benefit of

[3] This result is largely consistent across the following specifications: (1) re-weighting our sample so that it matches the UK and US populations in terms of age and gender; (2) removing those from the analysis who might misinterpret our beliefs questions; and (3) including a second instrument. Further, we do not find any significant differences in the effects of beliefs on behaviors for participants in the US and UK. These robustness checks can be found in the appendix.

[4] Kerwin (2018)—who studies HIV and risky sex behavior in Malawi—also finds evidence of fatalism among certain subgroups of the population he studies.

complying with social distancing measures.[5] Consistent with this explanation, we also find that increasing individual assessments of the infectiousness of the virus leads people to be less optimistic about their future prospects, suggesting that they interpret information about infectiousness in the way assumed by our model.

The fatalism that we document could cause substantial reductions in individual and societal welfare. For example, by making individuals less likely to regularly wash their hands, it makes them more vulnerable to respiratory illnesses like COVID-19 (Rabie and Curtis, 2006).[6] A conservative back-of-the-envelope calculation suggests that if average beliefs about the infectiousness of COVID-19 increase by eight units (e.g., someone with the virus is likely to infect 18 rather than 10 people), then we expect to see a mortality loss of \$2.7 billion in the US alone, solely as a result of reduced handwashing (not counting morbidity losses, spillovers, or further waves of infection).[7] Our findings thus suggest that there are dramatic gains from providing the public with accurate information insofar as this information revises exaggerated beliefs downwards.

This paper contributes to a number of areas in economics and psychology. First, we contribute to the literature on risk perception and behavior change, specifically with respect to the spread of COVID-19, by demonstrating that people misperceive risks and by examining the implications of such misperceptions.[8] Second, the finding that beliefs about the virus influence people's optimism has implications for the understanding the macroeconomic impacts of COVID-19.[9] Optimism is associated with key economic behaviors such as investments and savings (see, e.g., Cass and Shell (1983) and Akerlof and Shiller (2010)). Third, we contribute to the literature on how people update their beliefs in response to new information, and how this depends on individual characteristics, by for example showing that the treatments work less well for those that identify as conservative (see, for example, Eil and Rao (2011) and Garrett et al. (2018)). Fourth, we contribute to the growing literature on how policymakers can best respond to the COVID-19 pandemic by showing that it is both possible, and important, to correct people's beliefs about the virus (Acemoglu et al., 2020; Alvarez et al., 2020; Baker et al., 2020; Berger et al., 2020; Brynjolfsson et al., 2020; Cappelen et al.,

[5]Kremer (1996) and Kerwin (2018) develop similar models in the context of risky sexual decisions. However, their models view the risky action as a continuous variable so are less suited to the (binary) set-up of our experiment.

[6]We do not yet know exactly how handwashing reduces the risk of contracting COVID-19. Most guidance (see, for example, WHO (2020)) is based on past research about other infectious diseases.

[7]The lower-bound treatment reduced average beliefs about the infectiousness of COVID-19 by around eight units relative to the control group.

[8]See, for example, Brzezinski et al. (2020) and Fetzer et al. (2020) for contemporaneous work on beliefs and risk perceptions during COVID-19.

[9]See Atkeson (2020); Guerrieri et al. (2020); Eichenbaum et al. (2020); Barro et al. (2020); Jordà et al. (2020); Krueger et al. (2020) for studies that examine the macroeconomic implications of COVID-19.

2020; Farboodi et al., 2020; Van Bavel et al., 2020).[10]

Finally, our paper is related to the general economics literature on the relationship between beliefs and behavior.[11] We contribute to this literature by: (1) providing a novel way of holding confidence about the information constant when using instrumental variables to provide an unbiased estimate of the impact of changing beliefs on changing behavior; and (2) by providing quantitative estimates of the extent to which beliefs shape behavior at a time of crisis.

The remainder of the article is structured as follows. Section 2 reviews our experimental design. Section 3 presents the main empirical results. Section 4 develops a formal model of the fatalism effect. Finally, Section 5 concludes.

2 Experimental design

We conducted the experiment between March 26 and March 29, 2020.[12] Our sample consists of 3,610 participants (1,859 from the US and 1,751 from the UK). Participants were recruited via the panel provider Prolific Academic.[13][14] All participants were paid for their participation.[15]

Participants are randomly assigned to a control group that receives no intervention or one of two treatment groups. Those in the first group (the lower-bound treatment) are shown

[10] We also contribute to the literature on perceived self-efficacy (see, for instance, Bernard et al. (2011); Krishnan and Krutikova (2013); Tanguy et al. (2014)) by providing a theoretical model that explains when rational agents may believe that their actions make little difference to their outcomes.

[11] See, for example, Jensen (2010); Dupas (2011); Cruces et al. (2013); Wiswall and Zafar (2015); Liebman and Luttmer (2015); Armantier et al. (2016); Bergman (2020); Cavallo et al. (2017); Bleemer and Zafar (2018); Bursztyn et al. (2018); Conlon et al. (2018); Fuster et al. (2018); Dizon-Ross (2019). Two recent papers that use a similar methodology to the one adopted here are Cullen and Perez-Truglia (2018) and Bursztyn et al. (2019). Both use instrumental variables to estimate the casual effects of beliefs on behaviors.

[12] Over this period, the total number of confirmed (tested) cases worldwide rose from 468,049 to 656,866 (Roser et al., 2020). In the UK, they almost doubled from 9,529 to 17,089, and in the USA from 69,194 to 124,665. The death toll in the USA rose from 1,050 to 2,191, and in the UK from 463 to 1,019 (ibid). The UK introduced a full national lockdown two days prior (Holden, 2020), while various US states introduced restrictions on movement during the experimental period (Gershman, 2020).

[13] More information about Prolific Academic can be found at https://www.prolific.co/. Peer et al. (2017) show that participants recruited via Prolific Academic are less dishonest, are less likely to fail attention checks, and produce higher quality data than participants recruited via other comparable online research platforms.

[14] See Appendix D for descriptive statistics. The sample is not nationally representative. In Appendix E, we re-weight our sample to balance it on gender, age, and geography, and re-run our main statistical analyses.

[15] The survey also asked a range of socio-economic and demographic questions. We also collect data regarding, for example, media consumption, how informed participants are about COVID-19, which COVID-19 'best practices' they engage in, and whether they know someone that has been infected. A full list of variables can be found in Appendix D. We use these variables to conduct heterogeneity analyses, which can be found in Appendix F.

a message explaining that studies show that those who contract COVID-19 will, on average, infect two other people––see Figure 1. Those in the second group (the upper-bound treatment) are instead told that studies show that those who contract COVID-19 will, on average, infect five other people. Otherwise, the message they receive is the same.[16] The treatment messages are coupled with graphics illustrating how COVID-19 might spread if the virus is passed on three times at the respective levels of infectiousness.[17]

The statistic that we show participants in the treatments is known as R_0 in the epidemiological literature and indicates how many people one infected person is likely to infect. R_0 is a key input in, for example, the Susceptible-Infected-Removed (SIR) model (Anderson and May, 1992).

After being exposed to the treatments, we measure our key object of interest: participants' beliefs about the infectiousness of COVID-19. More specifically, we ask "On average, how many people do you think will catch the Coronavirus from one contagious person? Please only consider cases transmitted by coughing, sneezing, touch or other direct contact with the contagious person". Participants are free to enter any integer between 0 and 100.

Next, we ask participants about two other COVID-19-related beliefs: (1) the probability of being hospitalized conditional on contracting the virus; and (2) the probability of dying conditional on being hospitalized for the virus.[18][19] We do not to reward correct estimates with financial incentives since we do not want to encourage individuals to look up the true numbers online.[20]

[16]We do not deceive participants when displaying the two treatments. There is, at the time of the experiment, substantial uncertainty regarding the true infectiousness of COVID-19. For example, Liu et al. (2020) show that expert estimates of R_0 range from 1 to 6 in a recent review of epidemiological studies.

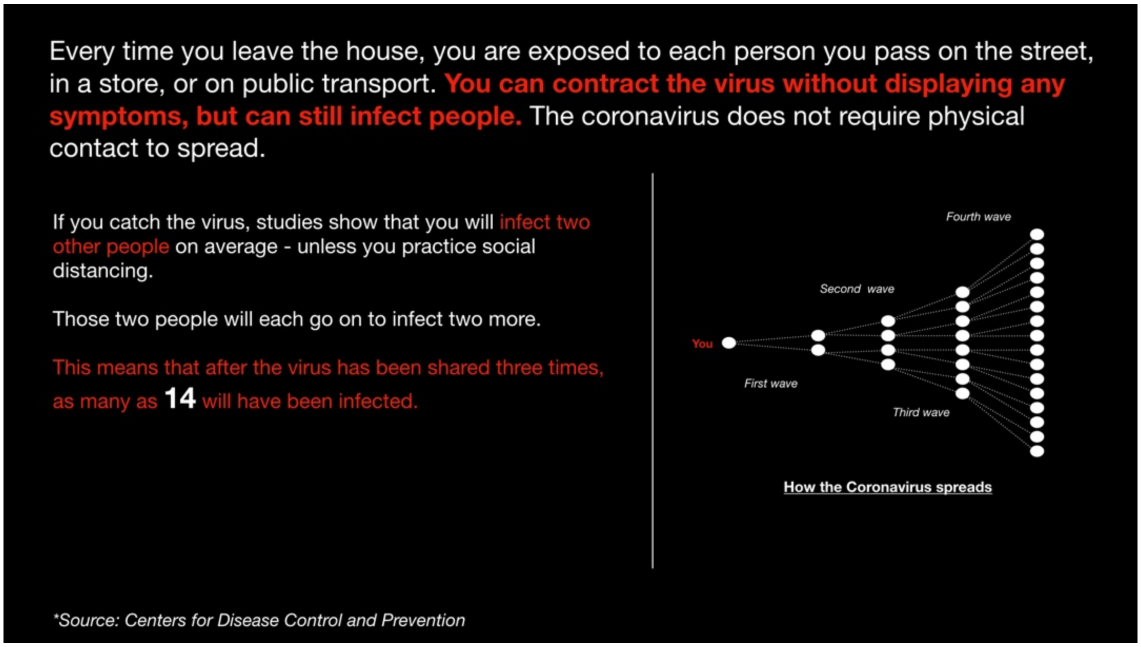
[17]The randomization is balanced. See Appendix C for a balance table.

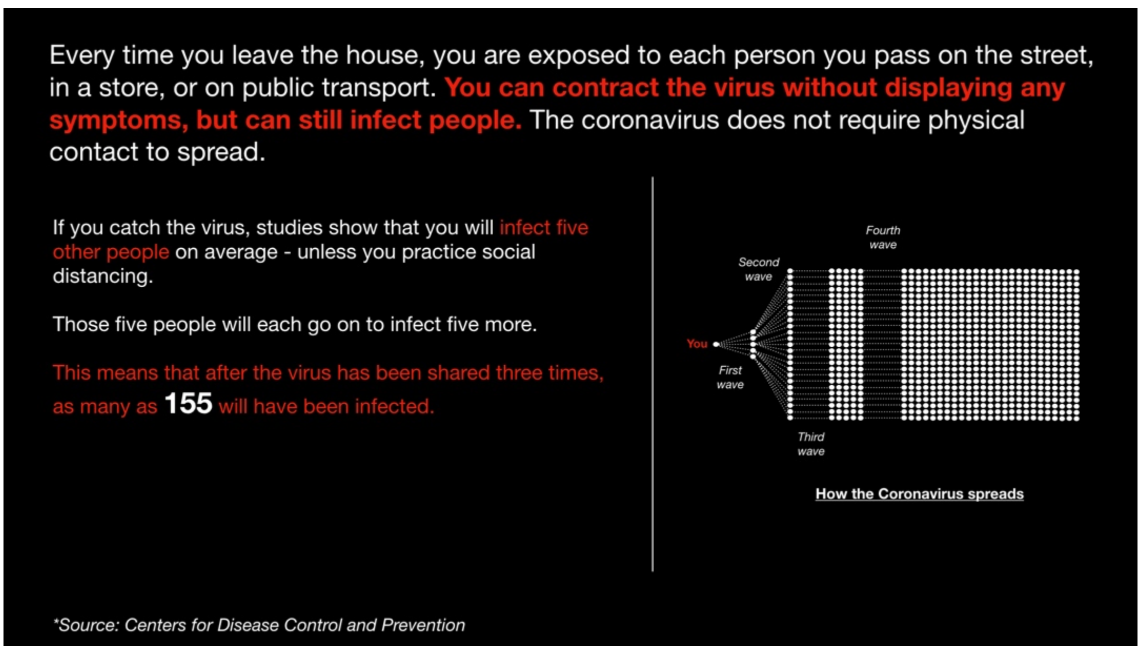
[18]By multiplying participants' beliefs regarding the risk of being hospitalized and the risk of dying conditional on being hospitalized, we obtain their implied beliefs about the Case Fatality Rate (CFR), which is the risk of dying conditional on contracting COVID-19.

[19]We conducted power calculations prior to launching the experiment, using beliefs about R_0 as our primary outcome of interest. We assumed that participants would, on average, believe that R_0 was 2 in the lower-bound group, with a standard deviation of 15. We set the minimum detectable effect size to 2. This meant that we needed around 883 participants per group (i.e., 1,766 in total) in order to achieve 80% statistical power with a 5% significance level when comparing the lower- and the upper-bound groups.

[20]It would not be suitable to incentivize correct answers for the pre-treatment beliefs, as we want to measure the extent to which they are misinformed. Further, it is also not suitable to incentivize post-treatment beliefs, as we risk encouraging participants to respond in ways that they think will result in a payoff, rather what they truly believe. Of course, the current approach also poses potential problems; some participants may, for example, not feel like it is worth spending enough time and thinking through the question. However, we rerun our main analyses dropping people who are likely to not have taken an adequate amount of time or who provided exaggerated answers, and find that our results are largely unchanged.

Figure 1: Treatment messages





Notes. The first image displays the treatment message showed to the lower-bound group. The second image displays the treatment message showed to the upper-bound group.

Further, we ask people about their willingness to comply with three COVID-19-related best practices for 1 week and 2 months. These best practices are: (1) frequent handwashing; (2) working from home; and (3) not meeting people in high-risk groups. We choose these outcomes because they represent behaviors that are common components of governments' COVID-19 mitigation strategies (see, for example, CDC (2020), CO (2020) and WHO (2020)).[21] We only measure stated intentions for future behavior and recognize the limitations of such measures; however, we see no reason to think that these limitations will have more of an effect on one treatment group than another.[22]

Finally, we ask people whether they are optimistic about their future prospects. Optimism and expectations about the future are key drivers of macroeconomic activity.[23] Measuring optimism also allows us to verify that our subjects interpret the information provided about infectiousness in the expected manner.

One of our objectives is to estimate the effect of beliefs about the infectiousness of COVID-19 on our outcomes of interest. Beliefs about the infectiousness of COVID-19 are, however, likely to be endogenous. Fortunately, we generate exogenous variation in people's beliefs about the infectiousness of COVID-19 using assignment to the lower-bound and upper-bound treatments. We are able to use this variation to conduct instrumental variable (IV) regressions. The IV regressions provide us with estimates of the Local Average Treatment Effect (LATE) of beliefs about the infectiousness of COVID-19 for each outcome variable.[24]

When analyzing the experimental data, we begin by conducting linear first-stage regressions, estimating the effects of random R_0 information assignment on beliefs:

$$\hat{R}_i = \gamma_0 + \gamma_1 upperbound_i + \gamma_2 \mathbf{controls}_i + \epsilon_i \tag{1}$$

where $\hat{R}_i$ represents beliefs about R_0; *upperbound* is a dummy variable indicating whether the participant is randomly assigned to the upper-bound R_0 information condition; and **controls** represents a vector of socioeconomic and demographic variables (e.g., age and years of educa-

[21] When recording whether participants are willing to work from home, wash their hands, or avoid seeing people in high-risk groups, we ask participants: (1) "How likely are you to do the following during the coming seven days?" and (2) "Assume that the coronavirus outbreak is still ongoing 2 months from today. How likely would you be to do the following during the average week?" Respondents could answer on a scale from 1 to 5, with 5 being extreme likely and 1 being extreme unlikely.

[22] Stated behaviors in online experiments have also been shown to be predictive of actual behaviors in a variety of domains (see, e.g., Mosleh et al. (2020).

[23] See, e.g., Cass and Shell (1983); Akerlof and Shiller (2010); Benhabib et al. (2016); Di Bella and Grigoli (2019).

[24] We believe that the exclusion restriction is met for two reasons. First, the only difference between the treatments is information regarding the infectiousness of COVID-19. Secondly, treatment assignment is unlikely to change how confident people are about the infectiousness of COVID-19 (which might happen if a treatment message is compared to a pure control), as participants are shown expert estimates in both conditions.

tion). Thus, γ_1 represents the average treatment effect on beliefs. We do not use participants in the control group when conducting this analysis (i.e., those in the lower-bound group are the "reference group").[25]

We then conduct Two-Stage Least Square (2SLS) regressions to estimate the LATE of beliefs about R_0 on people's optimism and their willingness to socially distance:

$$y_i = \beta_0 + \beta_1 \hat{R}_i + \beta_2 \mathbf{controls}_i + v_i \tag{2}$$

where y_i represents people's willingness to socially distance or whether they are optimistic about their future (binary variables); $\hat{R}_i$ represents the fitted values obtained using equation (1); and **controls** is a vector representing the same set of demographic and socioeconomic variables. Again, we exclude those in the control group when conducting this analysis to ensure that the exclusion restriction is met. Our estimate of β_1 is the LATE of changing beliefs about R_0 people's stated behavior and optimism.[26]

3 Results

In this section we present our analysis of the experimental data. We begin by providing an overview of participant characteristics. Next, we examine participants' baseline beliefs about COVID-19 and what the predictors of those beliefs are. We then investigate how providing new information about the infectiousness of COVID-19 influences beliefs. In the following section we estimate the causal effect of beliefs about the infectiousness of COVID-19 on participants' willingness to engage in beneficial behaviors, such as frequent handwashing. Finally, we study the link between beliefs about the infectiousness of COVID-19 and optimism.

[25] We use a similar specification as the one presented in equation (1) when estimating the Intention to Treat (ITT). The main difference is that we use people's stated willingness to socially distance (i.e., work from home, avoid seeing people in high-risk groups, and frequently wash their hands for seven days and two months, respectively) as the outcomes. We also include participants in the control group when conducting this analysis.

[26] These 2SLS regressions help us understand how beliefs are likely to influence people's decisions to socially distance. We also learn how beliefs about R_0 influence people's optimism. While we obtain unbiased estimates of the effects of beliefs on the aforementioned outcomes, we are unable to measure the extent to which beliefs influence action *through* optimism as an intermediary variable. This is an interesting question for future research.

3.1 Participant characteristics

Approximately 59% of respondents are female and 75% of respondents are between the ages of 18 and 44. The monthly average pre-tax household income was $4,461 in 2019.[27] [28] Sixteen percent of participants claim to know someone that has contracted COVID-19; 4% claim to have been in contact with someone that has been diagnosed with COVID-19; 38% of participants claim to display one or more of the known symptoms of COVID-19; and 48% of respondents believe that restrictions will remain in place for more than three months.[29]

3.2 People have exaggerated prior beliefs about the infectiousness and dangerousness of COVID-19

We begin by studying the accuracy of subject beliefs concerning the infectiousness (R_0) and Case Fatality Rate (CFR) of COVID-19. As shown in in Figure 2, we find that the overwhelming majority of subject estimates are outside of the bounds of expert consensus.[30] On average, participants believe that the typical person with COVID-19 gives it to 28 others; in contrast, expert estimates of R_0 at the time of the experiment put it in the 1 to 6 range (Liu et al., 2020). Similarly, participants, on average, believe that the CFR (the share of people who contract COVID-19 that die) is 10.79%; according to the CDC estimates, the case fatality rate in the US is between 1.8 and 3.4% (CDC, 2020).

The fact that participants have incorrect prior beliefs about COVID-19 is consistent with many of the findings from the literature on risk perception. According to this literature, the public is likely to overestimate risks when they are new or unfamiliar, seen as outside of their control, inspire feelings of dread, and receive extensive media coverage (see Slovic (2000) for a review). Clearly, all of these apply to COVID-19; so it is perhaps not surprising that subjects overestimate the risk and dangerousness of COVID-19. We also note that our finding is consistent with contemporaneous work by Fetzer et al. (2020) who find similar biases in

[27] Our sample is not perfectly representative of the general population in the UK or US, and we therefore provide results from a re-weighted analysis in the appendix, where the sample has been balanced on age, gender, and location.

[28] The pandemic appears to be having a profound effect on the economic outlook of the survey participants. For example, 89% believe that unemployment will grow by over 10 percentage points in the next three months, 57% claim to know someone that has become unemployed as a result of the pandemic, and 10% believe that they are likely to become unemployed as a result of the pandemic. See Appendix D for full descriptive statistics tables.

[29] The symptoms that we asked about are: (1) high temperature, (2) chest pains, (3) muscle soreness, (4) diarrhea, (5) headache, (6) nausea, (7) a persistent cough, and (8) difficulty breathing. See https://www.who.int/news-room/q-a-detail/q-a-coronaviruses for more information about the symptoms of COVID-19.

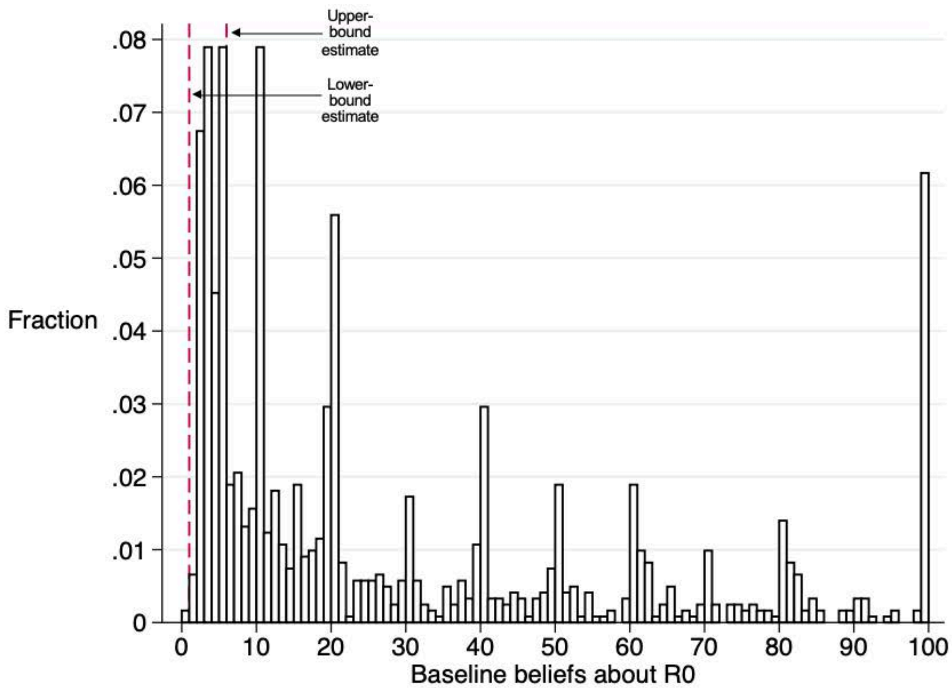
[30] As can be seen in Figure 2, many individuals estimate that R_0 is 100 (since they are not allowed to provide higher estimates). Our estimated effects remain similar after dropping such individuals from the analysis.

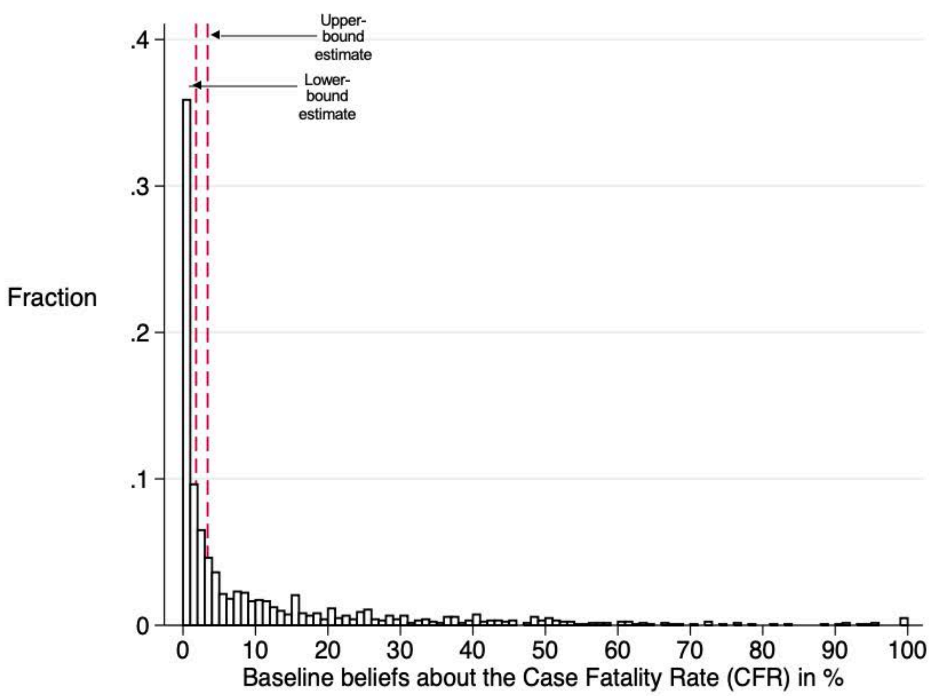
subject beliefs.

We estimate two linear probability models to investigate heterogeneity in subjects' beliefs. As detailed in Appendix D, we find that men, those who are not in a risk group, and the more educated are significantly less likely to overestimate R_0 and the CFR. People in both the UK and the US are likely to overestimate R_0, but those in the US are 12 and 9.5 percentage points more likely than those in the UK to overestimate CFR and R_0 respectively (ceteris paribus). Further, those that consume right-wing news are more likely to overestimate R_0. These results are consistent with the general finding that different demographic groups can perceive risks in different ways. It is also consistent with more specific findings from the literature on risk perception: for example, a large number of papers find, as we do in our particular context, that men tend to rate risks as smaller than women do.[31]

[31] See for instance Brody (1984); Steger and Witt (1989); Gwartney-Gibbs and Lach (1991); Savage (1993); DeJoy (1992); Spigner et al. (1993); Finucane et al. (2000).

Figure 2: Baseline prior beliefs about R_0 and the CFR





Notes. The first diagram displays the distribution of beliefs regarding R_0 at baseline. The second displays the distribution of beliefs regarding CFR at baseline. Participants' perceived CFR is calculated by multiplying their belief regarding the risk of being hospitalized conditional on contracting COVID-19 by the risk of dying conditional on being hospitalized for COVID-19. Participants can enter any integer between 0 and 100 for the aforementioned risks. Participants can also enter any integer between 0 and 100 when stating their beliefs about R_0.

3.3 Providing information about the infectiousness of COVID-19 corrects beliefs

Table 1 presents the effects of being assigned to the lower- and upper-bound conditions on beliefs regarding: (1) R_0 and (2) the CFR. In other words, Table 1 reports the difference in mean beliefs between the treatment and control groups (controlling for demographic variables).[32]

Table 1: Effects of randomly assigned R_0 information on beliefs

VARIABLES	(1) Beliefs about R_0	(2) Beliefs about the CFR
Assigned to lower-bound ($R_0 = 2$)	-7.889***	-0.425
	(1.139)	(0.720)
Assigned to upper-bound ($R_0 = 5$)	-2.797**	-0.303
	(1.260)	(0.698)
Constant	52.94***	45.15***
	(5.663)	(3.932)
Mean in control group	28.671	10.579
p-value lower v. upper means	0.000	0.555
Observations	3,577	3,577
R^2	0.048	0.114

Notes. This table presents results from OLS regressions examining the effects of being assigned to the lower- or upper-bound treatments on key beliefs (one per column). Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). All outcomes are measured on a scale from 0 to 100. Demographic control variables (e.g., age, geography, education, and income) are used in all specifications. Comparisons are made relative to the group that receives no treatment.

The table reveals that being shown lower- or upper-bound estimates of R_0 decreases average estimates of R_0 from 29 to 21 and 26, respectively (see column 1). We also find that, on average, being told that R_0 is one percent greater prompts respondents to revise their beliefs upward by 0.16 percent (i.e., the elasticity is 0.16). Further, we obtain an F-statistic of 16.71 when regressing treatment assignment on beliefs about R_0 (excluding the control group), suggesting that we have an informative instrument (i.e., a strong 'first stage') and can proceed to use treatment assignment as an instrumental variable for beliefs about R_0.[33][34]

Figure 3 reveals the effect of the treatments on the entire distribution of beliefs about

[32] Although the treatment assignment is random, we control country of residence, gender, age, years of education, living situation (with partner, children, parents, relatives, or flat/housemates), living in an urban, rural or suburban area, monthly income in 2019, social media use, and whether the survey was completed on a mobile phone. These control variables are used throughout the results section.

[33] We present a heterogeneity analysis in Appendix F, which, amongst other things, shows that the treatments are less effective for conservatives. Further, we find that the treatment had a smaller effect on beliefs about R_0 if participants were also asked to state their beliefs about R_0 at the start of the survey before the treatments were administered (we randomly elicited pre-treatment beliefs for 50% of the participants).

[34] Our finding that information updates people's beliefs about virus is broadly consistent with Bursztyn et al. (2020). The authors argue that two Fox News personas—–Tucker Carlson and Sean Hannity—presented differing assessments regarding the seriousness of the virus, with Carlson warning viewers and Hannity downplaying the threat posed by the pandemic. Their analysis suggests that Hannity viewers held incorrect beliefs and changed behavior later than Carlson viewers, and were subsequently more likely to contract COVID-19.

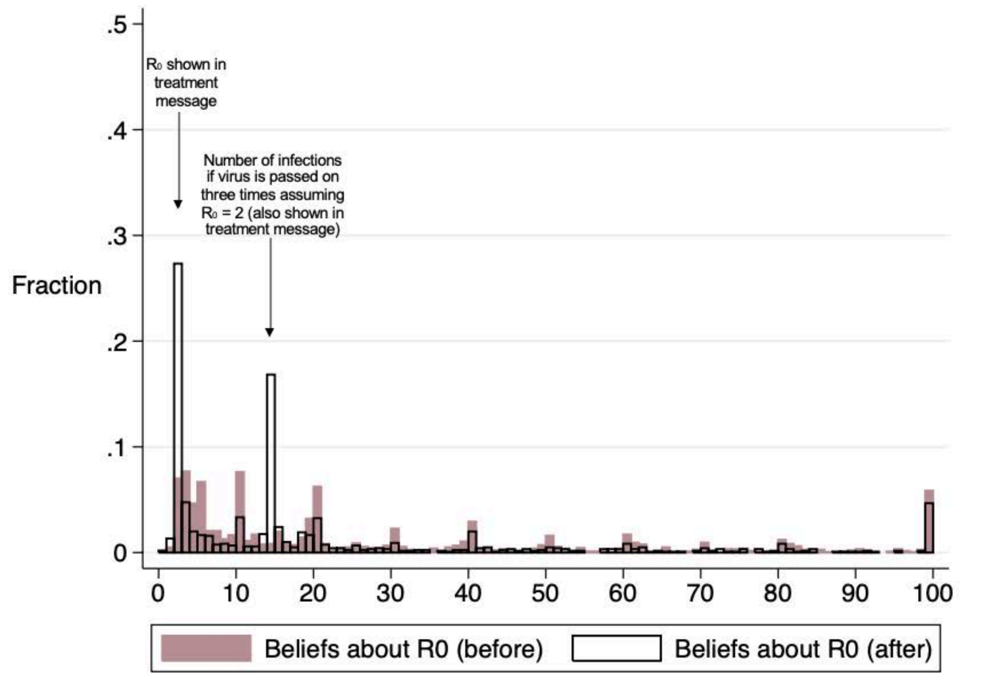
R_0. As can be seen, the treatments shift the modal belief in the expected way: these are 5 and 2 in the upper- and lower-bound groups respectively (i.e., the estimates that the respective groups were presented with). However, not all individuals change their beliefs in line with the information that they are given, with 46% and 61% of participants still believing that R_0 is above 6 in the upper- and lower-bound groups respectively.[35]

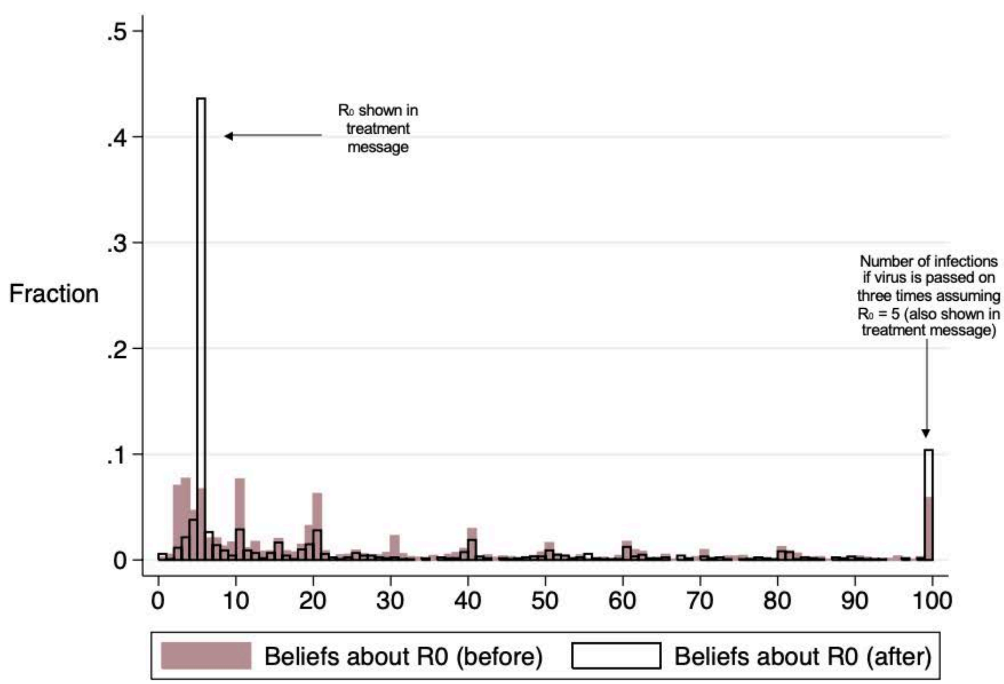
Since baseline beliefs are measured prior to information provision, it is also possible to run a before and after comparison. We find that there are substantial differences in pre- and post-treatment beliefs. Post-treatment beliefs are, for example, more centered around the R_0 values that the treatment messages convey, and a greater portion of participants hold beliefs within the expert estimates (i.e., between 1 and 6).

Our analysis suggests that expert information about the infectiousness of R_0 can update (and correct) people's beliefs––at least in the short-term. It also demonstrates that our instrument is informative; we thus proceed with the instrumental variable analysis in the next section.

[35]It is not immediately clear how risk perceptions and beliefs will update in response to new information. There are, for example, studies suggesting that individuals fail to update their beliefs when presented with expert information (see, for example, Nyhan and Reifler (2010)). There is, however, evidence that people are better at updating their beliefs when subjects are given good news (Eil and Rao, 2011), as is the case here (COVID-19 is not as infectious as people think), or when they are making decisions in a 'threatening' environment (Garrett et al., 2018).

Figure 3: Effect of treatments on posterior beliefs of R_0





Notes. The first diagram displays the distribution of beliefs about R_0 in the lower-bound group pre- (prior) and post-treatment (posterior). The second diagram displays the distribution of beliefs about R_0 in the upper-bound group pre- and post-treatment. Participants can enter any number between 0 and 100 when stating their beliefs about R_0.

3.4 Increasing people's posterior beliefs of the infectiousness of COVID-19 makes them less willing to engage in best practices

We now examine whether changing beliefs regarding R_0 changes participants' stated willingness to comply with best practice behaviors. We ask participants how willing they would be to frequently wash their hands, avoid seeing people in high-risk groups, and work from home assuming that "the Coronavirus outbreak is still ongoing 7 days/2 months from today." Participants provide answers on a five-point scale, with one representing 'extremely unlikely' and five representing 'extremely likely'. In our analysis, we transform this variable into a binary outcome, defined as one if participants state that they would be 'extremely likely' or 'likely' to adopt a given behavior and otherwise as zero.[36]

Table 2 reveals that the Local Average Treatment Effect (LATE) point estimates are consistently negative, and statistically significant for the willingness to wash hands frequently (2 months) and visiting risk groups (7 days and 2 months). In other words, we find that increasing the perceived infectiousness rate actually makes individuals less willing to engage in best practice behaviors, a phenomenon we dub the 'fatalism effect'. We view our point estimates as surprisingly large. For example, we estimate that decreasing individual estimates of R_0 by one unit makes individuals around 0.5 percentage points more likely to avoid meeting people in high-risk groups (see columns two and four in Table 2). Since the individuals in our sample, on average, overestimate the infectiousness rate by over 20 units, this suggests that there may be substantial gains from correcting public misconceptions on these and related issues.

[36]The vast majority of participants state that they are willing to adhere to best practices. For example, 98% of participants in the lower-bound group state that they would wash their hands frequently if the pandemic continues for two months. Further, 94% of participants in the same group state that they would avoid seeing people in high-risk groups if the pandemic continues for two months. Fewer state that they would be willing to work from home (47%) if the pandemic continues for two months, largely because they are unable to work from home. These statistics are important because people's willingness to engage in 'best practice' behaviors are central parameters in epidemiological models, and we do not yet have a good grasp of how behavior changes over time (Avery et al., 2020).

Table 2: The effect of posterior beliefs about R_0 on willingness to engage in best practices

	Willingness to avoid meeting people in high-risk groups			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.0233**		-0.0255**	
	(0.0111)		(0.0109)	
Beliefs about R_0		-0.00451*		-0.00492**
		(0.00232)		(0.00232)
Constant	0.909***	1.031***	0.826***	1.048***
Lower-bound mean	0.932		0.937	
Controls	Yes	Yes	Yes	Yes
Observations	2,404	2,404	2,405	2,405
R^2	0.021		0.023	
	Willingness to wash hands frequently			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.00591		-0.0132**	
	(0.00589)		(0.00603)	
Beliefs about R_0		-0.00114		-0.00255**
		(0.00118)		(0.00129)
Constant	0.989***	1.080***	1.008***	1.123***
Lower-bound mean	0.981		0.984	
Controls	Yes	Yes	Yes	Yes
Observations	2,404	2,404	2,405	2,405
R^2	0.014		0.017	
	Willingness to work from home			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.0276		-0.0190	
	(0.0186)		(0.0186)	
Beliefs about R_0		-0.00534		-0.00366
		(0.00381)		(0.00368)
Constant	-0.293	-0.0535	-0.264	-0.0992
Lower-bound mean	0.465		0.466	
Controls	Yes	Yes	Yes	Yes
Observations	2,391	2,391	2,405	2,405
R^2	0.079		0.071	

Notes. This table presents results from LPM and 2SLS regressions where assignment to the upper-bound exponential condition acts as an IV for beliefs regarding R_0. The outcomes of interest are whether participants comply with various behaviors if the pandemic continued for 7 days/2 months. Demographic control variables are used in all regressions. The control group is not included in this analysis. The first-stage regression is displayed in Table 1. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

We now examine the linearity of the relationship between people's beliefs about R_0 and their willingness to engage in best practices. It is important to do so because the point estimates might depend on our choice of instrument if the true relationship is non-linear (see, for example, Løken et al. (2012)). To do this, we instrument for beliefs using two binary variables: a dummy variable representing assignment to the lower bound group, and a dummy representing assignment to the upper-bound group. Thus, we introduce the control group into the analysis.[37] [38]

We then conduct a 2SLS IV estimation where we instrument beliefs about R_0 and squared beliefs about R_0 with the two aforementioned treatment dummies. We find that the estimated effects of beliefs about R_0 on people's willingness to engage in the three behaviors are similar to those presented in Table 3, and that the point estimates of the squared terms are smaller than 0.001 (with 95% confidence intervals tightly bound around zero).[39] While only suggestive, this provides some preliminary evidence that the relationship is roughly linear, at least over the relevant R_0 interval.

The "fatalism effect" that we document could cause substantial losses in welfare. For example, conducting a highly conservative back-of-the-envelope calculation, we find that if people in the US, on average, believe that R_0 is one unit greater, we expect to see a mortality loss of around \$340 million. This suggests that if we revise people's beliefs about R_0 downward by 8 units––which is what the lower-bound treatment accomplished relative to the control group––we would see a \$2.7 billion increase in welfare.[40]

[37] Using the control group creates a possible violation of the exclusion restriction insofar as it is possible that individuals in the control group are less confident in their beliefs that those in the treatment groups. However, it is implausible that the error term is mean-independent of any of our pre-treatment variables, so introducing the control group is necessary for the analysis. Note that we do not have this problem in the IV analysis presented in Table 2, as we drop participants in the control group, and use assignment to the upper-bound condition as our instrument.

[38] See Table A6 in the Appendix for first-stage regressions on beliefs. We also re-run the regressions displayed in Table 3 in order to see whether the point estimates differ when including two instruments, rather than one. We find that the point estimates remain qualitatively similar. See Table A7 in the Appendix.

[39] See Table C3 in the Appendix.

[40] To calculate this number, we assumed that handwashing reduces the risk of contracting the virus by 16% (see Rabie and Curtis (2006)) and that there will be an additional 150,000 COVID-19 deaths in the US (McAndrew, 2020). The figure is the median estimate of experts who were asked to forecast total US deaths up until the end of 2020. Because it ignores deaths after 2020, it likely understates the true number. As there have already been around 69,000 deaths, there are around 81,000 potential deaths that changes in handwashing behavior can affect. We also assumed a value of a statistical life of \$10 million (see Viscusi and Aldy (2003) for a review of such estimates) and ignored any positive spillovers from handwashing. Finally, we assume a linear effect of beliefs on handwashing behaviors.

3.5 Believing that COVID-19 is more infectious makes individuals less optimistic

Finally, we study the impact of changing people's beliefs about COVID-19 on their optimism about the future. We expect people to become less optimistic about the future if they are told that experts estimate that R_0 is greater, as this may imply that the virus is likely to have a greater impact on the economy (and society in general). This is exactly what we find. Table 3 shows that when participants are told that R_0 is five, as opposed to two, they become significantly less optimistic. Quantitatively, a one-unit increase in beliefs about R_0 leads to a one percentage point drop in the share of participants that are optimistic about the future.[41]

Table 3: The effect of beliefs about R_0 on optimism

	(1)	(2)
	ITT	LATE
VARIABLES	Optimism	Optimism
Upper-bound condition ($R_0 = 5$)	-0.0534***	
	(0.0202)	
Beliefs about R_0		-0.0103**
		(0.00461)
Constant	0.494**	0.960***
	(0.197)	(0.354)
Lower-bound mean	0.494	
Controls	Yes	Yes
Observations	2,405	2,405
R^2	0.032	

Notes. This table presents the results from two regressions. The regression in the first column is run using an LPM, with independent variables being assignment to the upper-bound condition in addition to demographic controls (these are listed in Section 3.1). The dependent variable is whether respondents feel optimistic about their future (a binary variable). The regression in the second column uses 2SLS, where assignment to the upper-bound exponential condition acts as an instrumental variable for beliefs regarding R_0. The dependent variable is whether participants are optimistic about their future. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

The results presented in Table 3 are of interest insofar as optimism affects the evolution of key macroeconomic variables. Further, the result suggests that subjects understand that a higher rate of infectiousness translates into a more severe impact from the virus in the future.

[41] Table 3 excludes participants in the control group because we cannot be sure that the exclusion restriction holds this group.

4 Towards a theory of fatalism

In this section, we propose a model that can explain the fatalism effect that we find in our experiment. The intuition behind the model is straightforward. If individuals come to believe that the virus is more infectious, then they revise upwards their assessment of the probability that they will get the virus even if they socially distance (or follow other best practices such as washing their hands frequently). But if individuals come to believe that they are likely to get the virus no matter what they do, then they may decide to ignore social distancing measures: in other words, we get a rational "fatalism effect".

More formally, we consider an individual who must choose between two actions: *socially distancing* (denoted $A = 0$) or instead *socializing as usual* (denoted $A = 1$). If they socially distance, then there is a probability $p \in [0,1]$ that they will contract the virus nonetheless (e.g. while doing essential shopping). If they socialize as usual, there is a further probability $q \in [0,1]$ that their friends will give them the virus. Assuming independence of risks for simplicity, their overall probability of contracting the disease is thus $p + q - pq$ in the $A = 1$ scenario.[42]

If the individual socializes, they receive a psychic benefit $B > 0$ and their expected utility is given by $U(A = 1) = B - \alpha(p + q - pq)$ where $\alpha > 0$ measures the rate at which they are willing to trade the benefit of socializing off against the risk.[43] If they instead socially distance, then their expected utility is $U(A = 0) = -\alpha p$. They therefore choose to socialize if and only if

$$\mathrm{U}(A = 1) \geq \mathrm{U}(A = 0) \iff q(1-p) \leq B' \tag{3}$$

where we have defined $B' \equiv B/\alpha$. To capture variation in the cost of socially distancing within the population, we will assume that B' is drawn from some strictly increasing probability distribution $F\colon [0,1] \to \mathbb{R}$. Thus,

$$\mathrm{P}(A = 1) = \mathrm{P}(q(1-p) \leq B') = 1 - \mathrm{F}(q(1-p)) \tag{4}$$

and so the probability that the individual socializes is strictly decreasing in $q(1-p)$. In other words, the greater the additional risk from socializing, the less likely the individual is to socialize.

Finally, note that the subjective probabilities p and q depend on the individual's estimate of the infectiousness of the disease, denoted $e \in \mathbb{R}$. Accordingly, we will write $p = p(e)$ and

[42] Recall that $\mathrm{P}(A \vee B) = \mathrm{P}(A) + \mathrm{P}(B) - \mathrm{P}(A)\mathrm{P}(B)$ for any two independent events A, B.

[43] The assumptions of additive utility with fixed α can be dropped entirely if we are willing to directly assume that the agent is less likely to socialize if the risk from doing so increases. In this sense, these assumptions are superfluous.

$q = q(e)$; and we will further assume that p and q are strictly increasing and differentiable functions.

We now examine how the individual's willingness to socialize depends on their estimate of the infectiousness rate. To this end, it will be convenient to define $\beta(e) \equiv p'(e)/q'(e)$, i.e. β is the ratio of derivatives of the risk functions. It is also helpful to define fatalism more formally. We will say that there is a *fatalism effect* if and only if

$$\frac{\mathrm{dP}(A=1)}{\mathrm{d}e} > 0 \tag{5}$$

that is, a small increase in the perceived infectiousness rate makes the individual more likely to socialize. We can then observe the following:[44]

Proposition 1. *There is a fatalism effect if and only if* $p(e) + \beta(e)q(e) > 1$.

Proposition 1 sheds some light on when fatalism is likely to arise. First, fatalism is more likely to arise when the background risk p is high. This is not a surprise: for example, in the extreme case of $p = 1$, the individual is certain to contract the disease anyway and therefore loses nothing from going outdoors. Second, fatalism is more likely to arise when the relative sensitivity of the background risk to the perceived infection rate is large. This is also not surprising: if increasing e dramatically increases the risk from staying at home, but only slightly increases the risk from socializing, then it may induce individuals to socialize. Finally, a fatalism effect becomes more likely when the socializing risk q becomes larger. While this effect is more subtle, the intuition can be readily grasped by considering the extreme case of $q = 0$: in that case, the individual will socialize with probability 1 (there is no risk in doing so), so increasing e cannot make them *more* likely to socialize (i.e. there can be no fatalism effect).

While useful, it may be hard to check whether the inequality in Proposition 1 holds in practice. As a result, we now study the relationship between the possibility of a fatalism effect and the overall probability that an individual contracts the disease if they socialize $p + q - pq$. To this end, let $p^S \equiv p + q - pq$ (suppressing the dependence of the probabilities on e for ease of notation) and define the function $g\colon \mathbb{R}^+ \to [0,1]$ as follows:

$$g(\beta) = \begin{cases} (4-\beta)/4 & \text{if } \beta \in (0,2] \\ 1/\beta & \text{if } \beta > 2 \end{cases} \tag{6}$$

We then have the following result:

[44] All proofs appear in Appendix A.

Proposition 2. *If there is a fatalism effect, then* $p^S \geq g(\beta)$*. Conversely, if* $p^S > g(\beta)$*, then there must exist probabilities* $p \in [0,1]$ *and* $q \in [0,1]$ *that are consistent with* p^S *and generate a fatalism effect.*

Proposition 2 provides an easily checked inequality that determines the possibility of a fatalism effect. For example, suppose that $\beta = 1$ (i.e. both probabilities are equally sensitive to the estimated infectiousness rate e). Then $g(\beta) = 3/4$, so fatalism is possible only if the individual thinks that they have at least a 75% chance of getting the disease if they socialize. Conversely, if the individual thinks that they have at least a 75% chance of getting the disease if they socialize, then we can always find probabilities p and q that generate a fatalism effect (e.g., if $p^H = 0.75$, then $p = q = 0.5$ will work). Note that, in general, the probability p^S need not be as high as 75% to generate fatalism. Indeed, given that $g(\infty) = 0$, fatalism is consistent with an arbitrarily low probability p^S provided that the ratio of derivatives β is sufficiently large.

In summary, our model demonstrates that fatalism is possible under a range of conditions; and that a fatalism effect is more likely to arise if the probabilities p, q and the ratio of derivatives β is large. Importantly, our model can also be reinterpreted in various ways. For example, while we described the action $A = 1$ as 'socializing as usual', it could also be interpreted as 'not regularly washing one's hands frequently' or 'refusing to work from home', allowing the model to explain the fatalism effect we also observe for these outcome variables. Similarly, the risks could be re-interpreted as not risks to oneself but rather as risks to others, allowing the model to explain why one might become fatalistic when (for example) deciding whether to visit an elderly relative.

As shown in the appendix, it is possible to extend the basic model in various ways. For example, it is possible to relax the assumption that the risks are independent; and it is also possible to allow for the conjunction of selfish and altruistic motives for social distancing behavior. These extensions slightly complicate the formulae above but do not change the main insights of the model. A more interesting extension is to recognize that the probabilities of contracting the disease p and q actually depend on the fraction who socially distance, which in turn depends on the probabilities p and q. It is thus possible to find 'equilibrium' probabilities and level of social distancing: i.e., probabilities p and q that induce a level of social distancing that is then consistent with p and q.

Finally, we recognize that, while the model provides one explanation for the observed effect, it is not the only plausible explanation. For example, it might be that increasing individual assessments of the infectiousness of disease makes them think that many others will likely get the virus anyway, thereby diminishing the perceived social value of efforts to depress R_0.[45] While this explanation is logically distinct from ours, it is similar in spirit insofar as both explanations stress the damaging effect of high R_0 assessments on individuals' motivation to combat the virus.[46]

5 Conclusion

This paper describes three key results of an online experiment that studies individual beliefs and behaviors during the COVID-19 pandemic. First, individuals overestimate both the infectiousness and dangerousnes of COVID-19 relative to expert opinion, a result that is in line with findings from the risk perception literature. Second, messages conveying expert estimates of R_0 partially correct people's beliefs about the infectiousness of COVID-19. Third, individuals who believe that COVID-19 is more infectious are less willing to comply with social distancing measures, a finding we dub the "fatalism effect".

We are not the first to uncover a fatalism effect in the context of decision-making under uncertainty. Earlier observational studies suggest that higher risk perceptions make anxious individuals less likely to engage in exercise, less likely to meet fruit and vegetable consumption guidelines and less willing to quit smoking (Ferrer and Klein (2015)). We contribute to this literature by demonstrating the existence of a fatalism effect using experimental methods and by providing evidence of such an effect in the context of a pandemic. We also develop a model that that is capable of explaining the fatalism effect.

Our study has several limitations. For example, we consider the impact on stated behaviors; we do not measure the long-run impact of beliefs on behavior; and there is a possibility that our results may not generalize to those who do not complete online experiments. These limitations could, perhaps, be overcome by conducting long-term and large-scale natural field

[45]For example, in the classic SIR model it can be shown (see, e.g., Weiss (2013)) that the maximum fraction of the population infected is

$$1 - \frac{1 + \ln R_0}{R_0}$$

which is strictly concave on the domain $R_0 > \sqrt{e}$. If individuals believe that R_0 individuals determines the maximum infection rate in this way, then they will believe that the effect of slightly depressing R_0 on the maximum infection rate is small is they believe that R_0 is large. For example, if they believe that R_0 is 26 (the mean assessment of participants in the upper-bound group), then the derivative of the maximum infection rate with respect to R_0 is just 0.5 percentage points.

[46]Another interesting area of study is the possibility of boundedly rational fatalism, and whether people are "selectively fatalistic" (Sunstein, 1998).

experiments.

These limitations notwithstanding, our findings may have important implications for policy in the face of the COVID-19 pandemic. In particular, they suggest substantial gains from providing the public with accurate information, insofar as this information revises public assessments of the virus' infectiousness downwards. To get a sense of the magnitude of this effect, we perform a conservative benefit calculation, and find that revising individual assessments of R_0 downwards by just 8 units could create at least \$2.7 billion in social benefits in the US simply by getting people to wash their hands more frequently. It might also be worthwhile for governments to track how people's beliefs and sentiments change over the course of the pandemic, as this would inform the need for—and help target—policy interventions.

More generally, our study has implications for how policymakers can best mobilize populations in the face of a crisis. In particular, we show that policymakers need to tread a fine line, communicating in ways that convey the seriousness of the crisis, but without triggering a fatalism effect. Understanding how exactly to tread that line is an important task for future research.

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A Proofs

Proof of Proposition 1. From (4), we see that

$$\frac{\mathrm{dP}(A=1)}{\mathrm{d}e} = -\mathrm{F}'(q(e)[1-p(e)])[q'(e)-q'(e)p(e)-p'(e)q(e)] \tag{7}$$

Since $\mathrm{F}'(q(e)[1-p(e)]) > 0$, it follows that

$$\begin{aligned}\frac{\mathrm{dP}(A=1)}{\mathrm{d}e} > 0 &\iff q'(e)-q'(e)p(e)-p'(e)q(e) < 0 \\ &\iff p(e)+\frac{p'(e)}{q'(e)}q(e) > 1\end{aligned} \tag{8}$$

which is precisely our result. □

Proof of Proposition 2. To prove the first claim, assume that there is a fatalism effect. Then $p+q\beta > 1$ (by Proposition 1) and so $p+q\beta \geq 1$. To find a lower bound on the probability p^S, consider the problem

$$\begin{aligned}\min_{p,q} \quad & p^S = p+q-pq \\ \text{s.t.} \quad & p+q\beta \geq 1 \\ & p \in [0,1], q \in [0,1]\end{aligned} \tag{9}$$

When $\beta > 2$, the solution is $p^* = 0$ and $q^* = 1/\beta$ at which point $p^S = 1/\beta$. We thus conclude that $p^S \geq 1/\beta$ in the case of $\beta > 2$. Meanwhile, when $\beta \in (0,2]$, we have the (interior) solution of $p^* = (2-\beta)/2$ and $q^* = 1/2$ at which point $p^S = (2-\beta)/4$. We thus conclude that $p^S \geq (2-\beta)/4$ in the case of $\beta \in (0,2]$. Either way, then, a fatalism effect implies that $p^S \geq g(\beta)$.

To prove the second claim, consider the pair of probabilities (p,q) defined by $p+q-pq = p^S$, $p = (2-\beta)/2$ if $\beta \in (0,2]$, and otherwise $p = 0$ (if $\beta > 2$). Clearly, these probabilities are consistent with p^S. Moreover, if $p^S = g(\beta)$, then $(p,q) = (p^*,q^*)$ and so $p+\beta q = 1$. Hence, if $p^S > g(\beta)$, it must be that $q > q^*$ and so $p+\beta q > 1$, i.e. the probabilities generate a fatalism effect. □

B Dependent risks and altruistic concerns

In this section, we show how the basic set-up can be extended to allow for (1) altruistic concerns and (2) dependent risks. To allow from (1), we will assume (for simplicity) that socializing as usual involves meeting just one friend whom the agent may accidentally infect. Let p^F

denote the probability that the friend who contract the virus even if they socially distance and let q^F denote the probability that the agent transmits the virus to their friend if they meet (so p^F and q^F are defined analogously to p and q). To allow for (2), let q_p denote the (conditional) probability that the agent contracts the virus from their friend given that they would have done so anyway; and define q_p^F analogously.

In this more general setting, the chance that the agent contracts the virus in the $A = 1$ scenario is $p+q-pq_p$; and so socializing increases their risk by $p+q-pq_p-p = q-pq_p$. Similarly, socializing increases their friend's risk by $q^F - p^F q_p^F$. Since the agent cares about both of these, the cost of meeting becomes

$$\gamma(q - pq_p) + (1-\gamma)(q^F - p^F q_p^F) \tag{10}$$

If $\gamma = 1$ (pure selfishness) and $q_p = q$ (independence), then we return to the baseline model.

As before, we have a fatalism effect if and only if

$$\frac{\mathrm{d}}{\mathrm{d}e}\Big[\gamma(q - pq_p) + (1-\gamma)(q^F - p^F q_p^F)\Big] < 0 \tag{11}$$

or equivalently

$$\gamma\frac{\mathrm{d}q}{\mathrm{d}e} + (1-\gamma)\frac{\mathrm{d}q^F}{\mathrm{d}e} < \gamma\left(q_p\frac{\mathrm{d}p}{\mathrm{d}e} + p\frac{\mathrm{d}q_p}{\mathrm{d}e}\right) + (1-\gamma)\left(q_p^F\frac{\mathrm{d}p^F}{\mathrm{d}e} + p^F\frac{\mathrm{d}q_p^F}{\mathrm{d}e}\right) \tag{12}$$

As in Proposition 1, then, fatalism is more likely when the probabilities p, q_p, p^F, q_p^F are high or when the baseline risks p and p^F are very responsive to e. Moreover, if we assume that both the agent and their friend have the same risk functions (i.e. $p(e) = p^F(e)$ and $q(e) = q^F(e)$ for all e), then this inequality reduces to

$$\frac{\mathrm{d}q}{\mathrm{d}e} < q_p\frac{\mathrm{d}p}{\mathrm{d}e} + p\frac{\mathrm{d}q_p}{\mathrm{d}e} \tag{13}$$

which is the same condition one would obtain by setting $\gamma = 1$. In this case, then, introducing altruistic concerns makes no difference to the analysis.

C Balance table

Table A1: Balance table

	Control	Lower-bound	Upper-bound	p-value
Country = UK	0.482	0.485	0.488	0.957
Gender = male	0.434	0.411	0.397	0.175
Ages 18-44	0.782	0.737	0.758	0.035
Ages 45-54	0.117	0.121	0.132	0.511
Ages 55-64	0.076	0.098	0.077	0.080
Ages 65-74	0.020	0.041	0.033	0.013
Ages 75-84	0.005	0.003	0.001	0.172
Years of education	14.611	14.585	14.611	0.943
Live with a partner	0.534	0.543	0.523	0.596
Live with children	0.327	0.317	0.324	0.864
Live with flat or housemates	0.100	0.086	0.087	0.384
Live with parents	0.239	0.208	0.234	0.157
Live with relatives	0.120	0.089	0.105	0.045
Live alone	0.118	0.142	0.140	0.146
Lives in a rural rea	0.111	0.105	0.101	0.736
Lives in a city	0.327	0.343	0.294	0.032
Lives in a suburban area	0.276	0.278	0.296	0.486
Lives in a village	0.078	0.060	0.076	0.180
Monthly income 2019 ($)	4536.483	4224.130	4487.000	0.042
Use social media	0.931	0.919	0.912	0.226
Took survey on mobile	0.297	0.292	0.303	0.820
n	1197	1200	1213	

Notes. All variables listed in this table are binary, with the exception of 'years of education' which is measured in full year increments. We use these variables as controls when conducting our statistical analyses. The final column reports the p-value from a joint orthogonality test of equality of means between the three treatment groups.

D Descriptive analysis

Table A2: Pre-treatment variables

VARIABLES	*n*	Mean	Min	Max
Gender = male	3,579	0.414	0	1
Age = 18 to 44	3,610	0.759	0	1
Age = 45 to 54	3,610	0.123	0	1
Age = 55 to 64	3,610	0.084	0	1
Age = 65 to 74	3,610	0.031	0	1
Age = 75 to 84	3,610	0.003	0	1
Years of education	3,610	14.60	6	18
Politics = liberal	3,610	0.544	0	1
Politics = conservative	3,610	0.219	0	1
Lives with partner	3,610	0.533	0	1
Lives with children	3,610	0.322	0	1
Lives with flat/housemates	3,610	0.091	0	1
Lives with parents	3,610	0.227	0	1
Lives with other relatives	3,610	0.105	0	1
Lives alone	3,610	0.134	0	1
Lives in rural area	3,610	0.106	0	1

Lives in city/urban area	3,610	0.321	0	1
Lives in sub-urban area	3,610	0.283	0	1
Lives in village	3,610	0.071	0	1
Monthly pre-tax income in 2019 ($)	3,608	4,416	1,000	14,634
Know anyone with COVID-19	3,610	0.158	0	1
Know anyone lost job due to pandemic	3,610	0.569	0	1
Been in contact with an infected person	2,468	0.046	0	1
Currently employed	3,610	0.658	0	1
Took survey on mobile	3,610	0.298	0	1
Furloughed	3,610	0.051	0	1
Consumes right-wing news	3,610	0.307	0	1
Has symptom: high temperature	3,610	0.016	0	1
Has symptom: chest pain	3,610	0.033	0	1
Has symptom: muscle soreness	3,610	0.100	0	1
Has symptom: diarrhea	3,610	0.043	0	1
Has symptom: headache	3,610	0.211	0	1
Has symptom: nausea	3,610	0.024	0	1
Has symptom: persistent cough	3,610	0.153	0	1

Has symptom: difficulty breathing	3,610	0.042	0	1
Number of symptoms	3,610	0.622	0	8
Has no COVID-19 symptoms	3,610	0.624	0	1
Likely to become unemployed	3,610	0.112	0	1
Believes unemployment will rise by 10 p.p. by August	3,610	0.889	0	1
Believes economy will shrink by August	3,610	0.094	0	1
Likely to experience food insecurity	3,610	0.273	0	1
Believes restrictions will last for more than 3 months	3,610	0.482	0	1
Country = UK (0 = US)	3,610	0.485	0	1
Uses social media	3,610	0.920	0	1
Misinformed about cures for COVID-19	3,610	0.264	0	1
Correct beliefs about ETA for vaccine	3,610	0.512	0	1

Table A3: Post-treatment variables

VARIABLES	n	Mean	Min	Max
Perceived risk of hospitalization after contracting COVID-19	2,428	31.74	0	100
Perceived risk of dying if hospitalized for COVID-19	2,428	20.26	0	100
Beliefs about R_0	2,428	23.58	0	100
Optimistic about future prospects	2,428	0.466	0	1
Willing to work from home for seven days	2,414	0.671	0	1
Willing to work from home for 2 months	2,428	0.674	0	1
Willing to avoid meeting people in risk groups for 7 days	2,427	0.920	0	1
Willing to avoid meeting people in risk groups for 2 months	2,428	0.925	0	1
Willing to frequently wash hands for 7 days	2,427	0.978	0	1
Willing to frequently wash hands for 2 months	2,428	0.978	0	1

Table A4: Predictors baseline CFR and R_0 beliefs

VARIABLES	Overestimate CFR	Overestimate R_0
In high-risk group	0.114***	0.0469*
No COVID-19 symptoms	-0.0180	-0.0129
Consumes right-wing news	0.0312	0.0452*
Currently employed	0.0132	0.0154
Conservative	0.00594	0.0114
Country = UK	-0.125***	-0.0954***
Gender = male	-0.174***	-0.133***
Over 55 years of age	0.243***	-0.0500
Years of education	-0.0207***	-0.0269***
Lives with partner	0.0150	0.0345
Lives with children	0.0748***	0.0307
Lives with flat/house mates	-0.0701	0.00319
Lives with parents	-0.00481	0.0589*
Lives with relatives	-0.00953	-0.0199
Lives alone	0.0833	0.0484
Lives in rural area	-0.0456	-0.0371
Lives in city	-0.00122	0.0381
Lives in suburban area	-0.0821*	-0.0251
Lives in village	-0.0493	-0.0661
Monthly income in 2019 (US $)	1.04e-06	4.45e-06
Uses social media	0.0693	0.0583
Took survey using mobile	0.0137	0.00899
Constant	0.754***	1.062***
Observations	1,793	1,793
R^2	0.095	0.048

Table A5: Treatment effects on beliefs about R_0

VARIABLES	% overestimate R_0	Change in R_0 beliefs
Assigned to lower-bound condition (R_0 = 2)	-0.118***	-10.61***
	(0.0191)	(1.035)
Assigned to upper-bound condition (R_0 = 5)	-0.269***	-4.564***
	(0.0192)	(1.374)
Constant	1.076***	-6.356
	(0.0877)	(6.723)
Control mean	0.728	0.216
Controls	Yes	Yes
Observations	3,577	1,793
R^2	0.073	0.046

Notes. This table presents the results from two regressions. The regressions presented in column 1 uses an LPM and the outcome is binary (whether someone overestimates R_0 post-treatment). The regression presented in column 2 uses OLS and the outcome is continuous (the difference in pre- and post R_0 beliefs). The sample is smaller for the second regression because we randomly elicit beliefs pre-treatment for half of the population. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

E Robustness checks and alternative specifications

Table A6: The effects of treatment assignment on beliefs about R_0

VARIABLES	Beliefs about R_0	Beliefs about R_0 squared
Assigned to lower-bound	-7.889***	-571.1***
	(1.139)	(108.7)
Assigned to upper-bound	-2.797**	50.80
	(1.260)	(123.6)
Constant	52.94***	3,734***
	(5.663)	(558.0)
F-statistic	23.1	18.25
Controls	Yes	Yes
Observations	3,577	3,577
R^2	0.048	0.044

Notes. This table presents two OLS regressions. The outcome in column 1 is beliefs about R_0, and the outcome in column 2 is squared beliefs about R_0. Demographic control variables are used in both regressions.

Table A7: Estimation with two instruments

	Willingness to avoid meeting people in high-risk groups			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.00740		0.0131	
Lower-bound condition	0.0169		0.0389***	
Beliefs about R_0		-0.00247*		-0.00495***
Constant	0.909***	1.031***	0.826***	1.048***
Control mean	0.918		0.901	
R^2	0.023		0.029	
	Willingness to wash hands frequently			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.00105		-0.00401	
Lower-bound condition	0.00485		0.00917	
Beliefs about R_0		-0.000682		-0.00134*
Constant	0.989***	1.080***	1.008***	1.123***
Control mean	0.977		0.975	
R^2	0.013		0.014	
	Willingness to work from home			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.0165		-0.00315	
Lower-bound condition	0.0113		0.0165	
Beliefs about R_0		-0.00193		-0.00231
Constant	-0.293	-0.0535	-0.264	-0.0992
Control mean	0.683		0.674	
R^2	0.079		0.071	

Notes. This table presents results from instrumental variable regressions (2SLS) where assignment to the lower-bound or upper-bound conditions act as instrumental variables for beliefs regarding R_0. The outcomes of interest are whether participants comply with various behaviors if the pandemic continued for 7 days or 2 months. We use robust standard errors (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). In all regressions, the sample size is $3,577$ and demographic control variables are used.

Table A8: Testing for linear causal effects

	Willingness to avoid meeting people in high-risk groups			
VARIABLES	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Assigned to upper-bound	-0.00740		0.0131	
Assigned to lower-bound	0.0169		0.0389***	
Beliefs about R_0		0.00168		-0.00474
Beliefs about R_0 squared		-5.29e-05		-2.66e-06
Constant	0.852***	0.871***	0.838***	1.004***
R^2	0.023		0.029	
	Willingness to wash hands frequently			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Assigned to upper-bound	-0.00105		-0.00401	
Assigned to lower-bound	0.00485		0.00917	
Beliefs about R_0		0.000177		0.000913
Beliefs about R_0 squared		-1.09e-05		-2.87e-05
Constant	0.962***	1.015***	0.971***	1.027***
R^2	0.013		0.014	
	Willingness to work from home			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Assigned to upper-bound	-0.0165		-0.00315	
Assigned to lower-bound	0.0113		0.0165	
Beliefs about R_0		0.00442		0.000482
Beliefs about R_0 squared		-8.09e-05		-3.56e-05
Constant	-0.189**	-0.398**	-0.124	-0.317
R^2	0.079		0.071	

Notes. This table presents ITT and LATE estimates for the effects of beliefs about R_0 (and squared beliefs about R_0) on participants' willingness to engage in best practice behaviors. Two instruments are used in the 2SLS estimation: assignment to the upper-bound condition and assignment to the lower-bound condition.

Table A9: The effect of treatment assignment on beliefs (re-weighted)

VARIABLES	Beliefs about R_0	Beliefs about the CFR
Assigned to lower-bound ($R_0 = 2$)	-6.092***	2.410*
	(1.422)	(1.435)
Assigned to upper-bound ($R_0 = 5$)	0.912	0.0574
	(1.732)	(1.388)
Constant	53.63***	39.88***
	(7.002)	(5.819)
Controls	Yes	Yes
Observations	3,577	3,577
R^2	0.051	0.190

Notes. This table presents results from OLS regressions examining the effects of being assigned to the lower- or upper-bound treatments on key beliefs (one per column). We use robust standard errors (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). All outcomes are measured on a scale from 0 to 100. Demographic control variables (e.g., age, geography, education, and income) are used in all specifications. Comparisons are made relative to the group that receives no treatment. All regressions use weights that adjust for age, gender, and location.

Table A10: Effects of R_0 beliefs on willingness to engage in best practices (re-weighted)

	Willingness to avoid meeting people in high-risk groups			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.0238		-0.0380*	
Beliefs about R_0		-0.00334		-0.00535
Constant	0.734***	0.901***	0.803***	1.070***
R^2	0.034		0.037	
	Willingness to wash hands frequently			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.0159		-0.0220**	
Beliefs about R_0		-0.00224		-0.00309*
Constant	1.052***	0.933***	1.088***	1.088***
R^2	0.019		0.020	
	Willingness to work from home			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Upper-bound condition	-0.0464		-0.0419	
Beliefs about R_0		-0.00653		-0.00588
Constant	-0.162	0.164	-0.0708	0.223
R^2	0.083		0.067	

Notes. This table presents results from instrumental variable regressions (2SLS) where assignment to the upper-bound exponential condition acts as an instrumental variable for beliefs regarding R_0. The outcomes of interest are whether participants comply with various behaviors if the pandemic continued for 7 days or 2 months. The sample sizes differ slightly between regression due to (as good as randomly allocated) missing values in the dependent variable. We use robust standard errors (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). The control group is not included in this analysis. The sample is re-weighted in terms of age, gender, and location.

Table A11: Effects of beliefs about R_0 on optimism (re-weighted)

	ITT	LATE
VARIABLES	Optimism	Optimism
Assigned upper-bound condition	-0.0368	
	(0.0310)	
Beliefs about R_0		-0.00517
		(0.00466)
Constant	0.427*	0.686**
	(0.236)	(0.344)
Controls	Yes	Yes
Observations	2,391	2,391
R^2	0.040	

Notes. This table presents the results from two regressions. The regression in the first column is run using an LPM, with independent variables being assignment to the upper-bound condition in addition to demographic controls (these are listed in Section 3.1). The dependent variable is whether respondents feel optimistic about their future (a binary variable). The regression in the second column uses 2SLS, where assignment to the upper-bound exponential condition acts as an instrumental variable for beliefs regarding R_0. The dependent variable is whether participants are optimistic about their future. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). We drop the control group in these analyses. The sample is re-weighted in terms of age, gender, and location.

Table A12: Effects of R_0 beliefs on willingness to engage in best practices (dropping outliers)

	Willingness to avoid meeting people in high-risk groups			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Assigned upper-bound condition	-0.0240**		-0.0246**	
Beliefs about R_0		-0.00443**		-0.00453**
Constant	0.843***	1.041***	0.822***	1.023***
R^2	0.020		0.021	
	Willingness to wash hands frequently			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Assigned upper-bound condition	-0.00602		-0.0134**	
Beliefs about R_0		-0.00111		-0.00246**
Constant	1.028***	1.077***	1.008***	1.117***
R^2	0.014		0.017	
	Willingness to work from home			
	7 days ITT	7 days LATE	2 months ITT	2 months LATE
Assigned upper-bound condition	-0.0288		-0.0190	
Beliefs about R_0		-0.00531		-0.00351
Constant	-0.305	-0.0684	-0.286	-0.130
R^2	0.081		0.073	

Notes. This table presents results from instrumental variable regressions (2SLS) where assignment to the upper-bound exponential condition acts as an instrumental variable for beliefs regarding R_0. The outcomes of interest are whether participants comply with various behaviors if the pandemic continued for 7 days or 2 months. The sample sizes differ slightly between regression due to (as good as randomly allocated) missing values in the dependent variable. We use robust standard errors (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Demographic control variables are used in all regressions. The control group is not included in this analysis. We drop participants that believe that R_0 is 100 at baseline, as they may have misunderstood the question.

F Heterogeneity analysis

Table A13: Heterogenous treatment effects on beliefs

VARIABLES	(1)	(2)	(3)	(4)	(5)
Assigned to lower-bound	-7.526***	-7.569***	-8.702***	-8.063***	-7.153***
Assigned to upper-bound	-3.304**	-1.795	-2.603	-4.086***	-3.592**
Over 55	-3.422				
Lower * Over 55	0.334				
Upper * Over 55	6.134				
Right-wing news		4.018**			
Lower * Right-wing news		0.333			
Upper * Right-wing news		-2.580			
Gender = male			-6.480***		
Lower * Gender = male			2.240		
Upper * Gender = male			-0.474		
Conservative				1.118	
Lower * Conservative				2.218	
Upper * Conservative				6.402**	
In high-risk group					0.841
Lower * In high-risk group					-1.966
Upper * In high-risk group					4.090
Constant	29.02***	27.37***	31.51***	28.42***	28.46***
Controls	No	No	No	No	No
Observations	3,610	3,610	3,579	3,610	3,610
R^2	0.012	0.014	0.021	0.016	0.013

Notes. This table presents five OLS regressions, where treatment assignment is interacted with participant characteristics. We use robust standard errors (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Demographic control variables are used in all regressions.

Table A14: Effect of eliciting pre-treatment R_0 beliefs on post-treatment R_0 beliefs

VARIABLES	(1)	(2)	(3)	(4)
Upper-bound condition			-5.051***	6.463***
Asked pre-treatment	2.390**	-1.697	-1.697	5.950***
Upper-bound * Asked pre-treatment			4.884*	-2.762
Lower-bound condition			-11.51***	
Lower-bound * Asked pre-treatment			7.647***	
Upper- or lower-bound condition		-8.178***		
Upper- or lower-bound * Asked pre-treatment		6.121***		
Constant	24.05***	29.52***	29.52***	18.00***
Controls	No	No	No	No
Observations	3,610	3,610	3,610	2,413
R^2	0.002	0.010	0.016	0.013

Notes. This table presents four OLS regressions. The outcome is, in each case, post-treatment beliefs about R_0. The first column shows the effect of eliciting pre-treatment beliefs about R_0 on post-treatment beliefs about R_0 and the regression includes the entire sample. The second column shows the interactive effect of eliciting pre-treatment beliefs and being assigned to one of the two treatment conditions on post-treatment beliefs about R_0 and includes the entire sample. The third column shows the interactive effect of being assigned to the upper- and lower-bound condition and eliciting pre-treatment beliefs and uses the entire sample. The final column shows the interactive effect of being assigned to the upper-bound condition and eliciting pre-treatment beliefs, with the lower-bound condition as the reference group (the control group is dropped). We use robust standard errors (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

G Survey questions

G.1 Overview and sampling

We conducted two surveys, one for UK residents and one for US residents. The questions administered to UK residents are listed below. Some questions were adjusted slightly for the US audience (e.g., spelling, currencies, and the names of education qualifications). The survey took around ten minutes to complete, participants were recruited via Prolific Academic, and the survey was conducted using the Qualtrics platform. No screening or eligibility criteria were applied. We dropped participants who did not complete the full survey from our analysis sample (there were few dropouts, and there was no differential attrition). We paid participants the equivalent of $7.50 an hour in exchange for completing the survey. The order of questions and the response options within questions were randomized when appropriate.

Participants were debriefed at the end of the survey, and we recommended that they visit the CDC or NHS websites (depending on country of residence) for more information about COVID-19.

G.2 Survey introduction

Welcome and thanks for participating!

This is a study about the recent Coronavirus pandemic. In this study, you will be asked a set of questions about yourself, your beliefs, and your habits.

The survey should take around 10 minutes to complete.

By clicking the button below, you acknowledge that your participation in the study is voluntary, that you are at least 18 years of age, and that you are aware that you can end your participation in the study at any time and for any reason.

Your data will be kept strictly confidential and will not be shared with any third party. Your data will only be used for research purposes.

G.3 Pre-treatment questions

Q1. What do you think the risk is that someone your age is hospitalised if they contract the Coronavirus?

Slider from 0-100%

Q2. What do you think the risk is that someone your age would die, if they are hospitalised as a result of the Coronavirus?

Slider from 0-100%

Q3. On average, how many people do you think will catch the Coronavirus from one contagious person? Please only consider cases transmitted by coughing, sneezing, touch or other direct contact with the first contagious person.

Slider from 0-100

Half of the sample was randomly asked to answer questions 1–3, the other began the survey by answering question 4.

Q4. Please select your gender.

(1) Male (2) Female (3) Other

Q5. Please select your age range.

(1) 18-44 (2) 45-54 (3) 55-64 (4) 65-74 (5) 75-84 (6) 85+

Q6. What is the highest level of education you have completed?

(1) Primary school
(2) Secondary school (GCSE, I-level, AS level, or equivalent)
(3) Secondary school (A-level, BTEC, or equivalent)
(4) University diploma
(5) Undergraduate degree
(6) Postgraduate degree (e.g., MSc or PhD)

Q7. Do you live with any of the following? Please select all that apply.

(1) Partner (2) Children (3) Flat or house mates (4) Parents (5) Other relatives

Q8. What type of area do you live in?

(1) City (2) Town (3) Village (4) Rural

Q9. What was your monthly household income in 2019 (pre-tax)?

(1) £0-1999 (2) £2000-3999 (3) £4000-5999 (4) £6000-7999 (5) £8000-9999
(6) £10,000-11,999 (7) £12,000+

Q10. Do you have any of the following health conditions? Please select all that apply.

(1) Cardiovascular disease (2) Diabetes (3) Chronic respiratory disease (4) Hypertension

(5) Asthma (5) Other serious condition (such as cancer) (6) None of the above

Q11. Have you had any of these symptoms within the last 48 hours? Please select all that apply.

(1) High temperature (2) Cough (3) Difficulty breathing or breathlessness (4) Chest pains (5) Headache (6) Muscle soreness (7) Nausea or vomiting (8) Diarrhea (9) None of the above

Q12. Do you personally know someone that has contracted Coronavirus?

(1) Yes (2) No

Q13. Do you personally know someone who has become unemployed because of how the Coronavirus has affected the economy?

Q14. Which political party do your views most align with?

(1) Conservative (2) Labour (3) Liberal Democrats (4) Other (please specify) (5) No political party

Q15. Do you use any of the following news sources (online or in person) on a weekly basis? Please select all that apply.

(1) The Sun (2) The Daily Mail (3) The Telegraph (4) The Guardian (5) The Times (6) The Financial Times (7) The Mirror (8) The Express (9) The Independent (10) The Star (11) BBC (12) ITV (13) Sky News (14) Metro Online (15) Huffington Post (16) Buzzfeed (17) The Canary (18) Westmonster (19) Another Angry Voice (20) Breitbart (21) None of the above

Q16. Do you use any of the following social media platforms? Please select all that apply.

(1) Facebook (2) Twitter (3) Instagram (4) LinkedIn (5) TikTok (6) Snapchat

Q17. Please identify the symptoms of the Coronavirus. Select all that apply.

(1) Fever (2) Dry cough (3) Wet cough (4) Sneezing (5) Rash (6) Chest pains (7) Fatigue (8) Stomach pain (9) Blindness (10) Shortness of breath (11) None of the above

Q18. In the last week, have you or a person who lives with you been in contact with someone who has the Coronavirus?

(1) Yes (2) No (3) Don't know

Q19. For how long do you believe that Coronavirus-related restrictions on behaviour and free movement are likely to last for in the UK?

(1) One month or less (2) One to three months (3) Three to six months (4) Six months to a year (5) Over a year

Q20. What do you expect the general economic situation in this country to be in August 2020 (compared to January 2020)?

Slider from 1–7 (1 = a lot worse, 4 = the same, 7 = a lot better)

Q21. How likely is it that unemployment will increase by at least 10 percentage points in the next three months?

Slider from 1–7 (1 = extremely unlikely, 4 = neither likely nor unlikely, 7 = extremely likely)

Q22. In how many months do you think a vaccine against the Coronavirus will be made available for the public in the UK? Please select 48 if you believe that it will take more than 48 months.

Slider from 0–48

Q23. Are any of the following effective treatments for the Coronavirus? Please select "Effective treatment", "Not an effective treatment", or "Not sure" for each option.

(1) Drinking water every 15 minutes and keeping your mouth moist (2) Avoiding eating ice cream (3) Exposing yourself to sunshine (4) Gargling warm water with salt or vinegar (5) Using a hairdryer to blow hot hair toward your face (6) Ingesting colloidal silver (7) Taking C vitamins

Q24. Are you currently employed?

(1) Yes (2) No (3) No, recently laid off (4) Yes, furloughed

(If response is (1) or (4) to Q24): Q25. How likely is it that you will become unemployed as a result of the Coronavirus pandemic?

Slider from 1–7 (1 = extremely unlikely, 4 = neither likely nor unlikely, 7 = extremely likely)

G.4 Treatments

One third of the participants are randomly allocated to the control group. One third of the participants are randomly allocated to the upper-bound group. One third of the participants are randomly allocated to the lower-bound group. Please see Figure 1 for the treatment images. Prior to administering the treatments, we say "We will now show you a poster about the Coronavirus pandemic. Please have a careful look at the poster and then press next to continue." Participants are required to stay on the page with the treatment for fifteen seconds before being allowed to proceed.

G.5 Post-treatment questions

Q25. What do you think the risk is that someone your age is hospitalised if they contract the Coronavirus?

Slider from 0-100%

Q26. What do you think the risk is that someone your age would die, if they are hospitalised as a result of the Coronavirus?

Slider from 0-100%

Q27. On average, how many people do you think will catch the Coronavirus from one contagious person? Please only consider cases transmitted by coughing, sneezing, touch or other direct contact with the first contagious person.

Slider from 0-100

Q28. How likely are you to do the following during the coming seven days? (Answer 1–5, 1 = extremely unlikely, 3 = neither likely nor unlikely, 5 = extremely likely).

(1) Work from home (2) Avoid people at high risk (i.e., those that are either at least 70 years of age, pregnant, have a long-term condition, or a weakened immune system) (3) Wash your hands with water and soap several times a day

Q29. Assume that the Coronavirus outbreak is still ongoing 2 months from now. How likely would you be to do the following during the average week? (Answer 1–5, 1 = extremely unlikely, 3 = neither likely nor unlikely, 5 = extremely likely).

(1) Work from home (2) Avoid people at high risk (i.e., those that are either at least 70 years of age, pregnant, have a long-term condition, or a weakened immune system) (3) Wash your hands with water and soap several times a day

Q30. How optimistic are you about your future?

Slider from 1–7 (1 = very pessimistic, 4 = neither optimistic nor pessimistic, 7 = very optimistic)

G.6 Debriefing

Thank you for completing our survey.

The Coronavirus pandemic is ongoing and we are still developing our understanding of the risks that it poses to society. As such, the information that you were presented with in this survey may be incorrect.

Please refer to nhs.uk/conditions/coronavirus-covid-19/ for the latest up-to-date information about the Coronavirus pandemic.