Information and Behavioral Responses during a Pandemic: Evidence from Delays in Covid-19 Death Reports*

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Information may be an important policy tool for managing epidemics. Focusing on Covid-19 in Mexico, we randomize an informational treatment in an online survey showing a higher or lower death toll by leveraging delays in death reports, and estimate its effects on individuals' beliefs and behavior. We find that reporting a lower death count – when delays are not accounted for – leads to a lower perceived risk of contagion and a lower intention to comply with social distancing. An equilibrium model incorporating the endogenous behavioral response documented by our intervention illustrates the implied differences for the evolution of the epidemic.

JEL codes: I12; I18; D83; H12

Key words: information; reporting delays; behavior; social distancing; Covid-19

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1 Introduction

Managing the current Covid-19 pandemic is particularly challenging since the usual pharmaceutical instruments, such as vaccines and antivirals, are not yet available on a large scale (Ferguson et al., 2020).[1] Controlling the epidemic has therefore relied on non-pharmaceutical interventions, such as country and city-level lockdowns and social distancing.[2] Recent contributions by economists (Eichenbaum et al., 2020a; Fernández-Villaverde and Jones, 2020; Bayraktar et al., 2020; Chudik et al., 2020) have highlighted how individual behavior matters for predicting the severity and size of epidemic curves. Hence, understanding the factors that shape individual behavior during pandemics is crucial.[3]

One such factor is information and how it is presented. In some settings, such as HIV in Africa, information provision has been found to have large effects on behavior (Dupas, 2011; Dupas et al., 2018), while in others, such as vaccination in the US, it has been shown to be mostly ineffective (Nyhan and Reifler, 2015; Sadaf et al., 2013). In the current setting of Covid-19, multiple projects led by economists explore – not surprisingly – how information provision may impact compliance with preventive measures and the evolution of the epidemic.[4] In light of widespread misinformation (Zarocostas, 2020), it remains to be seen whether these informational interventions indeed affect behavior and to what extent their effects may be replicated in other settings.[5]

[1]Although vaccines and medications are being developed and tested, there is no widespread available treatment or inoculation as of this writing. See, for example, https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html?searchResultPosition=1 and https://www.nytimes.com/2020/06/24/health/coronavirus-dexamethasone.html?searchResultPosition=6, last accessed July 1, 2020.

[2]Various papers in different settings have generally found that social distancing measures have a positive impact on containing the epidemic. See, for example, Hsiang et al. (2020); Dave et al. (2020); Alexander and Karger (2020); Juranek and Zoutman (2020); Jinjarak et al. (2020); and Ferguson et al. (2020).

[3]The emerging literature on Covid-19 has analyzed the roles of sociodemographic characteristics (Papageorge et al., 2020; Knittel and Ozaltun, 2020), political beliefs (Allcott et al., 2020; Baccini and Brodeur, 2020; Barrios and Hochberg, 2020), social capital (Bargain and Aminjonov, 2020; Brodeur et al., 2020; Ding et al., 2020; Durante et al., 2020), and the media (Simonov et al., 2020; Bursztyn et al., 2020).

[4]For example, we identified that at least 7% of the projects registered up to July 14, 2020, in IPA's RECOVR initiative are experimental trials with informational treatments. These projects span a wide range of interventions: reminders, precise information about the biology of the disease, risk-reducing techniques such as hand-washing or mask-wearing, and the format in which the information is presented (such as the identity of the sender). See https://www.poverty-action.org/recovr/research-projects.

[5]Some initial findings suggest that providing information increases the probability of reporting symptoms to public health workers and compliance with mitigating behaviors in India (Banerjee et al., 2020).

In particular, communicating information on the state of the epidemic (i.e., case and death counts) is thought to be a powerful tool for affecting behavior (WHO, 2013, 2005).[6] However, most of the existing evidence for the Covid-19 pandemic is non-experimental due to the obvious ethical concerns of withholding or presenting false information (Janssen and Shapiro, 2020; Maloney and Taskin, 2020; Goolsbee and Syverson, 2020; Ding et al., 2020; Gupta et al., 2020). Given the many differences across countries in testing strategies and the capacity of surveillance systems, the extent to which this information matters for individual behavior may provide an opportunity for low-cost interventions, such as predicting the full prevalence of the epidemic beyond lab-confirmed cases and deaths using statistical correction factors.

In this paper, we estimate the effect of a higher Covid-19 death toll on individual risk perceptions and intentions to comply with stay-at-home recommendations, by leveraging the fact that, in Mexico, Covid-19 deaths are reported with relatively large delays. We fielded an online survey which randomly showed individuals counts of total cumulative Covid-19 deaths by date reported or by date occurred. This intervention was feasible because the Mexican health authorities regularly present information on deaths in both formats (so that truthful information was presented to all respondents), and because reporting delays in Mexico are large enough to show a sizable difference between deaths by date reported and by date occurred (on average, the former are 41% smaller than the latter in the time frame used in the experiment).

We then compare respondents' beliefs regarding the severity of the epidemic and their reported intentions of complying with the government's shelter in place recommendations between groups that received different information on death counts. In order to illustrate the implications for the evolution of the pandemic, we develop a simple equilibrium model that incorporates the insights gleaned from the survey.

We focus on Mexico since this middle-income country provides an ideal setting for analyzing this issue for at least three reasons. First, the delays in Covid-19 death reports – defined as the time difference between when a death occurs and when it is reported in the centralized system – are particularly substantial.[7] Gutierrez et al. (2020) documents that these delays are relatively

[6] According to Brodeur et al. (2020), the key information during an epidemic is the number of tests, cases, and deaths. Other factors that may lead to imperfect measures of these indicators include differential times for processing tests, and undercounting of undiagnosed deaths, among others.

[7] Delays in reporting deaths are a well-known problem, documented across a variety of settings (AbouZahr et al., 2015; Bird, 2015). This issue may be particularly challenging in low and middle-income countries, where diminished

large, heterogeneous across space, and correlated with local measures of the capacity of the public healthcare system. Second, Mexican officials routinely present information on confirmed Covid-19 deaths over time, counting both by the actual date of death and the date on which the death was reported in the centralized system.[8] Lastly, the Mexican government chose a relatively lenient strategy that consisted of mostly optional lockdowns and stay-at-home recommendations, implying that understanding the determinants of individual behavior matters a lot for compliance in this setting.[9]

Leveraging these reporting delays, we conducted an online survey where we (i) elicited baseline priors and behaviors, (ii) provided information about the evolution of the outbreak, and (iii) recovered self-reported measures of perceptions about the risk of contagion and intended compliance with social distancing. Our randomized information treatments presented the cumulative death count either by date reported or by actual date of death from the onset of the epidemic up to 12 days before fielding the survey. Given the reporting delays, the former understated total deaths by up to 2,055 cumulative deaths in a given day relative to the latter.[10] Hence, while both treatments presented truthful information, one of them substantially underestimated the timing of the evolution of the epidemic given the lags in reporting.[11]

Our object of interest is the average difference between respondents that received the smaller death toll (based on reported deaths, which we call "lagged" information) relative to those that saw the larger one (based on deaths by date occurred or "unlagged" information). Our results indicate that the lower count due to information containing reporting delays leads to a perception of lower risk of contagion, and lower self-reported intention to comply with social distancing measures.[12]

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state capacity may impede the collection of reliable and accurate real-time information. Anecdotal evidence also suggests that this may be an issue in some parts of the US (see, for example, https://www.nytimes.com/2020/07/13/upshot/coronavirus-response-fax-machines.html, last accessed July 15, 2020).

[8]Information on deaths is presented by date occurred on this government website: https://coronavirus.gob.mx/datos/. During the nightly press conference, information is presented in both formats. See, for example, the first slide of the press conference presentation: https://presidente.gob.mx/conferencias-de-prensa-informe-diario-sobre-coronavirus-covid-19-ssa/.

[9]See, for example, https://www.informador.mx/mexico/No-habra-represion-para-detener-propagacion-del-COVID-19-reafirma-Lopez-Obrador-20200428-0039.html and https://piedepagina.mx/no-tenemos-camas-de-hospital-en-los-parques/, last accessed June 30, 2020.

[10]On average, we find that deaths occurring on a given date are reported with a delay of about six days.

[11]Given the differential reporting delays by date, our treatments also show (slightly) different shapes for the cumulative death curves. Gutierrez et al. (2020) explicitly shows how in this context the epidemic curves, as predicted by a classic epidemiological model, differ when considering either method of counting total deaths.

[12]Our results from this exercise show that despite the fact that government authorities in Mexico publicly present both total deaths by date reported and by date of death, individuals form different beliefs and report different

Informed by these findings and focusing on the specific issue of reporting delays that leads to a seemingly lower death toll, we develop a model of equilibrium behavior that showcases the differential responses of agents, who form beliefs based on lagged or unlagged information, in order to generate predictions on the evolution of the epidemic. We calibrate the model for Mexico and show the corresponding results. We find that in a world where individuals form beliefs without lags – that is, beliefs based on data without reporting delays – they will adopt mitigating behaviors sooner than a scenario where agents' beliefs are based on lagged data, which in turn leads to a smoother epidemic curve.

The model emphasizes the importance of information presented to individuals during an epidemic. Inaccurate real-time information due to reporting delays leads to individuals being slower to adopt protective behaviors and to more severe epidemic outcomes in terms of cases and deaths precisely because they perceive a lower risk of the disease. Moreover, the faster speed of the epidemic induced by slower reactions will tend to generate excessive responses later on, which may exacerbate the negative economic impacts of the pandemic.

We contribute to three strands of the growing literature on the economics of Covid-19.[13] First, our paper relates to those that have experimentally explored how messages and information affect various outcomes. Akesson et al. (2020) provides different information about the infectiousness of Covid-19, finding that individuals who received the larger estimate of contagion risk were actually less likely to report complying with mitigating behaviors, potentially due to an increased sense of fatalism. Binder (2020) randomizes information about the Fed cutting interest rates, increasing consumers' optimism regarding unemployment and inflation. Coibion et al. (2020) randomizes information about different US government policies, finding a null impact on beliefs and spending plans of consumers, likely due to households' priors about the effectiveness of macroeconomic policies. While these studies focus on the effect of receiving information, our paper emphasizes the role of the accuracy of information received.

Second, we contribute to the recent literature that attempts to incorporate changes in behavior over the course of the pandemic into dynamic models that are aimed at predicting its evolution over time (Fernández-Villaverde and Jones, 2020; Brotherhood et al., 2020). By explicitly incorporating

intended behaviors when presented with only one of the two. This suggests that individuals do not fully understand the implications of delays, and do not just incorporate this information when forming beliefs.

[13]See Brodeur et al. (2020) for an overview of the Covid-19 literature in economics.

the endogenous behavioral response resulting from lags in information, we illustrate how this specific channel may determine the evolution of the outbreak.

Lastly, we add to the set of papers focusing on identifying the additional restrictions and challenges that low and middle-income countries face in managing the pandemic and subsequent economic recovery. Various studies have focused on features 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). We contribute to this line of work by focusing on the potential consequences of issues in collecting reliable real-time information during the pandemic. Given the relationship between reporting delays and state capacity (Gutierrez et al., 2020), this is likely to be an issue for many other low and middle-income countries.

In terms of policy implications, we identify a specific dimension through which most countries can improve their information provision strategies: being clear and upfront about the shortcomings in the available data. For instance, statistical techniques could be developed in real time in order to provide reliable estimates of the death toll, despite common issues with undertesting and reporting delays.

The rest of the paper is organized as follows. Section 2 describes the survey. Section 3 presents the effects from the treatments. Section 4 outlines the equilibrium model and discusses the results. Section 5 concludes.

2 Survey and Descriptive Statistics

In order to explore whether differences in the information regarding the state of the Covid-19 epidemic affect individuals' perceptions about the evolution of the pandemic and, consequently, their behavior, we conducted an online survey with a randomized informational treatment that presented cumulative total deaths either by date reported or by actual date of death. The full survey consisted of 48 closed-response multiple choice questions and ran from May 28 to June 8, 2020.[14] We recruited participants via email and social media (namely, Twitter), and respondents were not compensated for participating.[15] Our final sample consists of 1,022 completed surveys.

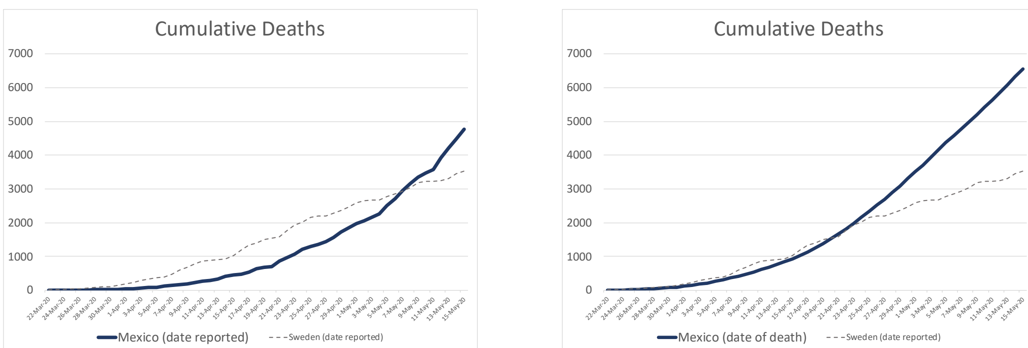
[14]See online appendix B for a full translation of the survey questions and response options.

[15]Our mailing list was obtained from ITAM, and consisted of all faculty, administrative staff, and students.

The first set of questions were aimed at recovering socioeconomic characteristics of respondents, as well as their pre-intervention perceptions about the state of the Covid-19 pandemic in Mexico. We asked questions related to age, gender, state of residence, household composition, income, employment status, and a self-reported estimation of the number of Covid-19 cases and deaths by May 20.

After these initial questions, respondents were taken to a new screen showing at random one of the two graphs depicted in Figure 1. A total of 508 participants were shown Figure 1a, which plots cumulative deaths in Mexico by date on which they were reported. The remaining 514 participants were shown Figure 1b, which instead plots cumulative deaths by actual date of occurrence. Both figures show data from March 22 to May 15, using data up to May 27.[16] Additionally, we include the cumulative number of deaths by date reported in Sweden as a reference.[17]

Figure 1:
Information Treatments in the Survey



(a) Cumulative deaths by date reported

(b) Cumulative deaths by date of occurrence

Notes: These graphs show the information treatments that we randomized in the survey. Respondents were shown these exact figures with captions translated into Spanish. Each plot shows data from March 22 to May 15, using information reported up to May 27, 2020. We include the cumulative number of deaths by date reported in Sweden as a reference. The plot on the left shows the cumulative deaths in Mexico based on the date they were reported. The plot on the right shows cumulative deaths by date on which they actually occurred.

Both figures contain truthful information as presented by government authorities themselves. Note that total deaths by date reported in Figure 1a understate total deaths by date occurred

[16] This means that we allow for deaths to be reported with a lag of at most 12 days.

[17] The data for Sweden were obtained from https://ourworldindata.org/coronavirus. Sweden followed a similar strategy to Mexico, imposing relatively light restrictions (Juranek and Zoutman, 2020). The trajectory of the epidemic in Mexico had been compared to that in Sweden by Mexican authorities a few days before the survey was implemented. See, for example, https://twitter.com/HLGatell/status/1257694745322819586?s=20 and https://www.milenio.com/politica/ya-aplanamos-la-curva-lopez-gatell, last accessed June 29, 2020.

(Figure 1b) by 41% on average, with a difference of up to 2,055 deaths on May 11. While not accounting for delays implies that the evolution of Covid-19 deaths appears to be slower and with a lower death toll thus far, it is not necessarily the case that this would induce a perception of lower risk, especially since neither plot shows a clear change in the growth rate of deaths. If sophisticated agents were aware of this data collection problem, then they could assess the true risk even when receiving information with delays.

After presenting the corresponding figure, participants answered additional questions regarding beliefs about the risk of contagion associated with attending social gatherings, the expected number of total Covid-19 cases and deaths over the whole epidemic outbreak, and the number of times they expected to leave their home the week after they participated in the survey, as well as four weeks later.

Table 1 tests for balance in observable characteristics between respondents in each of these treatment groups. Columns 1 and 2 present means for the sample that was shown the graph with cumulative deaths by date reported and by date occurred, respectively. Column 3 shows the corresponding difference in means. It is worth highlighting that, due to the nature of the survey conducted, the characteristics of participants suggest they belong to a relatively young, educated, and high-income group in Mexico. More than 78 percent of them live in Mexico City, and more than half of them live in a house with a yard. Evidently, this implies that none of our results can be used to infer the distribution of beliefs and behavior in the general Mexican population.[18] However, given the very small differences in observables between our two treatment groups, we can confidently interpret the results below as the impact of the information provided on the different outcomes.

3 Empirical Strategy and Results

3.1 Empirical Strategy

We explore the impact of the information provided in the survey on four different measures of perceptions about the risk of contagion and the evolution of the epidemic. Specifically, we focus

[18] Note also that our sample does not have enough variation to weight it so that it is representative of the entire population in Mexico.

Table 1:
Balance Table for Survey Covariates

	Informational treatments		
	Deaths by date reported	Deaths by date occurred	Difference in means
Female	0.496	0.490	-0.006
	(0.500)	(0.500)	(0.031)
Ages 18-22	0.321	0.383	0.062**
	(0.467)	(0.487)	(0.030)
Ages 23-29	0.274	0.253	-0.021
	(0.446)	(0.435)	(0.028)
Ages 30-49	0.230	0.216	-0.014
	(0.421)	(0.412)	(0.026)
Ages 50+	0.175	0.148	-0.027
	(0.381)	(0.355)	(0.023)
Works	0.409	0.329	-0.081***
	(0.492)	(0.470)	(0.030)
Attends school	0.368	0.416	0.048
	(0.483)	(0.493)	(0.031)
Works and attends school	0.157	0.158	0.000
	(0.365)	(0.365)	(0.023)
Other occupation/employment status	0.065	0.097	0.032*
	(0.247)	(0.297)	(0.017)
Lives in Mexico City	0.776	0.753	-0.023
	(0.418)	(0.432)	(0.027)
Lives in apartment	0.343	0.385	0.043
	(0.475)	(0.487)	(0.030)
Lives in house, no yard	0.124	0.117	-0.007
	(0.330)	(0.321)	(0.020)
Lives in house with yard	0.533	0.498	-0.035
	(0.499)	(0.500)	(0.031)
Household size: 1-2	0.232	0.251	0.019
	(0.423)	(0.434)	(0.027)
Household size: 3	0.207	0.245	0.038
	(0.405)	(0.431)	(0.026)
Household size: 4	0.252	0.226	-0.026
	(0.435)	(0.418)	(0.027)
Household size: 5+	0.561	0.504	-0.057*
	(0.497)	(0.500)	(0.031)
Has HH members over 70 years old	0.159	0.080	-0.080***
	(0.366)	(0.271)	(0.020)
Has HH members 60-70 years old	0.215	0.202	-0.012
	(0.411)	(0.402)	(0.025)
Has HH members 50-60 years old	0.461	0.471	0.010
	(0.499)	(0.500)	(0.031)
Does not seek healthcare when sick	0.140	0.154	0.014
	(0.347)	(0.361)	(0.022)
Self-medicates when sick	0.386	0.381	-0.005
	(0.487)	(0.486)	(0.030)
Observations	508	514	1,022

Notes: This table shows means and standard deviations for a series of covariates asked in the survey before the informational treatment was presented. We show statistics separately for each informational treatment, as well as the difference in the means. Stars denote significance from a difference in means test.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

on participants' responses to questions regarding the perceived risk of attending a gathering of 100 people in the week following the survey and in four weeks, as well as the predicted number of total Covid-19 cases and deaths over the course of the current outbreak. In terms of behavior, we focus on questions regarding the number of times respondents expect to leave their home in the week following the survey and four weeks later. Figures A2 and A3 in the online appendix show histograms of the responses to these six questions.

We estimate the following equation to measure differences in perceptions and behavior between our treatment groups:

$$y_i = \beta_0 + \beta_1 \times [\text{Info By Date Occurred}]_i + \Psi \mathbf{X_i} + \varepsilon_i \tag{1}$$

where y_i is the outcome variable for respondent i, β_0 is a constant, $[\text{Info By Date Occurred}]_i$ is a zero-one indicator for having received the informational treatment that displayed cumulative deaths by actual date of death, $\mathbf{X_i}$ is a vector of observable characteristics as listed in Table 1, and ε_i is the error term. Our estimate of interest corresponds to β_1, which measures the average difference in the outcome variable for survey respondents that were shown the cumulative death toll by date of occurrence with respect to those who were shown the information by date reported.

For simplicity, we construct binary measures of our risk perception variables, where a value of one denotes a high risk perception. Specifically, we assign a value of one if respondents considered the risk of contagion at a social event to be high or extremely high. We also assigned a value of one if participants responded that they expected the total number of Covid-19 cases and deaths to exceed 500,000 and 50,000, respectively. For the social distancing outcomes, our binary variables take a value of one if respondents expected to leave their house three or more times.[19]

3.2 Results

Given that the intervention consisted in presenting lower or higher cumulative death tolls, the direction in which this may affect beliefs about the evolution of the epidemic depends on respondents' priors. Before the treatment, survey participants were asked to report their knowledge about the total number of Covid-19 cases recorded in Mexico by May 20, a full week before the launch of

[19] For completeness, we show similar results in online appendix Figures A4 - A6 using indicators for each of the possible responses.

the survey. We use the responses to this question to stratify the sample into a low and high prior group.[20] The low prior subsample consists of those that reported that the total number of Covid-19 cases was lower than 50,000 (47.7 percent of the full sample), while the high prior group are those that reported over 50,000 cases.[21]

We present all our results for the full sample and separately for these two subgroups. If our informational treatment is shifting beliefs about the extent of the epidemic in Mexico, then we would expect to see stronger and larger effects among the low prior group, as they are the ones that would update their priors upward.

Table 2 shows our main results. Panel A corresponds to the perceived risk of contagion (next week in columns 1-3, and in four weeks in columns 4-6). Panel B corresponds to the expected number of total cases (columns 1-3) and total deaths (columns 4-6). And Panel C corresponds to our measures of compliance with social distancing (next week in columns 1-3, and in four weeks in columns 4-6). Throughout Table 2, columns 1 and 4 present results for the full sample, columns 2 and 5 restrict to the low prior subsample, and columns 3 and 6 focus on the high prior subsample.

For every risk measure, presenting the higher death toll based on cumulative deaths by actual date of occurrence seems to shift beliefs towards a higher risk level. For example, among individuals that were shown cumulative deaths by date of death, the percentage considering that the risk of contagion at a social event is high or extremely high is 3.3 percentage points higher, both for assessments next week and in four weeks. However, only the former is statistically significant. We find similar patterns for respondents predicting a high number of Covid-19 cases and deaths. These differences are larger, as expected, in the low prior sample.

The results in Panel C are consistent with the higher death toll from information on cumulative deaths presented by actual date of death having an effect on expectations to comply with social distancing measures. For expected behavior four weeks after the survey, having been shown the graph by date of occurrence is associated with a significant decrease in the number of times people expect to leave their homes. Once again, the effect is concentrated in the low prior sample.

[20] Tables A1 and A2 in the online appendix show balance tables separately for the low and high priors subsamples.

[21] The true number reported in the nightly press conference on May 20 was 56,594 cumulative cases in the country (see https://twitter.com/HLGatell/status/1263264663283908609?s=20, last accessed June 29, 2020). A histogram with the distribution of the responses to this question is presented in online appendix Figure A1. Stratifying the sample based on individuals' prior regarding total reported deaths by May 20 yields similar results (available upon request).

Table 2:
Estimates of Informational Treatments on Risk Perceptions and Expected Behavior

	(1) Full sample	(2) Low prior	(3) High prior	(4) Full sample	(5) Low prior	(6) High prior
Panel A: Risk of contagion	High perceived risk of contagion at gathering with 100 people					
	Next week			In 4 weeks		
Information by date occurred	0.0334*	0.0698**	-0.0043	0.0331	0.0737*	0.0047
	(0.019)	(0.027)	(0.026)	(0.026)	(0.039)	(0.035)
Observations	1,022	488	534	1,022	488	534
R-squared	0.055	0.074	0.081	0.028	0.051	0.044
Mean dependent variable	0.90	0.90	0.90	0.79	0.77	0.81
Panel B: Expected toll	High subjective prediction of the full toll of the epidemic					
	>500,000 cases			>50,000 deaths		
Information by date occurred	0.0549*	0.0728	0.0515	0.0383	0.0752*	0.0046
	(0.031)	(0.044)	(0.044)	(0.031)	(0.046)	(0.044)
Observations	1,022	488	534	1,022	488	534
R-squared	0.016	0.054	0.032	0.015	0.032	0.020
Mean dependent variable	0.36	0.34	0.39	0.41	0.41	0.42
Panel C: Social distancing	High number of times expected to leave the house (3+)					
	Next week			In 4 weeks		
Information by date occurred	0.0004	-0.0326*	0.0298*	-0.0553**	-0.0893**	-0.0243
	(0.012)	(0.017)	(0.017)	(0.025)	(0.036)	(0.035)
Observations	1,022	488	534	1,022	488	534
R-squared	0.660	0.658	0.680	0.346	0.354	0.356
Mean dependent variable	0.12	0.11	0.12	0.35	0.33	0.37

Notes: This table presents the results from estimating equation 1. Each panel corresponds to two different questions in the survey converted to a binary measure (see text for details). Columns 1 and 4 show results for the full sample. Columns 2, 5, 3 and 6 stratify the sample by respondents' prior on their knowledge of the number of Covid-19 cases in Mexico up to May 20 into low and high reported cases, respectively. The estimates are the average difference between the responses in the treatment group that received information based on the actual date of death relative to information based on date of reports. Robust standard errors are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Notwithstanding the limited statistical power due to the small sample size of the survey, we interpret the results presented in Table 2 as evidence that receiving different information about the current death toll due to the delays with which deaths are reported is very likely to affect perceptions about risk and, consequently, compliance with social distancing measures. These findings also suggest that the individuals surveyed, despite being a selected sample of higher-income respondents and despite the government providing information on both deaths by date reported and by date occurred, do not fully incorporate reporting delays when forming beliefs about the epidemic, and are thus unlikely to be fully aware of these delays. We proceed by taking these insights and incorporating them into an equilibrium model.

4 Model of Equilibrium Behavior during an Epidemic

The previous section documented that different death counts in the information presented to individuals may affect their beliefs and behavior during an epidemic. Given that in this context these differences are driven by reporting delays, in this section we develop a simple model of equilibrium behavior that introduces these misperceptions in how agents endogenously form beliefs and choose their level of exposure to illustrate how this may affect the evolution of the epidemic. The model's simplicity highlights the potential importance of lagged information due to reporting delays for agents' behavior, but standard extensions could be included.[22]

Following the seminal work of Kermack and McKendrick (1927), agents in the model are compartmentalized into different health states corresponding to susceptible, infected, and recovered. In the specific context of Covid-19, Fernández-Villaverde and Jones (2020) highlights the importance of including an additional state, where recovering agents cannot infect others, and of assuming a time dependent exogenous contact rate to allow for a better fit of the data. Our model also includes a similar state variable, but endogenizes the contact rate through behavioral reactions to the epidemic by introducing an equilibrium concept similar to Brotherhood et al. (2020).

[22] Extensions may include features that allow the study of macroeconomic implications (Eichenbaum et al., 2020a), saving decisions (Kaplan et al., 2020), non-pharmacy initiatives (Brotherhood et al., 2020), testing, quarantine, the introduction of vaccines (Eichenbaum et al., 2020b), optimal lockdown policies (Alvarez et al., 2020), and age or asset heterogeneity (Glover et al., 2020; Acemoglu et al., 2020), among others.

4.1 General Setup

We set up the model in discrete time, where each period corresponds to one day. The economy is populated with a continuum of ex-ante identical agents. Agents can spend time outside or at home. Given an outbreak of Covid-19, let j be an agent's health status. Define $j = s$ (**susceptible**) as the state in which the agent has never been infected. Only susceptible agents spending time outside are at risk of becoming infected, in which case the state changes to $j = i$ (**infected**). During this state, agents can infect others with a uniform mixing contact rate. This state subsequently changes to a non-infectious status $j = r$ (**resolving**) with probability γ. The resolving state ends with probability θ, where a share δ of agents die, while the remaining share fully recovers. We assume a recovered agent becomes immune with status $j = c$ (**recovered**). To summarize, $j = \{s, i, r, c\}$ and the future is discounted at a rate β.

Each agent is also endowed with a single unit of time every period, which is divided into n hours outside the home and d at home, such that $1 = n + d$. We assume that the flow utility of being dead is normalized to zero, while being alive generates flow utility from spending hours outside and at home:

$$u(n) = \log(n) + \lambda_d \log(1 - n) + b$$

where $\lambda_d > 0$ is a preference weight for hours spent at home, and b is a positive constant that captures the premium of being alive, so that the flow utility from being alive is larger than zero for reasonable values of n.[23]

Infections and Beliefs. The probability of becoming infected for susceptible agents is assumed to be proportional to the time spent outside the home n and an aggregate transmission risk Π_t:

$$\pi(n, \Pi_t) = n\Pi_t$$

We allow for misperceived beliefs about transmission risk by defining perceived risk as $\widetilde{\Pi}_t$, which may differ from the true Π_t. In the application below, we focus on agents that form beliefs based

[23] In practice, we are implicitly assuming that $\underline{n} < n < \bar{n}$, so that b must be larger than $-(\log(n) + \lambda_d \log(1 - n))$. Given the calibration described later in Section 4.3, simulation results never hit these bounds.

on reports containing lagged information due to reporting delays. Hence, for simplicity, we assume:

$$\widetilde{\Pi}_t = \Pi_{t-k}, \quad k \geq 0 \tag{2}$$

meaning that agents form subjective beliefs of contagion risk at time t based on information about the epidemic from k days before. In other words, if $k > 0$, beliefs are formed with a k-day lag, while if $k = 0$, beliefs form from contemporaneous (unlagged) information.[24]

Value Functions. Given the structure described above, we now specify value functions for agents in each of the different states during the course of the pandemic.

For susceptible agents, the value function $V(s,t)$ at time t is given by:

$$V(s,t) = \max_{n \in (0,1)} \left\{ u(n) + \beta \left[1 - \pi \left(n, \widetilde{\Pi}_t \right) \right] V(s, t+1) + \beta \pi \left(n, \widetilde{\Pi}_t \right) V(i) \right\} \tag{value susceptible}$$

where the value of being infected $V(i)$ evolves according to:

$$V(i) = \max_{n \in (0,1)} \left\{ u(n) + \beta \left[\gamma V(r) + (1-\gamma) V(i) \right] \right\} \tag{value infected}$$

For individuals that start resolving the disease, we assume that they cannot work due to the illness and flow utility is therefore zero. Thus their total value $V(r)$ is given by:

$$V(r) = \beta (1-\theta) V(r) + \beta \theta (1-\delta) V(c) \tag{value resolving}$$

Finally, the value for individuals that fully recover is:

$$V(c) = \max_{n \in (0,1)} \left\{ u(n) + \beta V(c) \right\} \tag{value recoverd}$$

Laws of Motion. Let $n(j,t)$ be the optimal choice of hours spent outside the home for states $j = s, i, c$. Then the following laws of motion characterize the evolution of the population mass in

[24] When $k > 0$, this setup is similar to the notion of adaptive expectations as introduced by Cagan (1956) or Friedman (1957), or a model in which agents herd on epidemic information provided by the government, which may be perceived as better quality (Banerjee, 1992). If $k = 0$, the model is consistent with the concept of rational expectations as presented in Muth (1961).

the different states of the epidemic:

$$M_{t+1}(s) = M_t(s)\left(1 - \pi\left(n(s,t), \Pi_t\right)\right) \tag{mass susceptible}$$

$$M_{t+1}(i) = M_t(s)\,\pi\left(n(s,t), \Pi_t\right) + M_t(i)(1-\gamma) \tag{mass infected}$$

$$M_{t+1}(r) = M_t(i)\,\gamma + M_t(r)(1-\theta) \tag{mass resolving}$$

$$M_{t+1}(c) = M_t(r)\,\theta(1-\delta) + M_t(c) \tag{mass recovered}$$

We can also define additional accounting variables, such as the measure of total Covid-19 deaths:

$$M_{t+1}^{deaths} = M_t^{deaths} + \theta\delta M_t(r)$$

Aggregate Probability of Infection. We assume that the instantaneous rate of infection within a period is given by:

$$\widehat{\Pi}_t = \Pi_0 M_t(i)\, n(i,t)$$

That is, within a period a susceptible agent can have multiple encounters with infected agents given by rate $\widehat{\Pi}_t$, resulting in contagion. Since it only takes one infection to change the status, the probability of an infectious contact within a period becomes:

$$\Pi_t = 1 - \exp\left(-\widehat{\Pi}_t\right) \tag{3}$$

4.2 Definition of the Equilibrium

A *belief-induced equilibrium* in this economy with an initial mass of agents $M_0(j)$ for each $j \in \{s,i,r,c\}$ consists of a sequence of infection rates $\{\Pi_t\}_{t=0}^{\infty}$ and hour allocations $\{n(j,t)\}_{t=0}^{\infty}$, such that:

1. given $\{\Pi_t\}_{t=0}^{\infty}$, induced expectations $\widetilde{\Pi}_t$ are formed from equation 2 with $n(j,t)$ solving the values in equations (value susceptible) to (value recoverd);

2. given $\{n(j,t)\}_{t=0}^{\infty}$ and initial $M_0(j)$ for $j \in \{s,i,r,c\}$, the resulting laws of motion from equations (mass susceptible) to (mass recovered) are consistent with $\{\Pi_t\}_{t=0}^{\infty}$ given the aggregate probability of infection in equation 3.

4.3 Model Calibration and Results

Note that the stylized structure of the model allows for a simple evaluation of the behavioral impact of lagged information due to reporting delays if agents form beliefs as described in equation 2.[25] Given our survey and recognizing that deaths in Mexico are reported with a 6-day delay on average, we calibrate the model by assuming that delays in reporting induce a belief that lags by $k = 6$ days from the correct one.

The remaining model parameters are summarized in Table 3. The discount factor $\beta = 0.98^{1/365}$ is set to capture a 2% annual interest rate. Parameters associated with infectiousness, the probability of resolving, and the death rate for Covid-19 are calibrated to target standard findings from the medical literature as documented in Bar-On et al. (2020). As for the remaining parameters, we capture certain features of the Mexican economy. We assume that the initial population is 120 million and the number of infected individuals at time zero are 1,200 or 0.001% of the population. We use Mexican time use surveys to calibrate the parameter λ_d by targeting an expenditure of 36% of available hours in activities outside the home prior to the epidemic. The utility function parameter b captures a drop in activity outside the home during the epidemic of 45% as suggested by evidence from Google Mobility data. Lastly, the baseline contagion rate parameter Π_0 is set to generate a basic reproduction number of 1.84 as documented by Marioli et al. (2020).[26]

Table 3:
Baseline Calibration of the Behavioral Contagion Model

Parameter in the model		Value	Target
Discount factor	β	$0.98^{1/365}$	Standard 2% yearly interest rate
Probability of infection	γ	0.166	6 days while infectious (Bar-On et al., 2020)
Resolving probability	θ	0.1	16 days to clear Covid-19 (Bar-On et al., 2020)
Death rate	δ	0.008	From medical literature (Bar-On et al., 2020)
Initial mass of infected	$M_0(i)$	0.001%	1,200 individuals in Mexico
Preference for staying home	λ_p	1.77	36% of hours spent outside home (ENUT)
Preference for staying alive	b	7.4	45% drop in outside home activity (Google Mobility Data)
Baseline contagion rate	Π_0	2.353	Basic reproduction number $R_0 = 1.84$ (Marioli et al., 2020)

Notes: This table shows the values for the parameters used to calibrate the model. ENUT refers to the Mexican Time Use Survey for 2014.

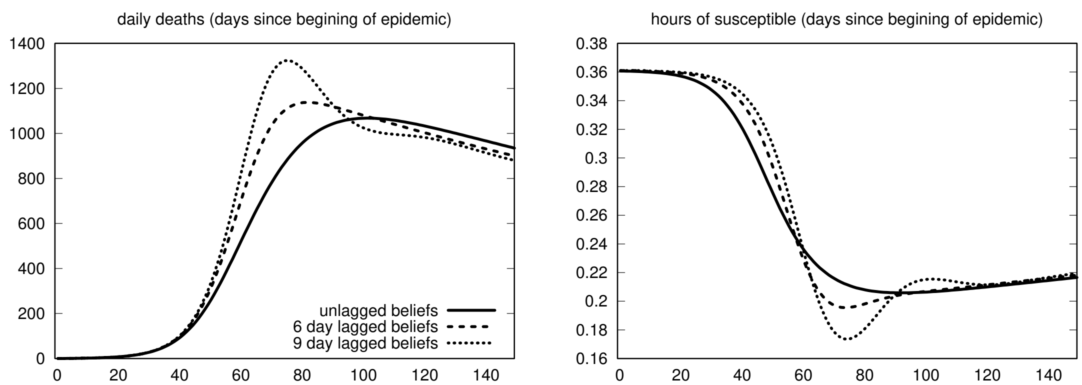
[25] Online appendix C provides a brief discussion of how belief formation about the pandemic affects agents' behavior within the model.

[26] Online appendix C provides additional details on the calibration used in the model simulation.

We then simulate the model by computing the solution to the equilibrium defined in Section 4.2. We compare the baseline results where $k = 6$ to a case with no delays $k = 0$ (equivalent to unlagged beliefs) and also to a case with more extreme delays with $k = 9$. The results of this exercise are summarized in Figure 2.[27]

The left panel in Figure 2 shows the results for the evolution of daily Covid-19 deaths under each scenario. With perfect information ($k = 0$), it would take 102 days to reach the maximum number of 1,069 daily deaths. If instead agents face a 6-day lag in information about the true contagion rate ($k = 6$), the maximum number of daily deaths would increase to 1,138 and would occur 19 days earlier on day 83 of the epidemic. Lastly, with an even longer delay of 9 days, the maximum number of daily deaths would be 1,324 and would occur on day 76 of the epidemic.

Figure 2:
Simulation Results of Behavioral Model



Notes: These graphs show the simulation results from the model by computing the equilibrium as defined in Section 4.2. We show results considering a 6-day delay in the formation of beliefs consistent with reporting delays, zero delay corresponding to contemporaneous beliefs, and a more extreme case of a 9-day lag. The plot on the left shows the number of daily deaths from Covid-19 over time from the onset of the epidemic. The plot on the right shows the percentage of hours in a day that susceptible individuals (those who have never been infected) spend outside the home since the beginning of the epidemic. The baseline percentage of hours away from home is 36%.

The force behind these different dynamics can be understood by looking at how time outside the home evolves in each scenario. This is shown in the right panel of Figure 2. We highlight three important results in this graph. First, delays slow down the endogenous adjustment in hours spent outside the home as a reaction to the risk of being infected. For instance, on day 45 of the epidemic, hours outside would fall by 15.8% (5.7 percentage points, pp) for $k = 0$ relative to only 11.1% (4 pp) for $k = 6$ and 7.2% (2.6 pp) for $k = 9$.

[27] For additional results and robustness of the model with respect to parameters, see online appendix C.

Second, since agents are slower to adjust in the presence of delays, the overall probability of being infected is larger at the peak of the epidemic. We find a 0.66% probability for $k = 6$ relative to 0.58% for $k = 0$. Under the extreme $k = 9$ scenario, the maximum daily probability of infection reaches 0.81%.

Lastly, the change in behavior over time is also considerably less smooth in the presence of delays. Total hours outside the home for susceptible agents fall from the 36% baseline to a minimum of 21.0% in the model with $k = 0$ in comparison to 19.8% for $k = 6$. In the more extreme case of $k = 9$, hours reach a minimum of 17.8%.

This exercise emphasizes the importance of clear and swift communication during an epidemic. Governments aiming to control the epidemic may care about behavioral responses, which could be affected if agents do not have a correct understanding of the risk of infection due to issues with the type of information available. In particular, reactions may be too slow, thus inducing harsher epidemic outcomes in terms of the daily number of infected individuals and deaths. This may be especially important in the presence of hospital capacity constraints.[28] Moreover, the faster progression of the epidemic when agents are slow to react will tend to generate excessive responses later in the pandemic, thus adding to the economic downturn that would likely be large even in a scenario with fully accurate real-time information.

5 Conclusion

Given the reliance on non-pharmaceutical interventions like social distancing, effecting change in individual behavior is paramount for managing the Covid-19 pandemic. Providing information on the state of the epidemic is an important policy tool, but its effectiveness may be hampered due to data collection issues. In particular, this paper analyzes how individual beliefs and behavior are affected by differing information in the cumulative death count due to lags from reporting delays.

Our randomized informational treatments in an online survey in Mexico show that participants that were shown total deaths over time by date reported – that is, a measure that understates the true death toll because of large reporting delays – were more likely to perceive a lower risk of contagion and to report lower intentions of complying with stay-at-home recommendations.

[28] For example, Gutierrez and Rubli (2020) show a strong relationship between hospital capacity and increases in in-hospital mortality during the 2009 H1N1 epidemic in Mexico.

We then develop an equilibrium behavioral model that shows that, if individuals receive lagged information because of reporting delays, they are slower to modify their risky behavior, which in turn leads to more severe epidemic outcomes.

Delays in death reports are a common feature across settings, but are likely to be exacerbated by the low state capacity in low and middle-income countries. Hence, our results suggest that data collection issues in these contexts may magnify the extent of the epidemic, adding to the particular challenges facing these countries. Furthermore, other issues with information linked to differential counting of tests, cases, and deaths across and within countries may also affect individual behavior via their effect on perceptions and beliefs, which in turn may limit effective management of the Covid-19 pandemic.

From a policy perspective, our results highlight the importance of collecting and disseminating reliable real-time information on the state of the epidemic, or at least being upfront and clear about the drawbacks of the available data. Evidently, improving data collection in real-time is costly, and scarce resources may be better spent on other mitigation strategies. However, low-cost measures, such as clearly explaining delays and developing correction factors to generate an estimate of the true death toll, could alleviate these shortcomings.

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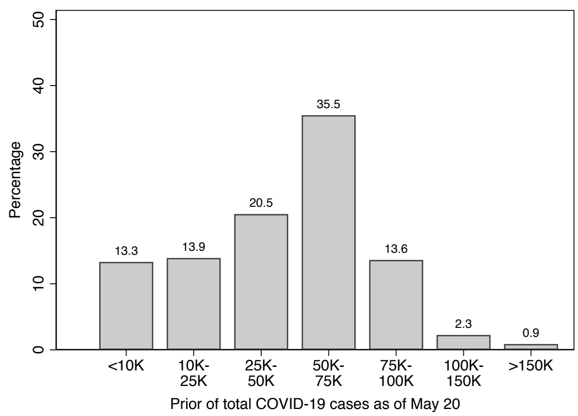
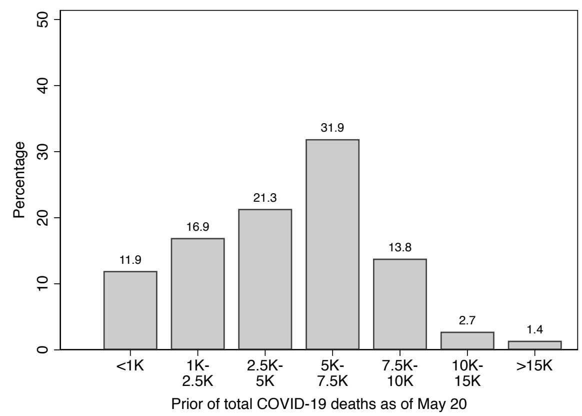
Appendix for Online Publication

A Supplementary Figures and Tables for the Survey

Figure A1:
Histograms of Prior Beliefs on Total Cases and Deaths



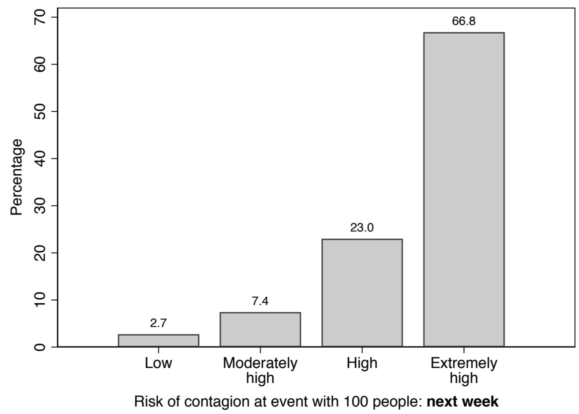
(a) Beliefs on total cases



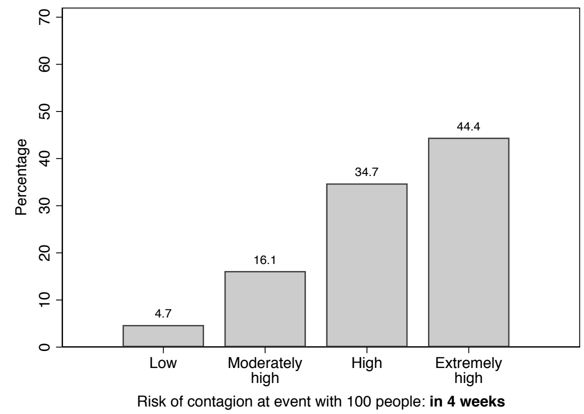
(b) Beliefs on total deaths

Notes: These graphs show histograms for the questions eliciting beliefs about total cases and total deaths up to May 20 (one week prior to when the survey was launched) for our full sample of participants. Each plot shows the percentage of total respondents that chose each of the answers. The actual number of cumulative cases reported by the government on May 20 was 56,594, and the cumulative deaths reported were 6,090 (see https://twitter.com/HLGatell/status/1263264663283908609?s=20, last accessed June 29, 2020).

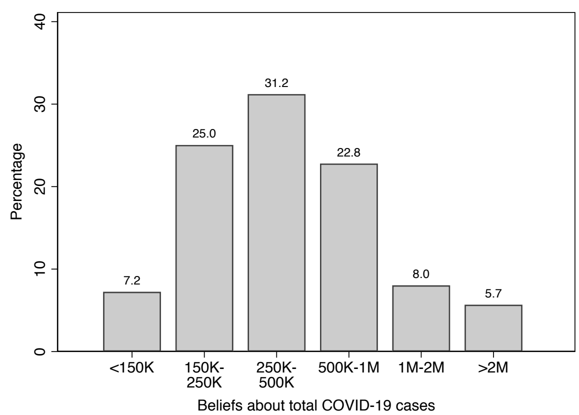
Figure A2:
Histograms of Risk Perceptions and Behavior



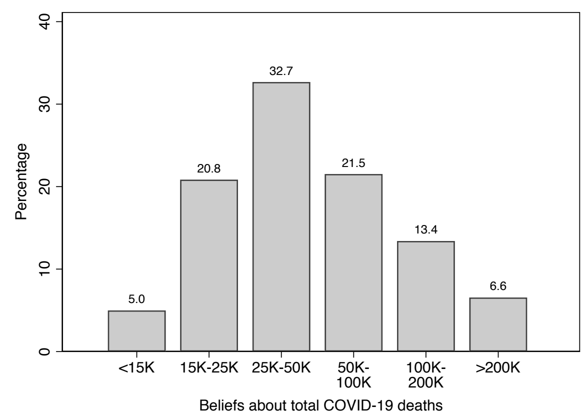
(a) Risk of contagion next week



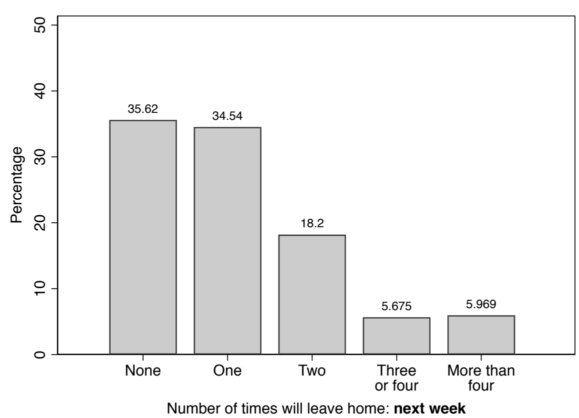
(b) Risk of contagion in 4 weeks



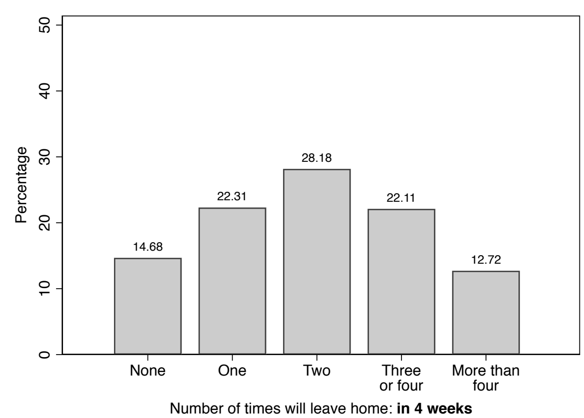
(c) Expected total cases



(d) Expected total deaths



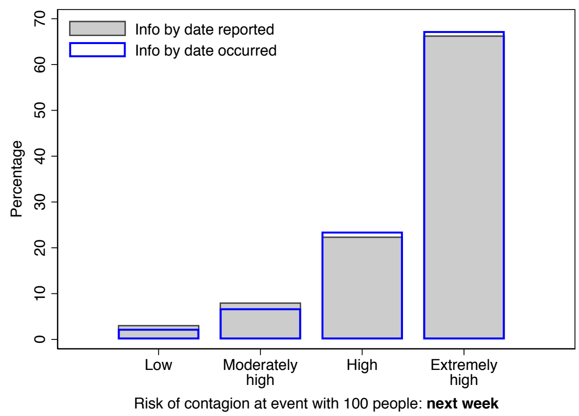
(e) Times leaving the house next week



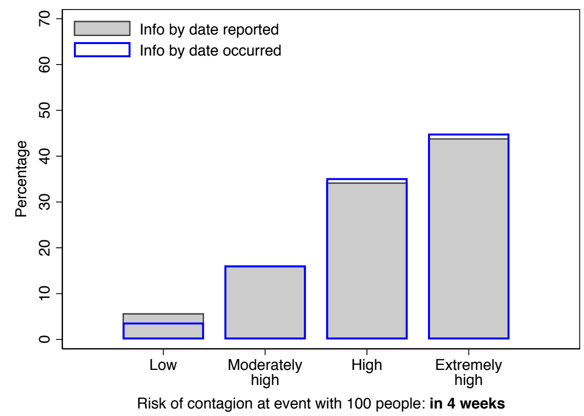
(f) Times leaving the house in 4 weeks

Notes: These graphs show histograms for the six outcome variables related to perceptions and expected behavior elicited in the survey for our full sample of participants. Each plot shows the percentage of total respondents that chose each of the answers.

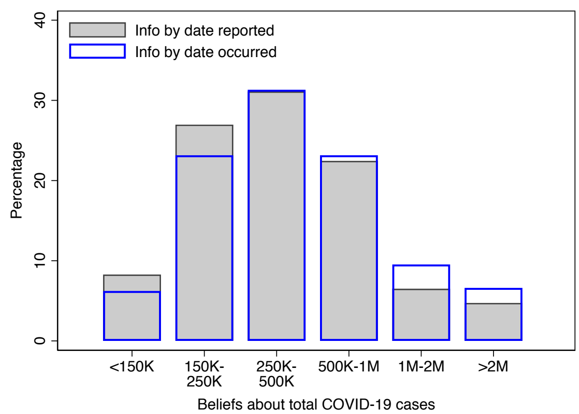
Figure A3:
Histograms of Risk Perceptions and Behavior by Informational Treatments



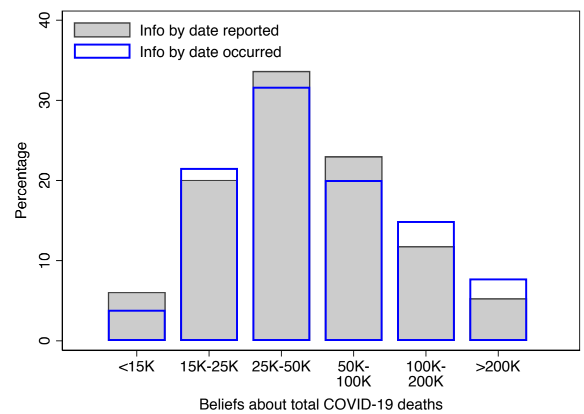
(a) Risk of contagion next week



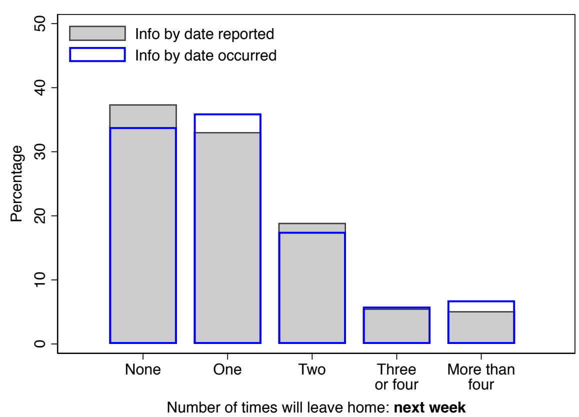
(b) Risk of contagion in 4 weeks



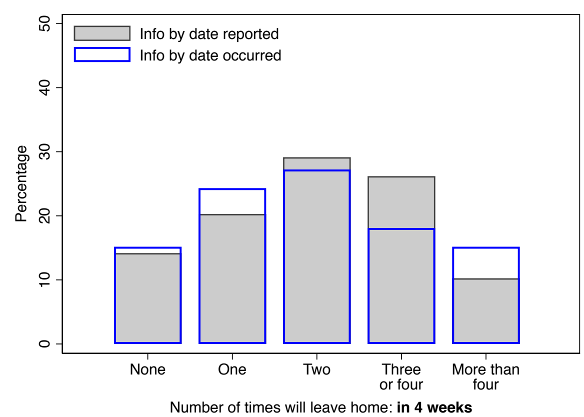
(c) Expected total cases



(d) Expected total deaths



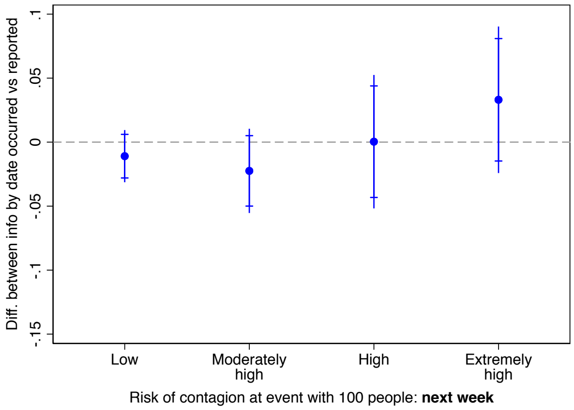
(e) Times leaving the house next week



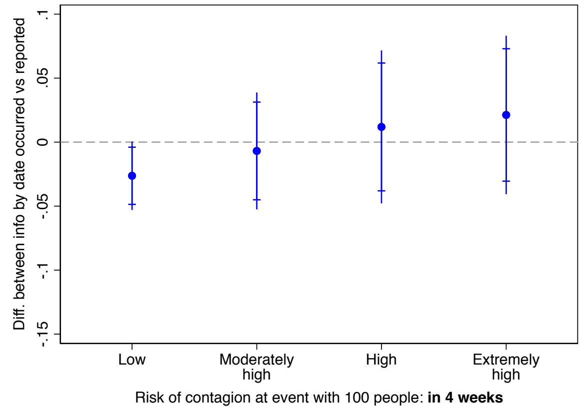
(f) Times leaving the house in 4 weeks

Notes: These graphs show histograms for the six outcome variables related to perceptions and expected behavior elicited in the survey for our full sample of participants. We distinguish between the two informational treatments. Each plot shows the percentage of total respondents that chose each of the answers.

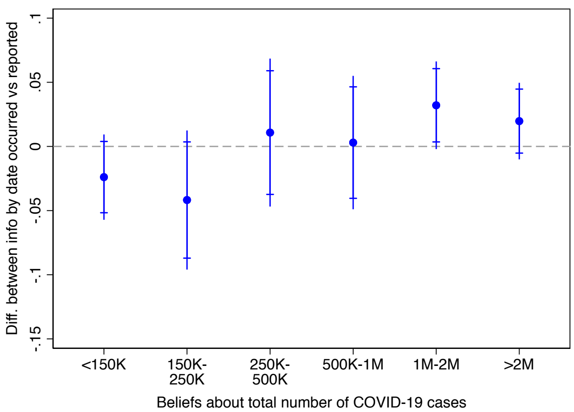
Figure A4:
Estimates of Informational Treatments for Full Set of Responses



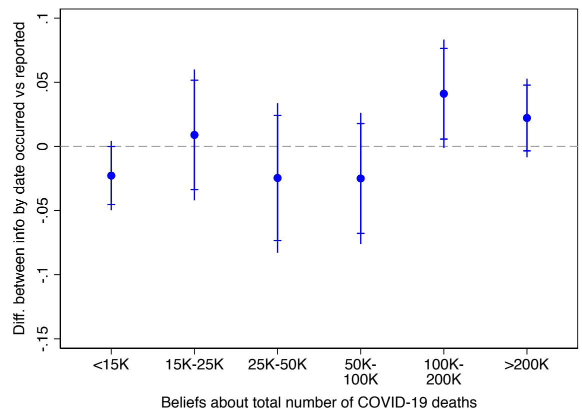
(a) Risk of contagion next week



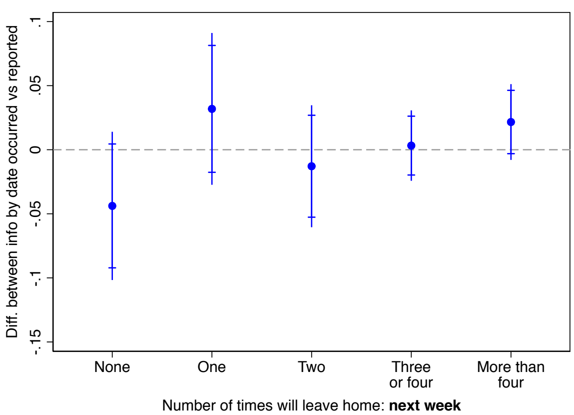
(b) Risk of contagion in 4 weeks



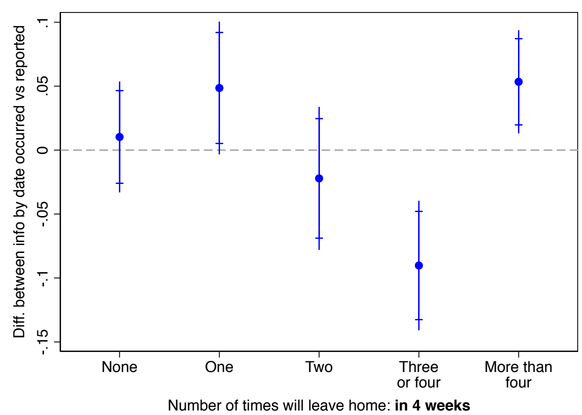
(c) Expected total cases



(d) Expected total deaths



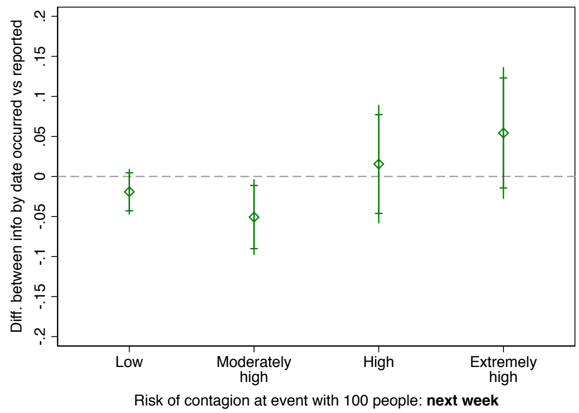
(e) Times leaving the house next week



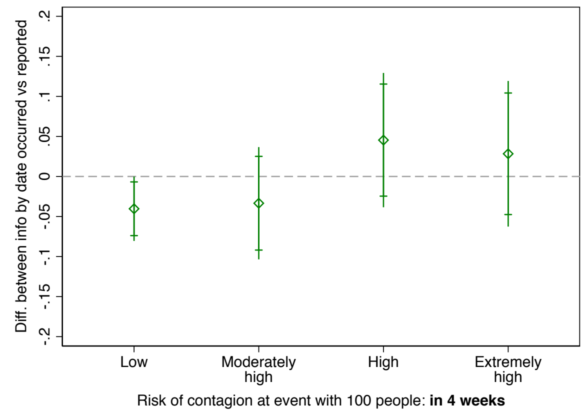
(f) Times leaving the house in 4 weeks

Notes: These graphs show estimates of the difference by informational treatment on the six outcome variables related to perceptions and expected behavior elicited in the survey for our full sample of participants. Each plot shows coefficients from multiple regressions with indicators for each response as the outcome variable. Coefficients correspond to the average difference between respondents that received information based on the actual date of death relative to those that received information based on date of reports. Vertical bars show 95 and 90% confidence intervals.

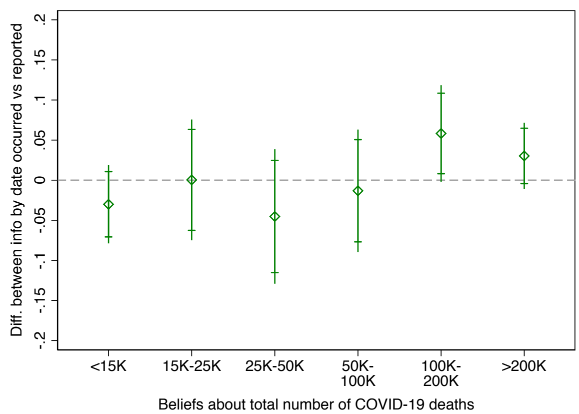
Figure A5:
Estimates of Informational Treatments for Full Set of Responses: Low Prior Sample



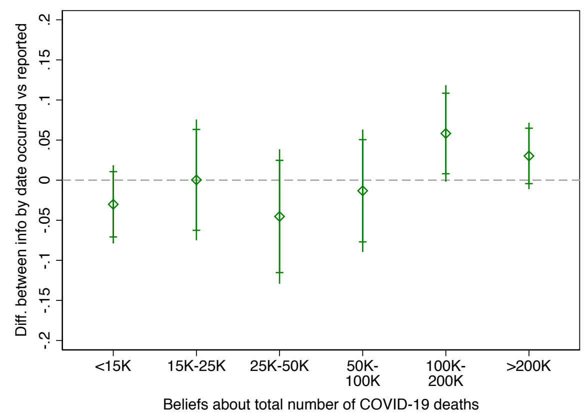
(a) Risk of contagion next week



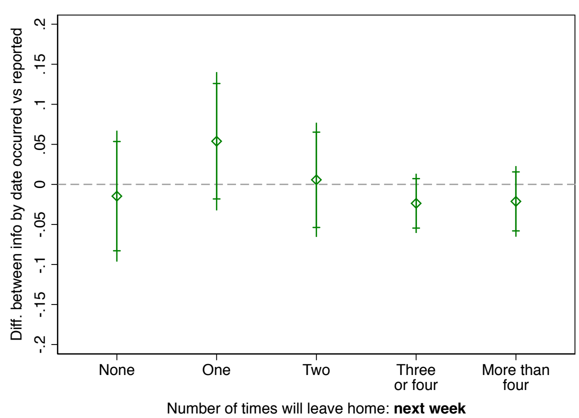
(b) Risk of contagion in 4 weeks



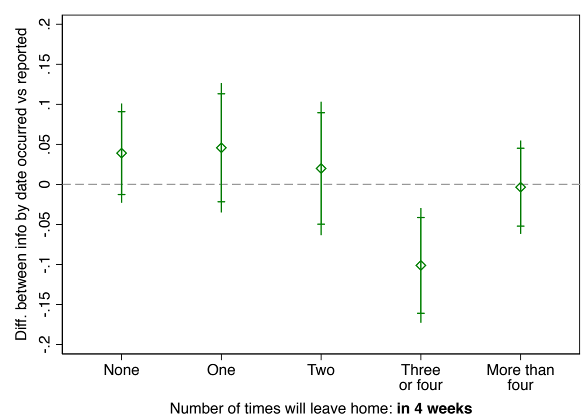
(c) Expected total cases



(d) Expected total deaths



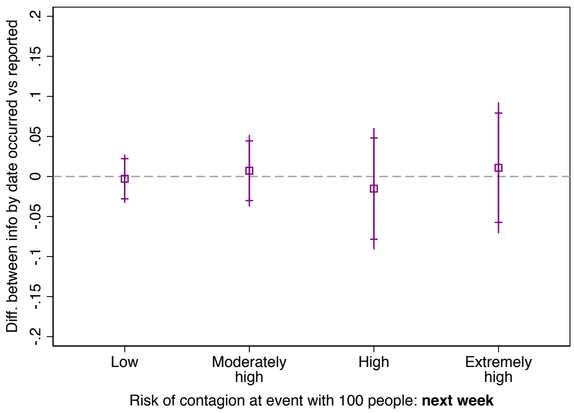
(e) Times leaving the house next week



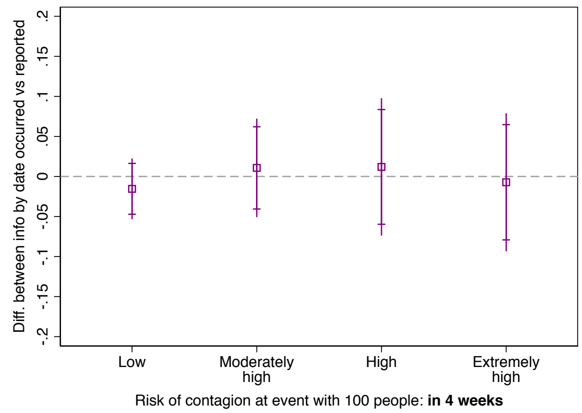
(f) Times leaving the house in 4 weeks

Notes: These graphs show estimates of the difference by informational treatment on the six outcome variables related to perceptions and expected behavior elicited in the survey for the sample of participants with a low prior of total Covid-19 cases as of May 20. Each plot shows coefficients from multiple regressions with indicators for each response as the outcome variable. Coefficients correspond to the average difference between respondents that received information based on the actual date of death relative to those that received information based on date of reports. Vertical bars show 95 and 90% confidence intervals.

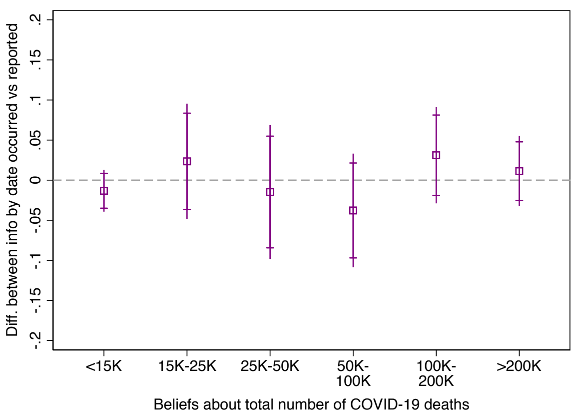
Figure A6:
Estimates of Informational Treatments for Full Set of Responses: High Prior Sample



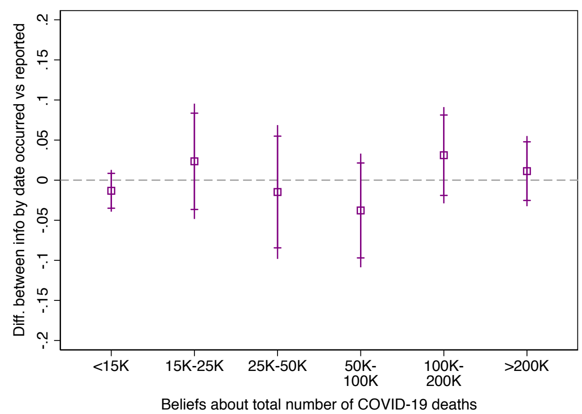
(a) Risk of contagion next week



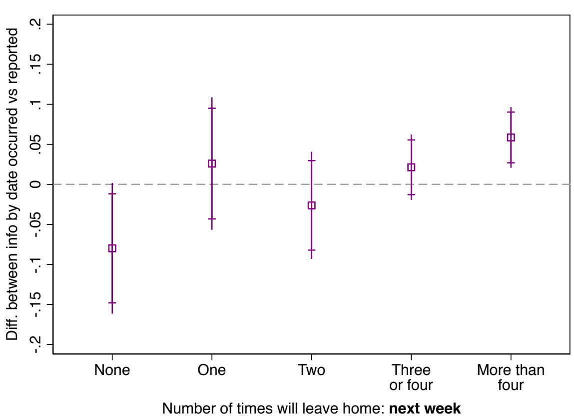
(b) Risk of contagion in 4 weeks



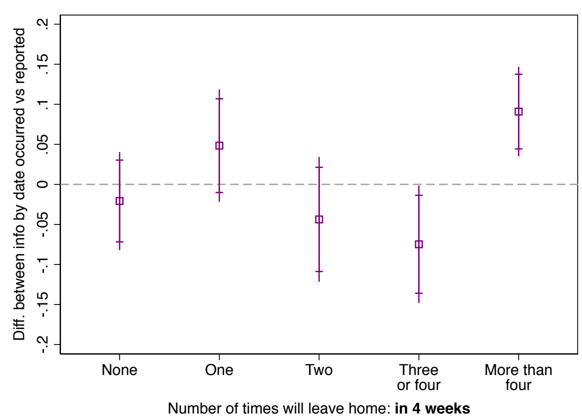
(c) Expected total cases



(d) Expected total deaths



(e) Times leaving the house next week



(f) Times leaving the house in 4 weeks

Notes: These graphs show estimates of the difference by informational treatment on the six outcome variables related to perceptions and expected behavior elicited in the survey for the sample of participants with a high prior of total Covid-19 cases as of May 20. Each plot shows coefficients from multiple regressions with indicators for each response as the outcome variable. Coefficients correspond to the average difference between respondents that received information based on the actual date of death relative to those that received information based on date of reports. Vertical bars show 95 and 90% confidence intervals.

Table A1:
Balance Table for Survey Covariates: Low Prior Sample

	Informational treatments		
	Deaths by date reported	Deaths by date occurred	Difference in means
Female	0.475	0.500	0.025
	(0.500)	(0.501)	(0.045)
Ages 18-22	0.324	0.412	0.088**
	(0.469)	(0.493)	(0.044)
Ages 23-29	0.252	0.232	-0.020
	(0.435)	(0.423)	(0.039)
Ages 30-49	0.248	0.192	-0.056
	(0.433)	(0.395)	(0.037)
Ages 50+	0.176	0.164	-0.012
	(0.382)	(0.371)	(0.034)
Works	0.420	0.344	-0.076*
	(0.495)	(0.476)	(0.044)
Attends school	0.353	0.432	0.079*
	(0.479)	(0.496)	(0.044)
Works and attends school	0.155	0.152	-0.003
	(0.363)	(0.360)	(0.033)
Other occupation/employment status	0.071	0.072	0.001
	(0.258)	(0.259)	(0.023)
Lives in Mexico City	0.773	0.764	-0.009
	(0.420)	(0.425)	(0.038)
Lives in apartment	0.340	0.396	0.056
	(0.475)	(0.490)	(0.044)
Lives in house, no yard	0.118	0.108	-0.010
	(0.323)	(0.311)	(0.029)
Lives in house with yard	0.542	0.496	-0.046
	(0.499)	(0.501)	(0.045)
Household size: 1-2	0.223	0.240	0.017
	(0.417)	(0.428)	(0.038)
Household size: 3	0.231	0.236	0.005
	(0.422)	(0.425)	(0.038)
Household size: 4	0.214	0.224	0.010
	(0.411)	(0.418)	(0.038)
Household size: 5+	0.546	0.524	-0.022
	(0.499)	(0.500)	(0.045)
Has HH members over 70 years old	0.181	0.076	-0.105***
	(0.386)	(0.266)	(0.030)
Has HH members 60-70 years old	0.206	0.228	0.022
	(0.405)	(0.420)	(0.037)
Has HH members 50-60 years old	0.496	0.432	-0.064
	(0.501)	(0.496)	(0.045)
Does not seek healthcare when sick	0.130	0.108	-0.022
	(0.337)	(0.311)	(0.029)
Self-medicates when sick	0.357	0.396	0.039
	(0.480)	(0.490)	(0.044)
Observations	238	250	488

Notes: This table shows means and standard deviations for a series of covariates asked in the survey before the informational treatment was presented for the sample of participants with a low prior of total Covid-19 cases as of May 20. We show statistics separately for each informational treatment, as well as the difference in the means. Stars denote significance from a difference in means test.
*** p<0.01, ** p<0.05, * p<0.1

Table A2:
Balance Table for Survey Covariates: High Prior Sample

	Informational treatments		
	Deaths by date reported	Deaths by date occurred	Difference in means
Female	0.515	0.481	-0.034
	(0.501)	(0.501)	(0.043)
Ages 18-22	0.319	0.356	0.038
	(0.467)	(0.480)	(0.041)
Ages 23-29	0.293	0.273	-0.020
	(0.456)	(0.446)	(0.039)
Ages 30-49	0.215	0.239	0.024
	(0.411)	(0.427)	(0.036)
Ages 50+	0.174	0.133	-0.041
	(0.380)	(0.340)	(0.031)
Works	0.400	0.314	-0.086**
	(0.491)	(0.465)	(0.041)
Attends school	0.381	0.402	0.020
	(0.487)	(0.491)	(0.042)
Works and attends school	0.159	0.163	0.004
	(0.367)	(0.370)	(0.032)
Other occupation/employment status	0.059	0.121	0.062**
	(0.237)	(0.327)	(0.025)
Lives in Mexico City	0.778	0.742	-0.035
	(0.417)	(0.438)	(0.037)
Lives in apartment	0.344	0.375	0.031
	(0.476)	(0.485)	(0.042)
Lives in house, no yard	0.130	0.125	-0.005
	(0.337)	(0.331)	(0.029)
Lives in house with yard	0.526	0.500	-0.026
	(0.500)	(0.501)	(0.043)
Household size: 1-2	0.241	0.261	0.021
	(0.428)	(0.440)	(0.038)
Household size: 3	0.185	0.254	0.069*
	(0.389)	(0.436)	(0.036)
Household size: 4	0.285	0.227	-0.058
	(0.452)	(0.420)	(0.038)
Household size: 5+	0.574	0.485	-0.089**
	(0.495)	(0.501)	(0.043)
Has HH members over 70 years old	0.141	0.083	-0.057**
	(0.348)	(0.277)	(0.027)
Has HH members 60-70 years old	0.222	0.178	-0.044
	(0.417)	(0.383)	(0.035)
Has HH members 50-60 years old	0.430	0.508	0.078*
	(0.496)	(0.501)	(0.043)
Does not seek healthcare when sick	0.148	0.197	0.049
	(0.356)	(0.398)	(0.033)
Self-medicates when sick	0.411	0.367	-0.044
	(0.493)	(0.483)	(0.042)
Observations	270	264	534

Notes: This table shows means and standard deviations for a series of covariates asked in the survey before the informational treatment was presented for the sample of participants with a high prior of total Covid-19 cases as of May 20. We show statistics separately for each informational treatment, as well as the difference in the means. Stars denote significance from a difference in means test.
*** p<0.01, ** p<0.05, * p<0.1

B Survey Text in English

This is an anonymous online survey that is being conducted by Profs. Emilio Gutierrez, Adrian Rubli and Tiago Tavares for an academic project aimed at better understanding the public's perceptions about the evolution of the Covid-19 pandemic in Mexico. Responding to the survey takes approximately 10 minutes. We ask you to please answer to all the questions if you choose to participate. Despite the fact that you received an invitation to participate in this survey via email or social media, the dataset where the information you provide will be stored does not collect any type of personal information (such as your name, phone number or IP address). We take all the relevant measures to safeguard your identity. Clicking on the "accept" button below you certify that you are over 18 years of age, and that you agree to respond to all the questions asked. The information you provide will only be used for academic purposes and statistical analyses, never revealing individual-level responses.

Sociodemographic Questions

Sex: Male / Female / Other or Prefer not to say

What is your age?: 18-22 / 23-29 / 30-39 / 40-49 / 50-59 / 60-69 / 70-79 / 80 or older

The highest schooling degree you have obtained is: Elementary school / Secondary school / Highschool / Undergraduate degree / Graduate degree

Occupation: Works / Attends school / Works and attends school / Unemployed / House work / Retired

Where do you live?: CDMX or its suburbs / Aguascalientes / Baja California / Baja California Sur / Campeche / Coahuila / Colima / Chiapas / Chihuahua / Durango / Guanajuato / Guerrero / Hidalgo / Jalisco / EdoMex outside CDMX metro area / Michoacan / Morelos / Nayarit / Nuevo Leon / Oaxaca / Puebla / Queretaro / Quintana Roo / San Luis Potosí / Sinaloa / Sonora / Tabasco / Tamaulipas / Tlaxcala / Veracruz / Yucatan / Zacatecas

How would you describe the house you live in: Apartment / House with yard / House without yard

Do you have internet access at home (Wi-Fi)?: Yes / No

Do you have access to a computer at home?: Yes, but I share it with others / Yes, and I am the only user / No

Apart from you, how many people live in your home?: 1 / 2 / 3 / 4 / 5 or more

Is anyone in your household aged more than 70?: Yes / No

Is anyone in your household aged between 60 and 70?: Yes / No

Is anyone in your household aged between 50 and 60?: Yes / No

What is your household's approximate monthly income?: 0-4,000 pesos / 4000-10,000 pesos / 10,000-20,000 pesos / 20,000-30,000 pesos / 30,000-40,000 pesos / 40,000-50,000 pesos / 50,000-75,000 pesos / 75,000-100,000 pesos / more than 100,000 pesos

Do you have access to private health insurance?: Yes / No

Do you have access to health services from IMSS, ISSSTE, PEMEX, SEDENA or SEMAR?: Yes / No

Do you have access to health services from INSABI or Seguro Popular?: Yes / No

When you fall sick, what do you usually do?: Nothing / Take OTCs / Go to a pharmacy-adjacent doctor's office / Go to a doctor's appointment in the private sector / Go to a doctor's appointment in the public sector / Use the medical services at my office or university

Who did you vote for in the last presidential election?: Andres Manuel Lopez Obrador / Ricardo Anaya / Jose Antonio Meade / Other candidate / No vote

What is your opinion about Andres Manuel Lopez Obrador's government's performance?: Completely approve / Approve / Disapprove / Completely disapprove

Covid-19 related questions

How often do you watch the press conference that Dr. Hugo Lopez-Gatell holds daily at 7pm?: Every day / Several times a week / Once a week / Sporadically / Never

How trustworthy do you think is the information about the evolution of Covid-19 shared by Mexican authorities during the daily 7pm press conference?: Very trustworthy / Somewhat trustworthy / Somewhat untrustworthy / Very untrustworthy

Have you received information regarding the evolution of Covid-19 through Facebook?: Yes / No

How trustworthy do you think is the information about the evolution of Covid-19 shared through Facebook?: Very trustworthy / Somewhat trustworthy / Somewhat untrustworthy / Very untrustworthy

Have you received information regarding the evolution of Covid-19 through Twitter?: Yes / No

How trustworthy do you think is the information about the evolution of Covid-19 shared through Twitter?: Very trustworthy / Somewhat trustworthy / Somewhat untrustworthy / Very untrustworthy

Have you received information regarding the evolution of Covid-19 through Whatsapp?: Yes / No

How trustworthy do you think is the information about the evolution of Covid-19 shared through Whatsapp?: Very trustworthy / Somewhat trustworthy / Somewhat untrustworthy / Very untrustworthy

Think of may 20th. According to you, approximately how many Covid-19 cases had be reported by that date?: Less than 10,000 / Between 10,000 and 25,000 / Between 25,000 and 50,000 / Between 50,000 and 75,000 / Between 75,000 and 100,000 / Between 100,000 and 150,000 / More than 150,000

Think of may 20th. According to you, approximately how many Covid-19 deaths had be reported by that date?: Less than 1,000 / Between 1,000 and 2,500 / Between 2,500 and 5,000 / Between 5,000 and 7,500 / Between 7,500 and 10,000 / Between 10,000 and 15,000 / More than 15,000

What is your opinion about the president's actions in face of the Covid-19 pandemic?: Completely approve / Approve / Disapprove / Completely disapprove

How many times did you leave home last week?: You did not leave home / Once / Twice / Three or four times / More than four times

Information treatments

Cumulative deaths by date reported: The following graph compares the evolution of total Covid-19 related deaths in Mexico and Sweden, from march 22nd to may 15th. The information is presented according to the date on which deaths were reported.

Cumulative deaths by date occurred: The following graph compares the evolution of total Covid-19 related deaths in Mexico and Sweden, from march 22nd to may 15th. For Sweden, rhe information is presented according to the date on which deaths were reported. For Mexico, according to the date on which deaths occurred.

Post-treatment questions

Dr. Hugo Lopez-Gatell has said that the evolution of the pandemic in Mexico is similar to the one experienced by Sweden. In your opinion, the Covid-19 pandemic in Mexico is evolving: Much faster than in Sweden / Faster than in Sweden / Similar to Sweden / Slower than in Sweden / Much slower than in Sweden

What is your opinion about Dr. Hugo Lopez-Gatell and other Mexican health authorities' strategy in face of Covid-19?: Completely approve / Approve / Disapprove / Completely disapprove

When do you expect that Mexico will reach 150,000 total confirmed Covid-19 cases?: Early June / Mid June / Late June / Early July / Mid July / Late July (or later) / There will be less than 150,000 total cases

When do you expect we will reach the maximum number of daily Covid-19 cases in Mexico?: Early June / Mid June / Late June / Early July / Mid July / Late July (or later)

How many cases of Covid-19 do you think will have been confirmed in Mexico by the end of this epidemic outbreak?: Less than 100,000 cases / Between 100,000 and 150,000 cases / Between 150,000 and 250,000 cases / Between 250,000 and 500,000 cases / Between 500,000 and one million cases / Between one and two million cases / More than two million cases

When do you expect that Mexico will reach 15,000 total confirmed Covid-19 deaths?: Early June / Mid June / Late June / Early July / Mid July / Late July (or later) / There will be less than 15,000 deaths

When do you expect we will reach the maximum number of daily Covid-19 deaths in Mexico?: Early June / Mid June / Late June / Early July / Mid July / Late July (or later)

How many deaths due to Covid-19 do you think will have been confirmed in Mexico by the end of this epidemic outbreak?: Less than 10,000 deaths / Between 10,000 and 15,000 deaths / Between 15,000 and 25,000 deaths / Between 25,000 and 50,000 deaths / Between 50,000 and 100,000 deaths / Between 100,000 and 200,000 deaths / More than 200,000 deaths

Imagine an extremely optimistic scenario (which would only happen with a probability lower than 10 percent). In such scenario, the total number of Covid-19 deaths in Mexico would be : Less than 3,000 deaths / Between 3,000 and 6,000 deaths / Between 6,000 and 9,000 deaths / Between 9,000 and 12,000 deaths / Between 12,000 and 15,000 deaths / Between 15,000 and 18,000 deaths / Between 18,000 and 21,000 deaths / Between 21,000 and 30,000 deaths / Between 30,000 and 50,000 deaths / Between 50,000 and 80,000 deaths / Between 80,000 and 120,000 deaths / More than 120,000 deaths

Imagine an extremely pessimistic scenario (which would only happen with a probability lower than 10 percent). In such scenario, the total number of Covid-19 deaths in Mexico would be : Less than 12,000 deaths / Between 12,000 and 15,000 deaths / Between 15,000 and 18,000 deaths / Between 18,000 and 21,000 deaths / Between 21,000 and 30,000 deaths / Between 30,000 and 50,000 deaths / Between 50,000 and 80,000 deaths / Between 80,000 and 120,000 deaths / Between 120,000 and 180,000 deaths / Between 180,000 and 250,000 deaths / Between 250,000 and 500,000 deaths / More than 500,000 deaths

When do you think that Mexico City will stop being under the maximum alter level due to Covid-19?: Early June / Mid June / Late June / Early July / Mid July / Late July / Early August / Mid August / Late August / September or later

Next week, how many times do you expect to leave home?: Will not leave home / Once / Twice / Three or four times / More than four times

If next week you had to attend a social gathering with 100 people, how high do you think the risk of being infected with the virus would be?: Very high risk / High risk / Moderately high risk / Moderately low risk / Low risk / Very low risk

In four weeks, how many times do you expect to leave home?: Will not leave home / Once / Twice / Three or four times / More than four times

If in four weeks you had to attend a social gathering with 100 people, how high do you think the risk of being infected with the virus would be?: Very high risk / High risk / Moderately high risk / Moderately low risk / Low risk / Very low risk

Do you think that most private universities in Mexico will be back on campus in August?: Yes, everything will go back to normal / Yes, but some courses will still be online / No, all courses will be online next semester

If the 2018 presidential election were today (with the same candidates), who would you vote for?: Andres Manuel Lopez Obrador / Ricardo Anaya / Jose Antonio Meade / Other candidate / Would not vote

C Additional Details and Results on the Model

C.1 Model Analysis

The optimization of static hours spent outside the home is given by:

$$\bar{n} = \arg\max_{n\in(0,1)} (u(n)) = \frac{1}{1+\lambda_p}$$

Note that these are also the hours spent by infected and recovered individuals:

$$n(i,t) = \overline{n}$$
$$n(c,t) = \overline{n}$$

This then implies closed-form solutions for:

$$\begin{aligned} V(c) &= \frac{u(\bar{n})}{1-\beta} \\ V(r) &= \frac{\beta\theta(1-\delta)V(c)}{1-\beta(1-\theta)} \\ V(i) &= \frac{u(\bar{n})+\beta\gamma V(r)}{1-\beta(1-\gamma)} \end{aligned}$$

As for the problem of the healthy agents, the first order conditions imply:

$$\begin{aligned} u_n(n) &= \beta\pi_n\left(n,\widetilde{\Pi}_t\right)(V(s,t+1)-V(i)) \\ \Rightarrow\frac{1}{n}-\frac{\lambda_p}{1-n} &= \beta\widetilde{\Pi}_t(V(s,t+1)-V(i)) \end{aligned}$$

Note that the simple implication of the model says that as long as the value of being healthy is larger that being infected, that is, if $V(s,t+1) > V(i)$ and $\widetilde{\Pi}_t > 0$, then $n(s,t) < \bar{n}$. This means that susceptible agents reduce the number of hours outside the house to prevent becoming infected between period t and $t+1$. Moreover, the larger the perceived infection rate $\widetilde{\Pi}_t$, the larger the response of susceptible agents in terms of how much they decrease their hours spent in the market place (outside the house).

C.2 Algorithm for the *Belief-Induced Equilibrium* Solution

In order to solve the above model, we use the following algorithm:

1. Choose a sequence for a large T and some sequence $\left\{\Pi_t^{(0)}\right\}_{t=0}^{T}$, making sure that $\Pi_T^{(0)} = 0$.

2. Solve for the values using backward induction and get policies on $n(j,t)$.

3. Compute the path of $\mathcal{M}_t$.

4. Update probabilities $\Pi_t^{(1)}$.

5. Iterate until $\left|\Pi^{(1)} - \Pi^{(0)}\right| < \varepsilon$ for small ε, otherwise set $\Pi^{(0)} = \Pi^{(1)}$ and go back to step 2.

C.3 Details of Model Calibration for Mexico

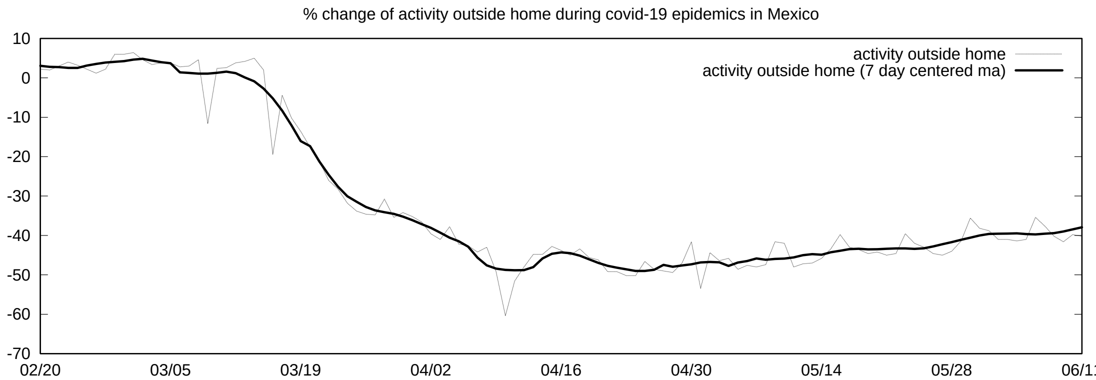
The calibration regarding the parameter λ_p that captures hours spent at vs outside the house in Mexico uses information from the 2014 household time use survey (*Encuesta Nacional sobre Uso del Tiempo 2014*) from the national office of statistics INEGI.[1] From the survey, we consider time spent outside the home as the sum of aggregate hours in market activities and consumption goods, entertainment and social activities, and studying (education) and related activities. As for time spent at home, we aggregate all hours in non-remunerated work at home, and personal activities (including sleeping, eating, and personal hygiene). We conclude that on average a Mexican household spends 36% of total time in activities outside the house, which corresponds to a parameter of $\lambda_p = 1.77$.

As for the parameter that regulates the preferences for staying alive b, we use data from Google Community Mobility Reports for Mexico to determine the reduction in non-home activities during the Covid-19 epidemic.[2] We average all non-home activity (retail and recreation, grocery and pharmacy visits, visit to parks, activity spent in transit, and workplace activity), and measure a 7-day centered moving average. We show the time series for these data in Figure A7. This analysis reveals that activity outside the home decreased by about 45% at the trough of the epidemic, and we use this decline to calibrate the parameter b in the model simulations.

[1] The time use survey data can be accessed at https://en.www.inegi.org.mx/programas/enut/2014/.

[2] Google mobility data can be accessed at https://www.google.com/covid19/mobility/.

Figure A7:
Mobility as a Response to Covid-19 in Mexico



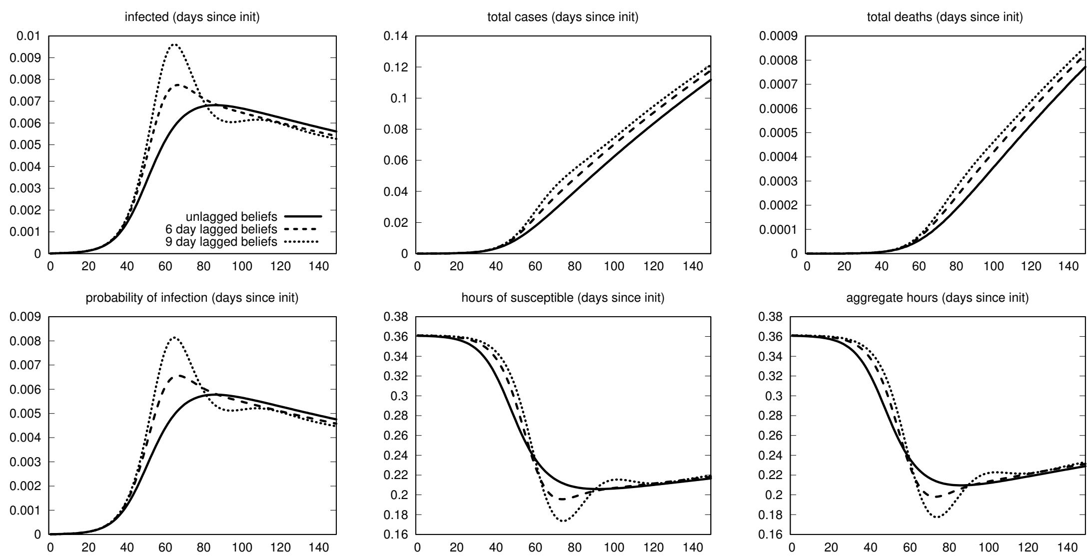
Notes: This graph shows the percentage change in activity outside the home using data from Google Community Mobility Reports for Mexico (available at `https://www.google.com/covid19/mobility/`). We show the actual daily data as well as a 7-day centered moving average.

Finally, to calibrate the baseline risk of transmission Π_0, we use estimates of the basic reproduction number R_0 from Marioli et al. (2020) that correspond to a Covid-19 $R_0 = 1.84$ for Mexico. Note that the model counterpart implies that $R_0 = n(s,0)\,\bar{n}\Pi_0/\gamma \approx (\bar{n})^2\,\Pi_0/\gamma$. It follows that for $\bar{n} = 0.36$, $\gamma = 0.166$, and $R_0 = 1.84$, we have $\Pi_0 = 2.35$.

C.4 Additional Results and Robustness of the Model

Figure A8 shows additional results of the simulation of the model without delays $k = 0$ and with delays $k = 6$ and $k = 9$. Additionally, Table A3 shows how the model results change when we either increase or decrease important parameters, while keeping all other constant to the baseline model.

Figure A8:
Additional Simulation Results of Behavioral Model



Notes: These graphs show additional results of the model simulation. We show results considering a 6-day delay in the formation of beliefs consistent with reporting delays, zero delay corresponding to contemporaneous (unlagged) beliefs, and a more extreme case of a 9-day lag. The top panel shows figures for the percentage of the population that becomes infected on a daily basis since the onset of the epidemic, the total cumulative cases as a percentage of the total population over time, and the total cumulative deaths as a percentage of the population over time. The bottom panel shows the probability of becoming infected since the beginning of the epidemic, the percentage of hours in a day that susceptible individuals (who have never been infected) spend outside the home (as in Figure 2), and the aggregate hours spent outside as the combined hours of susceptible, infected, and recovered agents.

Table A3:
Robustness Checks on the Model

	Delay	Peak infections (% of pop)	Days to peak infections	Maximum daily deaths (% of pop)	Total deaths on 120th day (% of pop)	Hrs. susceptible to infection at trough
Baseline	$k = 0$	0.68199	87	0.00089	0.05257	20.58527
	$k = 6$	0.77462	68	0.00095	0.05866	19.55523
	$k = 9$	0.96137	66	0.00110	0.06218	17.35130
Higher death rate $\delta = 0.016$	$k = 0$	0.36469	89	0.00096	0.06045	20.19884
	$k = 6$	0.40438	63	0.00100	0.06736	19.33626
	$k = 9$	0.50476	61	0.00116	0.07144	17.08112
Lower death rate $\delta = 0.004$	$k = 0$	1.19222	86	0.00077	0.04278	21.15268
	$k = 6$	1.38842	71	0.00084	0.04762	19.93799
	$k = 9$	1.70642	70	0.00098	0.05040	17.82880
Higher infection rate $1/\gamma = 10$	$k = 0$	2.81456	73	0.00217	0.13813	13.06772
	$k = 6$	3.54543	57	0.00249	0.15530	11.60159
	$k = 9$	4.92972	56	0.00321	0.16859	8.84075
Lower infection rate $1/\gamma = 5$	$k = 0$	0.36816	102	0.00058	0.02987	24.40736
	$k = 6$	0.39735	82	0.00061	0.03360	23.85656
	$k = 9$	0.45332	78	0.00066	0.03568	22.65139
Higher resolving probability $\theta = 0.2$	$k = 0$	0.70261	87	0.00093	0.05844	20.60921
	$k = 6$	0.79919	68	0.00104	0.06459	19.57020
	$k = 9$	0.99175	66	0.00126	0.06806	17.36984
Lower resolving probability $\theta = 0.05$	$k = 0$	0.64418	87	0.00080	0.04218	20.54111
	$k = 6$	0.73004	67	0.00081	0.04777	19.52695
	$k = 9$	0.90704	65	0.00086	0.05117	17.32289

Notes: This table shows results from changing parameters of the model. We consider a higher and lower death rate, infection rate and resolving probability. For each case, we show estimates from a 6-day delay in the formation of beliefs consistent with reporting delays, zero delay corresponding to unlagged beliefs, and a more extreme case of a 9-day lag. We present the estimates for the peak number of infections (expressed as a percentage of the total population), the number of days it takes from the onset of the epidemic to reach this peak, the maximum number of daily deaths as a percentage of the population, the total number of deaths accrued up to the 120th day as a percentage of the population, and the percentage of hours in a day susceptible to infection at the trough of the curve.