Motivated Optimism and Workplace Risk*

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Abstract

We provide field evidence that individuals engage in motivated optimism in the face of impending risk. Congruent with a dynamic anticipatory utility model, we demonstrate that belief distortions are time- and stake-dependent. Our study leverages variation in the time span between the survey and the externally imposed date when workers are required to return to their workplaces during the COVID-19 pandemic. We show that as the work return date approaches, individuals become relatively more optimistic about the increased infection risk associated with going back to the workplace, and about how severely their health may be impacted if they get infected. Belief distortions are larger among those facing potential health complications conditional on infection. Our results are informative about when and for whom interventions will be most effective.

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1 Introduction

Beliefs about our future prospects and the world around us are more than just inputs for decision-making. They directly impact well-being by evoking strong feelings such as hope and anxiety. Anectodal evidence and intuition suggest that individuals may distort their beliefs about future events to manage these emotions. For example, benzene plant workers often downplay the fact that the chemicals they worked with are dangerous (Ben-Horin, 1979). Modeling such belief distortions, Akerlof and Dickens (1982) discuss how workers in dangerous industries may choose their beliefs to reduce the psychic costs of "unpleasant feelings of constant fear or unsettling doubts." Examining the role of anticipatory emotions more generally, Loewenstein (1985) notes "because higher expectations result in greater pleasure from savoring — people have an incentive to upwardly manipulate their expectations." Building on these early intuitions, an expanding literature proposes that individuals engage in motivated optimism as a way to manage their anticipatory emotions by downplaying (inflating) their beliefs about the chances of undesirable (desirable) future outcomes (e.g., Brunnermeier and Parker, 2005; Bracha and Brown, 2012; Mayraz, 2018; Caplin and Leahy, 2019).

Evidence from a variety of settings are suggestive of motivated optimism. For example, individuals who face a higher chance of natural disasters are less likely to take out insurance (Kunreuther et al., 1978); smokers downplay the risks of smoking (Weinstein et al., 2005); and people at risk of a serious genetic disease refuse diagnostic tests and are overly optimistic about their future health (Oster et al., 2013). In these studies, however, it it not clear whether belief distortions are driven by motivated optimism, because comparisons are made between groups who made different choices. Two potential confounds come to mind. First, people typically choose their risk exposure (e.g., whether to work in a risky industry), therefore we may worry about selection on unobservables (e.g., initial risk assessments) when comparing groups who made different choices. Second, belief distortions may arise from a need to justify choices to others or oneself (e.g., to reduce cognitive dissonance).[1] Thus, the act of choice may, in and of itself, modify beliefs. In their seminal paper, Akerlof and Dickens (1982) discuss both motivated optimism and cognitive dissonance: individuals may downplay risks to have less anxiety about their future health, or to justify having chosen a risky profession. More broadly, many situations where individuals want to manage anticipatory emotions can also generate a desire to justify past choices. However, these two motives are con-

[1] Cognitive dissonance is a theory in social psychology describing people's tendency to seek consistency in their beliefs, values, and behaviors (Festinger, 1957). According to this theory, people experience mental discomfort when, for example, their behavior and beliefs do not align. Eyster (2002) and Eyster et al. (2021) provide economic models of cognitive dissonance.

ceptually distinct and imply different policies to reduce belief distortions, a point we return to in Section 5. Thus, providing evidence for anticipatory motives, distinct from the common confounds discussed above, is important. An ideal setting requires exogenous variation in anticipatory concerns, while keeping past decisions fixed, in order to control for both selection and justification concerns. Fixing past choices and experimentally exposing individuals to different levels of risk is, however, often not feasible in the field due to ethical concerns.

In this paper, we provide evidence for motivated optimism in a natural setting that parallels the context of Akerlof and Dickens (1982), yet features variation in anticipatory concerns that is orthogonal to any decisions or risk assessments individuals might have made previously. Specifically, we leverage the reopening of businesses in the U.S. after the initial wave of COVID-19 lockdowns in late April 2020. As Governors across states allowed industries to reopen in waves, companies began calling their employees back to work. At that time, feelings of anxiety about the looming health risks associated with physically returning to work were common.[2] However, workers who did not want to lose their jobs had no choice but to return to their workplaces when their employers called them back.[3] We ask workers who expect to have to go back when called about their subjective risk assessments of infection risk (both if they would continue working from home and if they would go back to their workplace), as well as the chance of being hospitalized or needing intensive care if infected. Focusing on workers who are all currently staying at home and will return to work when called back eliminates differences in return-to-work status and decisions, and thus concerns about selection bias and the possibility that return-to-work decisions may influence beliefs. In this context, we exploit two kinds of variation in anticipatory concerns — over return horizons and across health stakes.

The next section presents a simple model of the dynamics of motivated belief adjustments that underpins our empirical approach. We show that compared to workers who have a longer time until they have to return to work, those who have to return sooner are more optimistic about the health risks associated with returning to work relative to staying at home (*time-dependency*). This result reflects the intuition that anticipatory emotions may become more prominent as the date of return approaches. Our model also predicts that the motivation to distort beliefs is more pronounced when stakes are higher, such as when individuals have a relatively high risk of getting severely ill (*stake-dependency*). We then test these predictions using exogenous variation in the time left

[2] For example, see https://www.bbc.com/worklife/article/20200521-why-do-we-feel-uneasy-about-a-new-normal and https://www.limeade.com/wp-content/uploads/2021/05/2021-EmployeeCareReport-3.0.pdf.

[3] Workers had few legal options to refuse to go back to work without getting fired: https://time.com/5832140/going-back-to-work-coronavirus-rights.

before workers return to their workplaces as well as natural variation in health stakes arising from health conditions that the Centers for Disease Control (CDC) identified as high-risk factors.

To test for time-dependency, we exploit two sources of variation in the time horizon of going back to work. First, we run multiple waves of a survey in quick succession with workers who have no choice but to return to their workplaces upon being called back. Second, we use variation in industry re-opening dates across industries and states, which is plausibly orthogonal to workers' initial beliefs regarding the health risks associated with working during the pandemic, especially after controlling for a rich set of background variables (e.g., demographics, geographic risk factors, and county-level restrictions). Sections 3.1 and 3.2 describe our study design and identification strategy, while Section 3.3 presents our time-dependency results. We find that workers who are about to return to their workplaces are more optimistic about the infection risk they will encounter upon returning compared to those who have to wait longer before going back. Conversely, those who have to wait longer are more optimistic about the infection risk associated with staying at home. As a result, the perceived infection risk differential between going back to work and staying at home, which is about 20 percentage points for the median worker, is about *half as large* for workers who are about to go back compared to those who will return in four or more weeks. We also find directional evidence for increased optimism regarding beliefs about the severity of health outcomes among workers who are temporally closer to returning. Workers who are about to go back believe they have an 8.5 percent lower probability that they will end up in the hospital if infected compared to those who will return in four or more weeks.

In Section 3.4, we provide evidence for stake-dependency. We take a difference-in-differences approach and compare temporal differences in beliefs between workers who are more likely to develop severe health issues conditional on getting infected (i.e., 60 years or older or have medical conditions that put them in the high-risk group) and workers who are young and healthy. We find that the higher level of optimism is more pronounced among at-risk workers, both with regard to infection risk at work and disease severity. In fact, as shown in Section 3.5, the trend towards more optimistic beliefs about the chance of getting hospitalized (or worse) is almost entirely driven by the high-risk workers.

Section 3.6 presents several robustness checks. In particular, we can reasonably rule out learning correlated with return horizons and from the announcement of reopening dates as potential confounds. We also investigate the role of planned preventive actions in belief distortions, and conduct sensitivity analyses to ensure that our main results are not due to model specification, outliers, and sample selection. Overall, our empirical results confirm that motivated optimism exhibits both time- and stake-dependency, consistent with a dynamic model of anticipatory utility.

Our paper contributes to a broader literature on motivated reasoning in three ways. First, we provide evidence of motivated optimism in a field setting that is relevant to a large part of the population. Existing evidence on downplaying (inflating) beliefs about the chances of undesirable (desirable) future outcomes due to anticipatory concerns mainly comes from the lab (Mayraz, 2011; Coutts, 2019; Engelmann et al., 2019). Outside the lab, the literature has mostly focused on other motives to distort one's beliefs, especially the need for self-enhancement. This body of work is generally concerned with documenting overconfidence in a particular sub-population (e.g., Park and Santos-Pinto (2010) examine chess players, while Huffman et al. (2019) and Hoffman and Burks (2020) study overconfidence among managers and truck drivers, respectively).[4] Using a natural experiment, Schwardmann et al. (2022) provide evidence of a closely related concept — self-persuasion — by exploiting the random assignment to political positions in debate tournaments. More closely related to our study, in terms of its focus on motivated optimism, is Oster et al. (2013) who study health risk assessments among individuals who are at risk of Huntington's disease, a rare genetic degenerative illness. They find that at-risk individuals who chose not to take a diagnostic test have overly optimistic beliefs about developing the disease, even after starting to show symptoms. Some researchers (e.g., Klinowski and Paulsen, 2013) have suggested that individuals who will develop Huntington's disease may have impaired reasoning due to brain lesions that are present even before the onset of noticeable symptoms. This raises questions about the generalizability of these findings beyond this specific subpopulation. Our study indicates that the desire to downplay health risks, as reflected in Oster et al. (2013), do apply widely, both in terms of context and population. More generally, we contribute to the literature on motivated reasoning by providing evidence of motivated optimism from a high-stakes context that is experienced by many individuals in the workforce.

Second, our study provides evidence consistent with models of anticipatory utility as an explanation for motivated optimism while controlling for confounds that may arise due to justification motives. The desire to manage anticipatory emotions is forward-looking and inherently about flow utility from holding certain beliefs over a time horizon. In contrast, the desire to reduce cognitive dissonance or justify choices to others is backward-looking and about the disutility arising from the gap between beliefs and past choices. Because Oster et al. (2013) focus on individuals who have deliberately decided *not* to get tested, it is unclear whether the reported over-optimism

[4]There is also a related psychology literature documenting that individuals predict better outcomes for the sports team or political party of their choice (see Krizan and Windschitl 2007 for a discussion of this literature and associated inference issues).

reflects anticipatory concerns, cognitive dissonance, or some form of experimenter demand effect (e.g., justifying the decision of not getting tested to the researcher). More recently, Islam (2021) provides financial incentives to students to visit a coffee shop during the pandemic, and shows that those who visit the coffee shop become less worried about their chances of infecting others (but not about getting infected themselves). The beliefs that are used to argue for motivated reasoning were elicited immediately after individuals decided to visit the coffee shop. Therefore, belief adjustments can be driven by cognitive dissonance or justification of the decision to the experimenter. In contrast, we focus on workers who have all made the same choice, and use exogenous variation in the return horizon and health stakes to identify distortions in beliefs as anticipatory concerns get stronger.[5] Therefore, we provide evidence for motivated optimism arising from forward-looking concerns as distinct from other types of motivated beliefs arising from backward-looking concerns, such as the desire to justify past actions or reduce cognitive dissonance. The distinction between forward- and backward-looking concerns is not only relevant for theorizing, but it has also practical implications such as for the timing of debiasing interventions, as we discuss in Section 5.

Third, our study contributes to the literature by providing empirical support for time and stake dependency of motivated beliefs. Standard approaches in economics suppose that individuals' beliefs evolve over time due to new information. Our paper highlights a novel reason for why beliefs may change over time: the passage of time alters the anticipatory utility associated with a future event.[6] The effects of the passage of time on memory distortions were recently explored by Zimmermann (2020), who finds that as individuals become more distant from a past event, they are able to distort memories of the event in a more positive way. Our exploration is complementary — we show that as an upcoming event becomes nearer, individuals distort their predictions in a more positive way.[7] The evidence we present on time-dependency has implications for when to target individuals with information, a point we return to in Section 5. Our second result, stake-dependency, is an important comparative static emerging from many models of motivated beliefs (Bénabou and Tirole, 2016), for which some lab evidence has already been provided.[8] Our

[5] Our approach also has the advantage of not necessitating a comparison of beliefs to a rational benchmark (i.e., objective risks), which can be hard to ascertain in many natural settings.

[6] Although our empirical evidence is novel, it is presaged in early theoretical work by Loewenstein (1985), who considers the adaptation of motivated beliefs over time. A conceptually distinct contribution regarding the dynamics of motivated beliefs is offered by Gottlieb (2014), who explores how the benefits of belief distortion in any given time period evolves as the underlying priors change.

[7] There is a psychology literature on "bracing," formalized by Macera (2014), that shows that although individuals generally hold optimistic beliefs as they wait for self-relevant news, they conjure up pessimistic expectations right before receiving news about the outcome to protect themselves against disappointment (e.g., Shepperd et al. 1996, Sweeny and Krizan 2013). However, unlike these situations, we explore an environment with ongoing risk, i.e., without a certain date for uncertainty resolution.

[8] In the domain of monetary stakes, Kunda (1987), Babcock et al. (1995), Mijović-Prelec and Prelec (2010), and

paper extends this literature by empirically validating the implications of economic theories of belief distortions in an important field setting. In addition, stake-dependency is more in line with motivated optimism as a deliberate choice rather than a mistake. We provide a discussion of these implications in Section 5.

2 Theoretical Framework

We present a dynamic model of anticipatory utility that serves as the foundation for our empirical approach. This model allows us to derive predictions about when and how individuals adjust their beliefs regarding uncertain and anxiety-inducing future events. Specifically, we focus on a model where individuals motivate their beliefs but do not have a choice of actions. As we discuss in Section 4, the implications of distorted beliefs on the choice of actions are sensitive to the initial level of risk in any given period prior to taking actions, the marginal change in risk resulting from those actions, and the number of periods faced by the decision-maker. Thus, when incorporating actions into the model, making robust predictions about the relationship between beliefs and actions becomes challenging. Therefore, to highlight the key feature of motivated beliefs models — the adjustment of beliefs in response to changing circumstances — we focus on a situation without actions.[9]

Our model builds on Bracha and Brown (2012), one of the workhouse approaches to motivated beliefs, in two ways. First, individuals face explicit intertemporal concerns. Second, we allow for individuals to hold multiple beliefs and distort each independently.

We consider a representative individual who is initially at home (h) until period T before returning to her workplace (w). In any given period t while the individual is in h, the chance of getting sick is p_h. That chance increases to p_w when the individual transitions to w. Each period, the individual gets a flow utility from being healthy (G) or sick (B), which she discounts at a rate δ. To clarify our exposition, and without loss of generality, we normalize the flow utility of being healthy to 1 and the present discounted value (PDV) of being sick to 0.[10]

We assume that the actual probabilities of getting sick are time invariant. Like Bracha and

Mayraz (2011) present evidence from experiments consistent with stake-dependency of motivated beliefs, although not always in the context of motivated optimism.

[9]Note that both Bracha and Brown (2012) and Caplin and Leahy (2019) use a similar model to ours and discuss in more detail the interaction between beliefs and actions, assuming a single period, which allows them to make clearer comparative static statements.

[10]Given our cardinal utility representation, we can normalize two payoffs. We will later allow the flow utility from being healthy to vary when we examine the role of stakes. Note that the PDV of being sick takes into account the flow utility of being healthy post recovery, given the discount factor.

Brown (2012), we model individuals as experiencing anticipatory utility from thinking about future outcomes. In particular, in any given period the individual gains flow utility from three sources. The first component is standard utility, which depends on actual outcomes — the PDV of flow utility based on true probabilities (p_h, p_w). The second component is anticipatory utility: each period individuals receive utility from thinking about their future outcomes (i.e., the PDV of their flow utility over outcomes) based on their *perceived* probabilities of future events.[11] We denote the perceived risk of getting sick after returning to the workplace that is held by the individual in Period t (and used when calculating the perceived PDV of payoffs from the perspective of Period t) as $\hat{p}_{w,t}$, and similarly $\hat{p}_{h,t}$ for the perceived risk of infection when staying at home. The third component is a continuous (in all beliefs), convex cost of adjusting beliefs to $(\hat{p}_h, \hat{p}_w)$ given true probabilities (p_h, p_w) — this is a cost that prevents beliefs from straying too far from reality (for simplicity we assume that costs are additively separable in each belief, convex in $\hat{p}_i$, and fixing p_i, increasing in the distance between $\hat{p}_i$ and p_i for $i = h, w$).[12] We suppose that once an individual is sick they cannot distort their beliefs anymore. A weight α is placed on anticipatory utility. As it goes to infinity, the individual cares only about anticipatory utility, whereas if the weight goes to 0 we recover the standard model.

Such a framework can be thought of as a "dual-self" model, where the subconscious self knows the true probabilities and cares about realized outcomes, and the conscious self only knows the perceived probabilities and consumes anticipatory utility. The "subconscious" self chooses, for each period, a pair of beliefs $\hat{p}_h, \hat{p}_w$ in order to maximize the discounted sum of their flow utility. The utility function that the individual maximizes is:

[11] The model focuses on anticipatory utility from beliefs about infection risk. In Appendix F, we extend our model to examine what happens if individuals can manipulate beliefs both about infection risk as well as infection severity. We do so in order to match our empirical findings, which also document changes in beliefs about the severity of infection, conditional on being infected. As we discuss, the model we present in the body of the paper can be thought of as a reduced form model of the model in Appendix F, where the individual cannot manipulate their beliefs about the severity of infection, but only their beliefs about infection chance. Thus, individuals take the expected value of being infected as given.

[12] One can think of this formulation as a reduced form way of psychological distortion costs, as well as any costs imposed by taking suboptimal actions, given a fixed set of past actions (e.g., fixing a set of actions, we obtain a convex loss function for taking actions that are optimal for adjusted, rather than true, probabilities).

$$\sum_{t=0}^{T-1} \delta^t \underbrace{(1-p_h)^t}_{\text{Probability of staying healthy until period } t<T} \left(\overbrace{\alpha[\frac{1}{1-\delta(1-\hat{p}_{h,t})} - \frac{\delta^{T-t}(1-\hat{p}_{h,t})^{T-t}}{1-\delta(1-\hat{p}_{h,t})} + \frac{\delta^{T-t}(1-\hat{p}_{h,t})^{T-t}}{1-\delta(1-\hat{p}_{w,t})}]}^{\text{Anticipatory utility in period } t<T} \underbrace{-c_h(p_h,\hat{p}_{h,t}) - c_w(p_w,\hat{p}_{w,t})}_{\text{Cost of adjusting beliefs in period } t} \right)$$

$$+ \sum_{t=T}^{\infty} \delta^t \underbrace{(1-p_h)^{T-1}(1-p_w)^{t-T}}_{\text{Probability of staying healthy until period } t \geq T} \left(\overbrace{\alpha \frac{1}{1-\delta(1-\hat{p}_{w,t})}}^{\text{Anticipatory utility in period } t\geq T} \underbrace{-c_h(p_h,\hat{p}_{h,t}) - c_w(p_w,\hat{p}_{w,t})}_{\text{Cost of adjusting beliefs in period } t} \right)$$

$$+ \overbrace{[\frac{1}{1-\delta(1-p_h)} - \frac{\delta^T(1-p_h)^T}{1-\delta(1-p_h)} + \frac{\delta^T(1-p_h)^T}{1-\delta(1-p_w)}]}^{\text{Realized utility}}$$

We now turn to explaining each component of the utility function, starting with anticipatory utility. The first line considers the situation where an individual has not yet returned to the workplace in Period $t < T$ and is still healthy, which happens with chance $(1-p_h)^t$. In such situations, the PDV of current and future anticipatory utility flows depends on both $\hat{p}_{h,t}$ (for the periods the individual has not yet returned to work) and $\hat{p}_{w,t}$ (for the periods after the individual has returned to work). In particular, the PDV can be written in a simple way: begin with the PDV of staying at home forever, $\frac{1}{1-\delta(1-\hat{p}_{h,t})}$; subtract off the part of the PDV that captures the value of being at home after period T when the individual returns to work, $\frac{\delta^{T-t}(1-\hat{p}_{h,t})^{T-t}}{1-\delta(1-\hat{p}_{h,t})}$;[13] and add in the PDV of being at work starting in Period T, conditional on having stayed healthy at home until T, $\frac{\delta^{T-t}(1-\hat{p}_{h,t})^{T-t}}{1-\delta(1-\hat{p}_{w,t})}$.[14] Recall that once an individual gets sick they can no longer gain anticipatory utility from believing they are healthy. We therefore normalize the anticipatory flow utility to 0 for the rest of time. Of course, after returning to the workplace (i.e., $t \geq T$), the probability of not having gotten sick while at home and still being healthy after returning to the workplace is $(1-p_h)^{T-1}(1-p_w)^{t-T}$ and the calculation of anticipatory utility becomes simpler, as it is just the PDV of being at the workplace ($\frac{1}{1-\delta(1-\hat{p}_{w,t})}$). The third component of utility, realized utility, is computed as per standard, and is simply the PDV of payoffs using the true probabilities.

This model embeds the assumptions that the choice of perceived beliefs is made independently across time periods, beliefs are adjusted every period, that in any given period t the cost of holding subjective beliefs (e.g., $\hat{p}_{w,t}$) is always calculated by comparing the perceived probability in period t to the objective probability (i.e., p_w), and that payoffs are additively separable across time periods.[15]

[13] By assumption, the value, from Period T's perspective, of being healthy in Period T and staying at home for the rest of time is $\frac{1}{1-\delta(1-\hat{p}_{h,t})}$. The value of this in Period t must be discounted by $\delta^{T-t}(1-\hat{p}_{h,t})^{T-t}$.

[14] When calculating the PDV individuals assume that the risk of infection depends only on period t perceived beliefs.

[15] This gives rise to a form of dynamic inconsistency in beliefs. This implies that although in Period t the individual calculates their Period t anticipatory utility by assuming that the risk in Period $t' > t$ will be $\hat{p}_{w,t}$ and $\hat{p}_{h,t}$. However,

Of course, if we are interested in eliciting the current period beliefs before returning to work (i.e., $t = 0$), under the assumption that the individual is currently healthy, the optimization problem becomes simpler. The optimal beliefs for $t = 0$ (i.e., the current period) can be shown to be the solution to maximizing the following expression by choice of $\hat{p}_{h,0}$ and $\hat{p}_{w,0}$:

$$\left(\overbrace{\alpha\Big[\frac{1}{1-\delta(1-\hat{p}_{h,0})} - \frac{\delta^T(1-\hat{p}_{h,0})^T}{1-\delta(1-\hat{p}_{h,0})} + \frac{\delta^T(1-\hat{p}_{h,0})^T}{1-\delta(1-\hat{p}_{w,0})}\Big]}^{\text{Anticipatory utility}} \underbrace{-c_h(p_h,\hat{p}_{h,0}) - c_w(p_w,\hat{p}_{w,0})}_{\text{Cost of adjusting beliefs}} \right)$$
$$+ \overbrace{\Big[\frac{1}{1-\delta(1-p_h)} - \frac{\delta^T(1-p_h)^T}{1-\delta(1-p_h)} + \frac{\delta^T(1-p_h)^T}{1-\delta(1-p_w)}\Big]}^{\text{PDV of realized utility}}$$

To inform our empirical analyses, we compare three types of individuals. One type, NOW, returns to work immediately ($T = 0$). The second type, LATE, returns to work in an intermediate period ($T \geq 1$). The third type, LATER, returns to work in the distant future ($T >> 1$).[16] We define $\Delta_i \equiv \hat{p}_{w,i} - \hat{p}_{h,i}$ as the perceived infection risk differential between returning to work and staying at home for type $i \in \{NOW, LATE, LATER\}$. In stating our results, we will maintain one assumption, namely that adjusted beliefs preserve the natural ordering of infection risk (as is true in the data):

A0: At the optimum $\hat{p}_w > \hat{p}_h$

We present five results, with detailed proofs in Appendix E. Our first result, summarized in Proposition 1, compares individuals returning to work NOW to those returning LATER. According to this result, we expect to observe a smaller difference between the perceived risk of infection in w and h for individuals who have to return to work NOW, as compared to those with a LATER return date:

Proposition 1 *The difference between the perceived risk of infection in w and h is smaller for*

when Period t' arrives, the perceived probabilities they use to calculate their anticipatory utility in Period t' will be $\hat{p}_{w,t'}$ and $\hat{p}_{h,t'}$. Because we only elicit current beliefs about risk, and not current beliefs about future beliefs about risk, these assumptions are not testable.

[16] The precise timing of each of the three dates is not essential. Similar results, albeit with slightly more restrictive conditions, can be obtained so long as we have three dates, one sufficiently early and one sufficiently late.

individuals returning to work NOW compared to those returning at a LATER time: $\Delta_{NOW} < \Delta_{LATER}$.

The second proposition says that this change in the belief differential Δ is driven by both a change in the beliefs about the chance of getting sick after returning to the work, as well as the chance of getting sick while staying at home.[17] In other words, individuals who must return sooner become more optimistic about the infection risk at work ($\hat{p}_w$ decreases) and reduce their optimism regarding the infection risk at home ($\hat{p}_h$ increases):

Proposition 2 *The perceived risk of infection in w is smaller for individuals returning to work NOW compared to those returning at a LATER time:* $\hat{p}_{w,NOW} < \hat{p}_{w,LATER}$. *Conversely, the perceived risk of getting sick at h is larger for individuals returning to work NOW compared to those returning at a LATER time:* $\hat{p}_{h,NOW} > \hat{p}_{h,LATER}$.

The intuition driving these results is quite simple: temporal proximity to return increases the marginal benefit of distorting beliefs about the infection risk at w, and reduces the marginal benefit of distorting beliefs about the infection risk at h. As the time to return to the workplace draws nearer, the risk in more periods is being driven by $\hat{p}_w$, and the risk in fewer periods is being driven by $\hat{p}_h$. Because individuals discount the future by $\delta < 1$, this leads to a balancing act between belief distortions regarding risks that govern temporally close and distant periods. In particular, as the return date draws nearer, the anticipatory utility from future risk is being driven more by $\hat{p}_w$ than $\hat{p}_h$, which increases the marginal return to distorting $\hat{p}_w$ relative to $\hat{p}_h$.[18] Thus, the marginal benefit to distortion increases for $\hat{p}_w$ and falls for $\hat{p}_h$. As a result, the closer individuals get to returning to the workplace, the more optimistic they become about the infection risk at work and the less optimistic they become about the infection risk at home.

The third proposition states that the perceived probabilities of individuals who have to return to work in an intermediate period (LATE) fall between the beliefs of individuals in the NOW and LATER groups:

Proposition 3 $\Delta_{NOW} - \Delta_{LATER} < \Delta_{LATE} - \Delta_{LATER}$.

Again, the intuition behind this result arises from the increasing marginal benefit of distorting beliefs about the infection risk associated with returning to work and the decreasing marginal

[17] Proposition 1 is a direct consequence of Proposition 2. However, we list it first and separately because we conduct distinct empirical tests of the two results.

[18] We suspect that in reality additional forces could be at play which would amplify the motivated distortions described here, such as selective attention or salience of risks that increase as time to return gets closer. Such considerations would reinforce the effects generated by discounting alone.

benefit of distorting beliefs about the infection risk associated with staying at home as the time of return approaches.

By imposing stronger assumptions on the cost function, we can establish a fourth result, which indicates that temporal adjustments in $\hat{p}_w$ are more pronounced compared to adjustments in $\hat{p}_h$. To achieve this, first we introduce additional structure to the cost function:[19]

A1: $c_h(\hat{p}_h, p_h) + c_w(\hat{p}_w, p_w) = \gamma(|.5 - p_h|)\frac{k}{2}(p_h - \hat{p}_h)^2 + \gamma(|.5 - p_w|)\frac{k}{2}(p_w - \hat{p}_w)^2$

We also assume that $\gamma(\cdot)$, which maps the true belief into the marginal cost of distortion, is a continuous increasing function, is sufficiently steep, and that $\gamma(0) > 0$. In addition, we suppose that the true probability of getting sick at work is larger than the true probability of getting sick at home, but still less than $\frac{1}{2}$:[20]

A2: $\frac{1}{2} > p_w > p_h$

We focus, as is true in the data, on situations where the distorted beliefs are in the interior range. Given these conditions, we can now indicate the following:

Proposition 4 *Suppose A1 and A2 hold, $\gamma'(x)$ is sufficiently large for all $x \in [0, 1]$, and both $\hat{p}_h$ and $\hat{p}_w$ are strictly greater than 0 for both NOW and LATER. Under these conditions, the change in $\hat{p}_w$ is larger than the change in $\hat{p}_h$ between NOW and LATER: $\hat{p}_{w,LATER} - \hat{p}_{w,NOW} > \hat{p}_{h,NOW} - \hat{p}_{h,LATER}$.*

The intuition behind this proposition differs slightly from the previous ones. Here, the intuition revolves around shifts in the marginal cost. Our assumptions imply that as the perceived probabilities p_h or p_w become more extreme (i.e., closer to 0), the marginal cost of distorting these beliefs increases. Consequently, extreme values of p_h and p_w (i.e., more certain beliefs) dampen the effects described in Proposition 1. Thus, under the specified conditions, we observe greater shifts in work beliefs compared to home beliefs, because p_h on average tends to be closer to zero. If we assumed that γ was a constant (so that γ' was 0), the result would not be true. In fact, we would observe the opposite: home beliefs shifting more than work beliefs. This is because the benefit function embeds some convexities with respect to decreases in perceived probabilities (i.e., consider an individual who has to return to work NOW — the marginal benefit of a .1 reduction

[19] Observe that the functional form imposed in A1 still satisfies the general properties imposed on c_h and c_w previously: continuous in beliefs, convex in both distorted beliefs, and increasing in the difference between true and chosen beliefs.

[20] Although A2 is difficult to directly verify, we feel it is both natural, and so long as beliefs are interior and costs strictly convex, it also implies A0, which is true in the data.

in perceived probabilities is larger if p_w is .2 compared to if it is 1). There is evidence supporting our assumptions: Loewenstein (1985), Engelmann et al. (2019) and Sloman et al. (2010) find that more extreme beliefs impede motivated reasoning.

The first four propositions provide insights into the time-dependency of beliefs, while the final result, Proposition 5, explores the stake-dependence of belief adjustments. Individuals naturally differ in the extent to which they may be affected by the disease (e.g., older individuals may face more severe health consequences). We classify individuals with a higher difference in flow payoff between being healthy and sick as "high stakes" (HS), while others are classified as "low stakes" (LS) individuals. Formally, we assume (without loss of generality) that the flow payoff to being healthy is $H > 1$ for high-stakes individuals, while our original individuals, who are considered as low stakes, have a flow payoff of 1 when they are healthy. Proposition 5 states that high-stakes individuals are expected to display larger adjustments in their beliefs as the date of return approaches:[21]

Proposition 5 $\Delta_{NOW,HS} - \Delta_{LATER,HS} < \Delta_{NOW,LS} - \Delta_{LATER,LS}$.

Intuitively, stake dependency arises because a higher difference in utility between the desired and undesired state of the world increases the marginal benefit of adjusting beliefs, while the marginal costs remain the same. This stake-dependency result is a key comparative static that emerges not just from our framework, but from most of the extant models of motivated beliefs (Bénabou and Tirole, 2016).

3 Empirical Investigation

3.1 Field Survey

Throughout the month of May 2020, we conducted a survey comprising four waves, employing Lucid as our chosen platform. Lucid serves as a marketplace designed to facilitate the recruitment of survey participants from diverse online panels. The target group for our survey are working individuals in the U.S. who were furloughed or working from home at the time of the survey. A pre-screening survey administered by Lucid made sure that only qualified individuals were admitted who specified that they (1) "worked outside the home before and working from home now (or furloughed)", and (2) "have no choice but to return to the workplace." Those who reported working from home before, were unemployed, or continued to work outside their homes during the

[21] We obtain this result without requiring the additional assumptions that are necessary for Proposition 4.

pandemic did not qualify. Similarly, individuals who thought they would have a choice to decide on when to return to the workplace, who thought they may not return to the workplace, or who had the option to continue working from home also did not qualify. These requirements guarantee that our respondents are not yet back to their workplaces at the time we surveyed them, and that they will have to return to their workplaces at some point in the future. Therefore, the survey only includes people who are staying at home at the time they are surveyed and expect to be returning to their workplaces when called back. Our survey also included employment status verification and attention checks at the beginning to disqualify any remaining respondents who were not eligible to participate or were not paying sufficient attention to the survey questions. A total of 3,877 individuals successfully completed the survey.[22]

Lucid provides demographic information about each respondent such as their age, gender, ethnicity, education, household income, and political leaning. This includes respondents' zip-codes, which we use to match geographic data such as population density, COVID-19 cases and deaths by county, state identifiers, and county-level restrictions on mobility and economic activity. We report summary statistics of these variables in Tables A.1-A.4 of the Online Appendix. As reflected by the first two of these tables, our sample draws from a diverse population in terms of age, ethnicity, education, income, and political attitudes, and has an over-representation of women.

After presenting the consent form, and a few general questions about the health and economic impact the pandemic already had on the respondent, the survey asked respondents of the date of when their industry was being allowed to reopen (next week, in two weeks, etc.). The survey also elicited when respondents expected to return to work.[23] We denote state mandated reopening dates with κ and an individual's expected return date with T. In May of 2020, the US economy was starting to re-open as the initial stay-at-home orders were being lifted. Governors in each state announced a sequence of dates for different industries to reopen, specifying the restrictions that would be in place for each industry. We chose May 2020 as our study period, specifically targeting a period marked by variation in permitted reopenings.

Once reopening was allowed for an industry, companies in that industry decided when to reopen. Therefore, while companies could delay reopening, they could not start calling employees back to the workplace before it was permitted. We find that 3,172 out of 3,877 workers expected to return to the workplace immediately after the restrictions were lifted for their industry (T and κ are separated by

[22] Of the 3,904 respondents who qualified, 6 reported invalid zip-codes and 21 had already tested positive for COVID-19, and are therefore excluded from the analysis.

[23] Almost half of the respondents expected to return in 4 weeks or later, ranging from 40%-52% across survey waves. The percentage of respondents who expected to return within a week ranges from 18-39% across waves.

less than a week).[24] The remaining 705 workers expected to return with a delay of more than a week between κ and T (of which 70% expected to return within a month of the reopening date). Delays may be due to exogenous reasons, such as less demand for employees (e.g., curbside pickup only) or capacity restrictions (e.g., only 3 employees at a time), or for endogenous reasons, such as when a workplace cannot be made safe for high-risk individuals. One concern for identification is that the decision to delay reopening, or staggering the time by which employees return to the workplace, may be correlated with the respondents' health risks (see Section 3.2). Therefore, if a participant indicated that they expect to return more than a week after the industry reopening date, they were also asked an open ended question about their reason for expecting a delay. Answers were coded by independent research assistants so that we could determine whether the reason is exogenous to risk or risk perceptions. Of the 705 individuals who expected to return with a delay, 140 of them mentioned exogenous reasons, such as low demand conditions and operational restrictions (e.g., only curbside service). Our main analysis sample of 3,312 workers includes these 140 workers. The results are not sensitive to excluding all respondents who expected to return to their workplaces after the industry was allowed to reopen (see Column 2 of Table B.2 in the Online Appendix).

The survey proceeded to elicit participants' counterfactual beliefs about getting infected with the virus under two scenarios:[25]

1. **Probability of getting sick while staying at home**: What are the chances that you will get infected with the coronavirus in the next three months if your current living/working conditions did not change? [0%, 1-10%, . . . , 91-100%]

2. **Probability of getting sick after returning to work**: What would your infection chance be if you went back to working outside the home next week? [0%, 1-10%, . . . , 91-100%]

The answers to these questions correspond to respondents' $\hat{p}_h$ and $\hat{p}_w$, respectively. Crucially, the time frame for the questions was kept the same for all participants. Thus, even though there is variation in the time before respondents return to their workplaces, they all have to consider the same time horizon when answering those questions (e.g., risk of infection if returning *next week*). This feature allows us to infer the impact of time left before returning to work on individual infection risk beliefs without confounds about the time horizon for which beliefs are elicited. The

[24] This finding is congruent with the results of a large survey of business owners, showing that a majority of businesses decided to reopen immediately after they were allowed to do so (Balla-Elliott et al., 2022).

[25] In the first wave, the survey also included a block of questions asking participants' how worried they felt about the health and economic well-being of the following sets of people: themselves, spouses, children, extended family. The response range was 1 (not at all worried) – 5 (extremely worried) with an option to indicate N/A if the target person did not exist. In subsequent surveys, this block was removed.

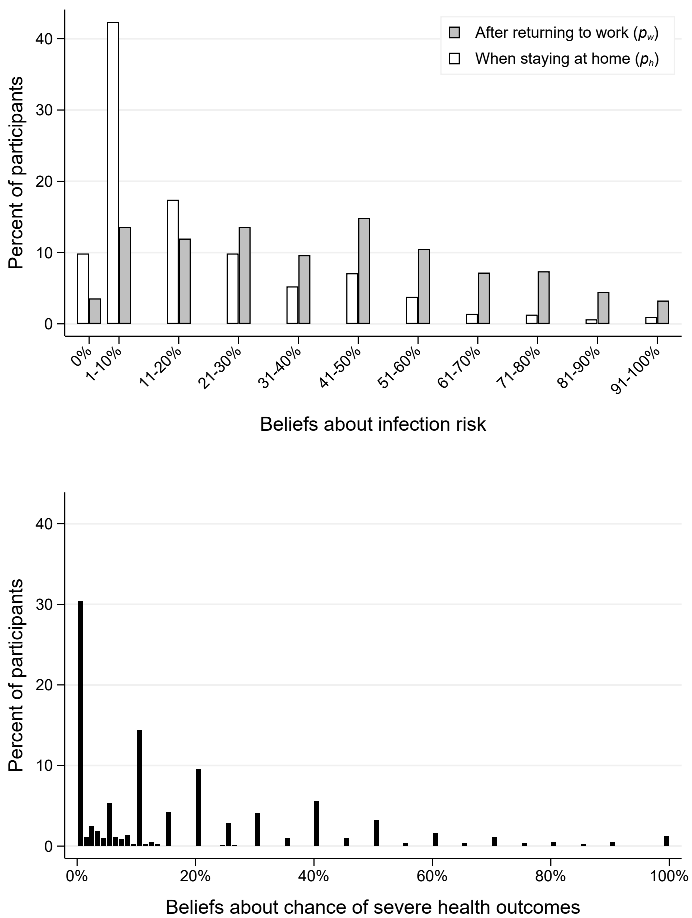
top panel in Figure 1 plots the distribution of $\hat{p}_h$ and $\hat{p}_w$. Whereas a majority of participants thought the infection risk at home is 1-10%, the most common response for the infection risk at work is 41-50%. We take the midpoints of the elicited ranges to construct $\hat{p}_w$ and $\hat{p}_h$. The resulting average belief about the infection risk associated with staying at home is 17.7%, and the corresponding belief associated with returning to work is 38.8%. These numbers are largely consistent with other studies examining the same time period (e.g., Fan et al., 2020 and Heffetz and Ishai, 2021). Figure A.1 in Online Appendix A shows the distribution of Δ, the difference between $\hat{p}_w$ and $\hat{p}_h$. As evident from this figure, most respondents associated a higher risk of infection with returning to the workplace. The median participant believes that the infection risk is 20 percentage points larger if they returned to the workplace compared to staying at home — reflecting an odds ratio of approximately two between the risk after returning to the workplace and the risk associated with staying at home. This ratio is in line with much evidence regarding relative risks at that time.[26]

At first glance, infection risk beliefs (i.e., $\hat{p}_h$ and $\hat{p}_w$) seem high compared to the 1% infection rate suggested by the 3,577,132 cases recorded in the U.S. between May 1 and July 31st, 2020. However, it would be misleading to rely on data regarding case counts to predict p_h or p_w. Not only do overall cases not inform us about the risk of being infected in h compared to w, but the number of actual infections are known to be at least 10 times under-counted due to insufficient testing and the presence of asymptomatic infections during our study period (e.g., see Anand et al., 2020; Rosenberg et al., 2020; Sood et al., 2020 for seroprevalence studies in that time period). Also, at the time of our study, several salient news reports cited studies that found higher infection rates than what was suggested by case counts (e.g., 19% among meat-packers, Herstein et al., 2021; 15% among pregnant women in New York City, Sutton et al., 2020; about 8% of a national sample of dialysis patients, Anand et al., 2020). These figures may even be lower bound estimates for the true 3 month risk in a general population (i.e., our data) since these studies tested their respective subjects once over the study period, tests that may not have been able to detect an infection if it occurred after or a couple of weeks before the testing, and the latter two studies involve high-risk individuals who may have been especially cautious in avoiding exposure to the virus relative to the general population. Of course, behavioral biases may also play a part in individuals' subjective risk assessments. Individuals generally tend to overestimate (by orders of magnitude) low probability

[26] Fisher et al. (2020) finds that approximately twice the number of positive COVID tests are acquired at work compared to at home. News reports said that individuals have twice the chance of catching COVID at work (e.g., `https://www.yahoo.com/lifestyle/going-every-day-doubles-chances-113444265.html`). Herstein et al. (2021) finds that meat-packers had between 2.8 and 15 times the chance of catching COVID relative to surrounding community members. Mulligan (2021) provides a survey of these risks.

events (see, e.g., Gerber et al., 2020 in the context of gubernatorial elections and Barseghyan et al., 2013 on insurance choice), as consistent with predictions of well-known formulations of probability weighting. While precise estimates of the true infection risk probabilities at the workplace and at home remain unknown to date, and the level of rational infection risk expectations is thus elusive, it is worth noting that our model predicts distorted beliefs $\hat{p}_h$ and $\hat{p}_w$ to be lower than rational expectations of infection rates at h and w.

Figure 1: Distribution of beliefs about infection risk and severe health outcomes



Notes: The top panel of this figure provides a histogram of the beliefs about the infection risk after returning to the workplace ($\hat{p}_w$) and the infection risk associated with staying at home ($\hat{p}_h$). The bottom panel shows a histogram of the beliefs about the chance to be hospitalized or needing treatment in the ICU conditional on getting infected.

Respondents reported whether they have certain medical conditions (e.g., asthma or chronic lung disease) that the CDC has identified as conditions that increase the likelihood of severe outcomes. A total of 32% of participants report having a health condition that may put them at a higher risk for severe illness from COVID-19. The top drivers are cardiovascular disease, diabetes, respiratory disease, hypertension, and cancer. When combined with people who are 60 years of age or older, 40% of our respondents are classified as high-risk. For comparison, CDC estimated that about 45% of the U.S. population may have heightened risks (Adams et al., 2020).

The survey also elicited respondents' beliefs regarding the potential severity of disease if they contract the virus. In particular, they indicated the chances they believe they would be symptom free, have a mild version of the disease, have a more severe version without hospitalization, would be hospitalized without further interventions, and the chances they would require intensive care. In our analyses, we operationalize adverse outcome expectations as the probability of hospitalization and/or intensive care. The distribution of beliefs about the probability of severe health outcomes is plotted at the bottom of Figure 1. On average, participants believed there is about a 16.5% chance that they would end up in hospital (or worse) if they get infected. Yet, roughly a third of participants thought that the chance of developing severe health issues is close to zero. As with infection rates, it is difficult to calculate the rate of hospitalization. Based on models developed by Reese et al. (2021) and Iuliano et al. (2021), the CDC estimates hospitalization rates of 18% among those who are 65 and older, 7% for 50-64 year-olds, and 2.7% for 18-49 year olds.[27] Also, the CDC announced that individuals with underlying conditions are more likely to be hospitalized than otherwise healthy individuals.[28] Congruently, those who were categorized as high-risk by the CDC guidelines reported higher expectations of hospitalization and/or ICU care (see Online Appendix Table A.6).

We also asked participants about their expectations of the number of COVID-19 deaths in the U.S. as well as the impact of the pandemic on the economy (unemployment rate, GDP growth). These general beliefs allow us to perform a placebo test for whether changes in beliefs are due to differences in people's knowledge of the current situation of the pandemic. Table A.5 summarizes all elicited beliefs about individual risks and expectations of national outcomes, and Tables A.6 and A.7 report how these beliefs vary with demographics. It is reassuring to see that the patterns of belief variations by age, gender, income, and political attitudes are similar to those documented by other surveys in the same time period. For example, we see that older people are more worried about the severity of the disease, even though they estimate their risk of infection to be lower (as

[27]Source: Table 2 in `https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/burden.html`. Other studies have reported higher hospitalization rates. For example, Jehi et al. (2020) find a hospitalization rate of 21% among patients who tested positive at a Cleveland clinic between March and June 2020.

[28]The CDC report in early May, 2020, can be found here: `https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/past-reports/05082020.html`

in Bordalo et al., 2020).[29] Also, women and those who consider their political view to be on the liberal side are more pessimistic about infection risks, consistent with these groups being generally more worried about the pandemic (see also Allcott et al., 2020; Bundorf et al., 2021; Galasso et al., 2020; Fan et al., 2020). Online Appendix A provides further details.

The final section of our survey included a series of questions that varied across different survey waves and are not the primary focus of our paper. Notably, in all waves except for the first one, participants were asked about the precautionary actions they intended to undertake upon their return to their workplaces. Specifically, we asked them about their intentions regarding indoor masking, outdoor masking, glove usage, and surface sanitization within the workplace. Each response was measured using a five-point scale, ranging from 1 ("Definitively not") to 5 ("Definitively yes"). Additionally, in those same waves, we collected data on participants' inclination towards information avoidance. This was achieved by presenting them with a choice between reading a short summary of a research article about the potential long-term health effects of COVID-19 or a summary regarding sleep deprivation. Finally, in the last two waves, participants were asked about their recent or planned activities for the upcoming week that entailed a certain level of infection risk, such as dining at a restaurant (sit-down) or visiting a gym. In the last two waves, we also incorporated a hypothetical choice scenario where respondents were requested to indicate their willingness to pay for health insurance that would cover a portion of the out-of-pocket expenses in the event of hospitalization due to COVID-19. The survey concluded by asking about respondents' news consumption habits and offering an open-ended feedback opportunity for additional comments. Online Appendix D details the survey.

3.2 Identification Strategy

In our field setting, all workers eventually have to return to their workplaces and survey timing is externally imposed. We define return horizon (i.e., the time left before people have to go back to the workplace) as $\vec{t} = T - \tau$, where T denotes expected time of return and τ is the time of the survey. The data feature two sources of variation in $\vec{t}$. The first source of variation comes from the staggered nature of the survey: fixing T, variation in $\vec{t}$ arises from individuals participating in different waves τ of the survey. The second source comes from the staggered re-opening dates: fixing the timing of the survey τ, the return time T varies across workers.

In Section 3.3, we examine how $\hat{p}_w$ and $\hat{p}_h$ respond to $\vec{t}$. In Section 3.4, we investigate how this

[29] This may be perhaps because older people have been reported to adopt more preventive behaviors (Kim and Crimmins, 2020), or as proposed in Bordalo et al. (2020), the pandemic may have made mortality salient for the first time to young people.

response varies by individuals' health stakes. We empirically confirm that the natural variation in health stakes, i.e., in age and pre-existing risk factors, is independent of $\vec{t}$.[30] To identify how beliefs about the infection risk regarding staying at home and going back to the workplace ($\hat{p}_w$ and $\hat{p}_h$) respond to $\vec{t}$, the variation in $\vec{t}$, i.e., the timing of the survey (τ) and the timing of work return (T), should be independent of an individual's actual infection risks (p_h and p_w). Although the timing of the survey waves is exogenously induced, risks of COVID-19 infection may have varied over waves and across geographies. In the main analysis presented in Section 3.3, we control for wave fixed effects as well as the number of cases and deaths per million in the respondent's county, the most recent two-week changes in the number of cases and deaths in the county, and county population density in our regressions to account for variation in infection risks over time and across geographies. Conditioning on the county-wave level COVID-19 risk controls, the variation in $\vec{t}$ induced by the survey timing is plausibly independent of residual individual-specific p_w and p_h.

Variation in return time T has three possible components: (i) variation across geographies in reopening speeds (e.g., counties in California and Michigan keeping businesses closed for a longer period of time than Texas and Ohio), (ii) variation in reopening allowances across industries within a geography (e.g., schools in Michigan reopening later than grocery stores), and (iii) variation in return timing after the industry is allowed to reopen (e.g., two bars in the same county reopening on different dates after it is allowed). The variation in T across states is plausibly independent of p_h and p_w after controlling for general COVID-19 risk factors at the county-wave level, worker demographics, political affiliation, and health risk factors. Even after conditioning on these controls, the variation in T across industries within a state could still be correlated with an individual's p_w if policy decisions about lifting restrictions for specific industries are governed by industry-specific health concerns. In particular, we may be concerned that the industries that pose the greatest contagion risks are (or are perceived to be) allowed to reopen later, inducing a spurious positive correlation between the length of the return horizon and p_w. However, examining correlates of industry reopening decisions, Balla-Elliott et al. (2022) find that the lifting of restrictions was driven mainly by politics, whether the business is deemed essential, and the local COVID-19 situation, rather than industry-specific factors. Therefore, we expect the variation across industries to be plausibly independent of p_w after controlling for general COVID-19 risk factors at the county level. That said, in order to address any remaining concerns about the potential correlation between the variation in industry reopening timings and p_w associated with different industries, we provide

[30] A logistic regression of the indicator for the individual being classified as high-risk on return horizon length shows that individuals returning the same or next week of the survey (β_1 = 0.024, p = 0.242) and the individuals returning in 2-3 weeks (β_2 = 0.013, p = 0.518) are not significantly different than individuals returning in 4 weeks or later.

robustness checks in Section 3.6 that rely solely on the variation in $\vec{t}$ generated by the survey waves.

The third source of variation could arise from reopening decisions of employers that are systematically correlated with workers' health risks. For example, an employer may decide to delay or stagger the reopening if COVID-19 is rampant and the workplace is dangerous to work in (e.g., poor ventilation and crowding) or if most of the employees are at higher risk (e.g., older workforce).[31] Therefore, as detailed in the previous section, the main analysis sample excludes workers for whom we suspect that their expected return timing may be related to health risks at work, either individual or general.

In Section 3.5, we examine how beliefs about disease severity respond to $\vec{t}$. Our main specification again includes wave fixed effects, worker demographics, political affiliation, and health risk factors. However, the variation in $\vec{t}$ could still be correlated with disease severity if the data included individuals with higher health risks who chose to delay their return. To address this concern, as discussed above, we exclude respondents who expect a delayed return due to health concerns. Conditional on this sample and the controls, $\vec{t}$ is plausibly independent of an individual's disease severity propensity.

3.3 Time-dependency of Motivated Optimism

Our main specification tests whether beliefs differ systematically with temporal distance to the work-return date by estimating the following OLS equation:

$$\Delta_{i(\tau)} = \beta_0 + \beta_1 1(\vec{t}_i \in \{0,1\}) + \beta_2 1(\vec{t}_i \in \{2,3\}) + \mathbf{X}_i + \mathbf{\Gamma}_{i(\tau)} + \eta_\tau + \varepsilon_{i(\tau)} \tag{1}$$

where i denotes a respondent, (τ) reminds us of the time variation across survey waves, $\Delta_{i(\tau)}$ is the difference between $\hat{p}_{w,i(\tau)}$ and $\hat{p}_{h,i(\tau)}$, and $\vec{t}_i$ is the number of weeks a respondent expects to stay at home before returning to the workplace. The coefficients of interest, β_1 and β_2, measure the belief differences between respondents who are returning back to work in four weeks or later (reference group, n=1,546) and those who are returning in the same or next week of the survey ($\vec{t}_i \in \{0,1\}$, n=891), and also those returning back in two to three weeks after the survey ($\vec{t}_i \in \{2,3\}$, n=875), respectively.

The baseline model includes wave fixed effects η_τ to control for common changes in p_w and p_h

[31] This concern only applies to a small minority of workers, both in our survey, and in general. In our data, only 15% of workers expected delays due to reasons related to health concerns. Surveying business owners, Balla-Elliott et al. (2022) also document that the large majority expected to reopen within a few days of the lifting of legal restrictions, and if delays were expected, they were primarily driven by demand expectations and ability to serve customers online, rather than health concerns for employees and customers (e.g., health-risk factors such as employee proximity and the proportion of elderly customers at high risk of severe illness did not predict the owners' reopening decisions).

over time. It also features individual specific controls $\mathbf{X}_i$, which includes demographics (indicator variables for gender, ethnicity, education level, household income groups; political leaning, measured on a 7-point scale) and health risk factors (indicators for age groups, and for whether the individual has any comorbidities). These controls capture any belief differences across respondents arising from differences in the background characteristics of workers returning to work at different times. To account for geographic COVID-19 risks, the regression also features county-date level controls $\mathbf{\Gamma}_{i(\tau)}$, which includes population density, the number of COVID-19 cases and deaths per million at the time of the survey, the most recent two-week changes in the number of cases and deaths. It also includes indicators for public health interventions (i.e., stay-at-home orders, closures of entertainment venues, closures of restaurants, restrictions on 50+ or 500+ gatherings) at the county-day level to account for changes in policies and accompanying attitudes and communications that may impact beliefs.

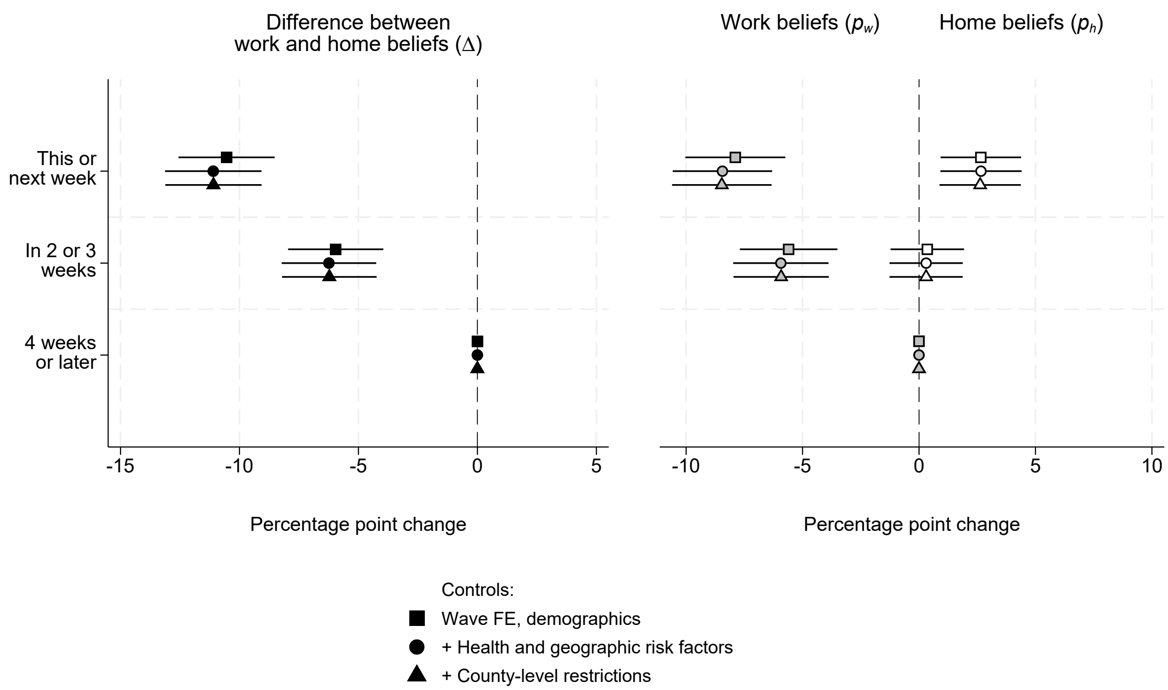
Test of Propositions 1 and 3 Combining the results in these two propositions, we hypothesize that $\Delta_{NOW} < \Delta_{LATER}$, $\Delta_{LATE} < \Delta_{LATER}$, and $\Delta_{NOW} - \Delta_{LATER} < \Delta_{LATE} - \Delta_{LATER}$. These imply, respectively, that $\beta_1 < 0$, $\beta_2 < 0$, and $|\beta_1| > |\beta_2|$ in equation 1 when the dependent variable is $\Delta_{i(\tau)}$.

Moreover, our model predicts movements specifically for $\hat{p}_w$ and $\hat{p}_h$. Therefore, we therefore estimate equation (1) separately for $\hat{p}_{w,i(\tau)}$ and $\hat{p}_{h,i(\tau)}$ as dependent variables as well. For brevity, let $\beta_{1,h}$ and $\beta_{2,h}$ denote the parameters of interest obtained from equation 1 when the dependent variable is $\hat{p}_{h,i(\tau)}$; and similarly, let $\beta_{1,w}$ and $\beta_{2,w}$ denote the parameters of interest obtained from equation 1 when the dependent variable is $\hat{p}_{w,i(\tau)}$.

Test of Propositions 2 and 4 Based on Proposition 2, we hypothesize that as the return date approaches, perceived infection risks associated with returning to the workplace decrease ($\hat{p}_{w,NOW} < \hat{p}_{w,LATER}$), and the perceived infection risks associated with staying at home increase ($\hat{p}_{h,NOW} > \hat{p}_{h,LATER}$). These imply that $\beta_{1,w} < 0$ and that $\beta_{1,h} > 0$. We also test whether $\beta_{2,w} < 0$ and $\beta_{2,h} > 0$. Proposition 4 states that the change in beliefs associated with workplace return are larger than the change in beliefs associated with staying at home ($\hat{p}_{w,LATER} - \hat{p}_{w,NOW} > \hat{p}_{h,NOW} - \hat{p}_{h,LATER}$), which implies $|\beta_{1,w}| > |\beta_{1,h}|$. We also test whether $|\beta_{2,w}| > |\beta_{2,h}|$.

Figure 2 plots β_1 and β_2 (and the associated 95% confidence intervals) both where the dependent variable is $\Delta = \hat{p}_w - \hat{p}_h$ (left panel) and where we separately examine changes in $\hat{p}_h$ and $\hat{p}_w$ (right panel). In all panels, the figure displays the results from sequentially expanding the set of controls. First, it presents results from a specification that only includes wave fixed effects and demographic controls (indicated by squares), then reports estimates from consecutive specifications that add health risk controls (age and having a health condition that puts the individual at a heightened risk of severe health outcomes) and geographic risk controls (local infection and death rates, population density) (indicated by circles), and finally, county-level restrictions (indicated by triangles).

Figure 2: Differences in infection risk beliefs across return-to-work horizons



Notes: This figure provides the coefficient values and 95% confidence intervals for the effect of time horizon on the percentage point change in beliefs about infection risk. The black symbols (■, ●, ▲) in the left panel are the estimates for the perceived infection risk differential between returning to work and staying at home (Δ). The right panel presents the results separately for beliefs about the infection risk after returning to the workplace ($\hat{p}_w$) and the infection risk associated with staying at home ($\hat{p}_h$). The grey symbols (■, ●, ▲) are the estimates for $\hat{p}_w$, and the white symbols (□, ○, △) are the estimates for $\hat{p}_h$. The squares indicate estimates from regressions that control for wave fixed effects and demographics. The circles indicate estimates that additionally account for health and geographic risk factors. The triangles represent estimates from regressions with the full set of controls which also includes county-level restrictions.

The estimates are remarkably stable across specifications (see also columns (1) to (3) in Table 1). Using all controls, we estimate the difference between $\hat{p}_w$ and $\hat{p}_h$ to be about 11 percentage points smaller for people who are about to return to work compared to those who expect to return in four or more weeks ($p < 0.001$). This finding supports proposition 1. The estimate implies a reduction in the belief differential of more than 50 percent, given a median belief differential of

20 percentage points. In other words, individuals who are about to return to the workplace think that the infection risk is more similar between staying at home and going back to the office than those who return later. Individuals who expect to return within two or three weeks also adjust their beliefs, but to a lesser extent than those who return within a week: their belief differential is about 6 percentage points smaller compared to those who return in four or more weeks ($p < 0.001$), providing evidence for proposition 3.

The right panel of Figure 2 depicts how $\hat{p}_w$ and $\hat{p}_h$ change across return horizons. As people get temporally closer to returning to work, they become more optimistic about the infection risk at work (with all controls, $\beta_1 = -8.5$, $\beta_2 = -5.9$; both $p < 0.001$). On the other hand, they become less optimistic about the infection risk at home (with all controls, $\beta_1 = 2.6$, $p = 0.003$, $\beta_2 = 0.3$; $p = 0.705$). These results provide support for the hypotheses proposed in proposition 2. Also, across all specifications, the belief adjustment in absolute terms is more pronounced for $\hat{p}_w$ than $\hat{p}_h$ (with all controls: $|\beta_{1,\hat{p}_w}| - |\beta_{1,\hat{p}_h}| = 5.8$, $p = 0.001$; $|\beta_{2,\hat{p}_w}| - |\beta_{2,\hat{p}_h}| = 5.6$, $p < 0.001$), which is consistent with the prediction of an extension of our model that assumes that the costs of adjusting beliefs are higher when beliefs are more certain (proposition 4). Collectively, these results provide support for our hypotheses regarding the time-dependency of motivated optimism.

3.4 Stake-dependency of Motivated Optimism

Next, we empirically test for heterogeneity in belief distortions with respect to health stakes. Specifically, we estimate the following OLS equation:

$$\Delta_{i(\tau)} = \beta_0 + \beta_1 1(\vec{t}_i \in \{0,1\}) + \beta_2 1(\vec{t}_i \in \{2,3\}) + \beta_3 m_i + \beta_4 1(\vec{t}_i \in \{0,1\}) \cdot m_i + \beta_5 1(\vec{t}_i \in \{2,3\}) \cdot m_i + \mathbf{X}_i + \mathbf{\Gamma}_{i(\tau)} + \eta_\tau + \varepsilon_{i(\tau)} \quad (2)$$

where m_i indicates whether a respondent is a high-stakes individual (i.e., older than 60 or has any of the health conditions identified by the CDC as a risk factor). Recall that 40% of our sample fall into this category. Other notations are the same as in equation (1).

Test of Proposition 5 We hypothesize that $\Delta_{NOW,HS} - \Delta_{LATER,HS} < \Delta_{NOW,LS} - \Delta_{LATER,LS}$, i.e., high-stakes individuals distort their beliefs to a greater extent than low-stakes individuals. This suggests that $\beta_4 < 0$ in equation 2. We also test whether $\beta_5 < 0$.

Panel B in Table 1 reports the results from estimating equation 2. Consistent with our model, we find that belief adjustments are more pronounced for people who face a higher difference in payoffs between staying healthy and getting infected. Among high-stakes individuals, the belief differential is 13.5 percentage points smaller for people who return to work within a week compared to those who have at least a month to do so (column 3, with all controls). Among those who are young and healthy, this difference is only 9.4 percentage points. Thus, the difference-in-differences between high- and low-stakes individuals is 4.1 percentage points ($p = 0.044$), providing support for proposition 5. The difference-in-differences is close to zero and not significant when comparing respondents who return to work in two or more weeks to those who return later ($p = 0.865$).

3.5 Beliefs regarding severity of disease

We now turn to considering a different, but related belief — beliefs about outcomes conditional on being sick. Before turning to our empirical analysis, we summarize how our previous theoretical analyses can be extended to this situation (details of the extension can be found in Online Appendix F). We allow for two payoffs, i.e., degrees of severity of illness, conditional on catching COVID-19. In particular, individuals may be severely ill, with a very low payoff, or only mildly ill, with a payoff which is between that of severe illness and full health. The base model, laid out in Section 2, assumes that beliefs about the likelihood of different degrees of severity are fixed. In contrast, in this extended model, we allow individuals to distort both their beliefs about getting ill, and how sick they will get, conditional on being ill. We assume that first the chance of being ill is realized, and then, conditional on being ill, whether or not a severe (or mild) illness occurs. We demonstrate, under mild assumptions, that individuals who have to return to work sooner will distort their beliefs about the severity of their illness in an optimistic fashion relative to those who return to work later.

We next empirically examine beliefs regarding disease severity. Consistent with motivated optimism, we find directional evidence for individuals downplaying the possibility of being hospitalized or admitted to the ICU. In particular, individuals who are about to return assign a 1.4 percentage points lower probability to severely negative health outcomes compared to those who have a month or longer to go before returning to work ($p = 0.089$, see Column 9 of Table 1). This implies a 8.5 percent reduction from an average belief of about a 17% chance. The difference is smaller and not significant when comparing respondents who return to work in two or three weeks to those who return later ($p = 0.949$).

In line with the results on infection beliefs, we find that belief adjustments regarding disease severity are also more pronounced among high-stakes individuals. High-stakes individuals who are about to return to work are more likely to downplay the likelihood of severe illness than those who

Table 1: Impact of time horizon and health stakes on beliefs about infection risk and severity of health outcomes

	Belief Differental (Δ)						Chance of severe symptoms					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel (a) Main Effects												
This or next week	-10.541	-11.101	-11.093	-6.873	-7.577	-7.607	-1.251	-1.343	-1.425	-0.067	-0.403	-0.417
	(1.030)	(1.034)	(1.032)	(1.443)	(1.441)	(1.438)	(0.880)	(0.834)	(0.837)	(1.225)	(1.158)	(1.158)
Two or three weeks	-5.954	-6.239	-6.223	-5.259	-5.494	-5.484	0.093	0.087	0.055	-0.112	0.024	0.010
	(1.021)	(1.014)	(1.014)	(1.089)	(1.085)	(1.083)	(0.918)	(0.849)	(0.850)	(0.999)	(0.930)	(0.931)
Panel (b) Moderation												
This or next week	-9.144	-9.361	-9.387	-5.314	-5.690	-5.759	0.321	0.600	0.500	1.572	1.562	1.530
	(1.290)	(1.288)	(1.286)	(1.648)	(1.643)	(1.641)	(0.845)	(0.853)	(0.856)	(1.211)	(1.210)	(1.210)
Two or three weeks	-6.112	-6.368	-6.378	-5.311	-5.554	-5.573	0.936	1.029	1.002	0.950	0.986	0.977
	(1.291)	(1.290)	(1.289)	(1.349)	(1.345)	(1.343)	(0.815)	(0.819)	(0.821)	(0.890)	(0.893)	(0.894)
High Stakes	3.108	-2.274	-2.485	3.194	-1.934	-2.146	15.704	-3.523	-3.555	15.720	-3.440	-3.464
	(1.296)	(2.509)	(2.511)	(1.291)	(2.486)	(2.489)	(1.190)	(3.305)	(3.306)	(1.191)	(3.298)	(3.300)
This or next week × High Stakes	-3.496	-4.244	-4.147	-3.811	-4.561	-4.461	-4.192	-4.709	-4.657	-4.251	-4.748	-4.705
	(2.076)	(2.057)	(2.057)	(2.076)	(2.055)	(2.056)	(1.840)	(1.811)	(1.811)	(1.840)	(1.811)	(1.811)
Two or three weeks × High Stakes	0.369	0.272	0.343	0.164	0.071	0.144	-2.095	-2.409	-2.420	-2.214	-2.514	-2.525
	(2.041)	(2.021)	(2.022)	(2.034)	(2.013)	(2.015)	(1.932)	(1.874)	(1.877)	(1.936)	(1.877)	(1.880)
Controls												
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	-	✓	✓	-	✓	✓	-	✓	✓	-	✓	✓
Geographic Risk Factors	-	✓	✓	-	✓	✓	-	✓	✓	-	✓	✓
County Interventions	-	-	✓	-	-	✓	-	-	✓	-	-	✓
Return Week FE	-	-	-	✓	✓	✓	-	-	-	✓	✓	✓
N	3312	3312	3312	3312	3312	3312	3312	3312	3312	3312	3312	3312

Note: The dependent variable in Columns (1)-(6) is the difference between subjective beliefs about infection risks associated with staying at home and infection risks associated with returning to the workplace. The dependent variable in Columns (7) - (12) is the subjective probability of being sick enough to be hospitalized or needing treatment in the ICU conditional on getting infected. Panel (a) reports estimated coefficients (and associated standard errors) from Equation 1 and Panel (b) reports results from Equation 2, staggering different sets of control variables and fixed effects.

have a month or longer to go. Specifically, they assign a 4.16 percentage points lower probability to severely negative health outcomes than those who return in a month or longer. In contrast, young and healthy individuals who are about to return to work assign a 0.5 percentage points higher risk of severe illness compared to those who return later. The resulting difference-in-differences between high- and low-stakes individuals is 4.66 percentage points and statistically significant, with a p-value of 0.010. The difference-in-differences between the two groups is smaller when comparing respondents who return to work in two or three weeks to those who return later (p = 0.197).

Overall, our results suggest that belief adjustments are larger for people who have more at stake, and these adjustments arise especially when the return horizon is short. Online Appendix C.1 reports additional results from tests of moderation by gender, risk aversion, education, household income, the impact of the pandemic on the household's income, individual's news consumption patterns, and political views. We do not find differences in belief adjustments across any of these other factors.

3.6 Robustness

3.6.1 Examining the role of information in belief movements

One may naturally wonder if an information-based account could provide an alternative explanation for the belief adjustments we document. Information acquisition could serve as a confound in several potential ways and we consider each in turn.

First, we discuss whether our results could have been driven by agents accessing unbiased information over time. We note that learning over (absolute) time is not a concern, as wave fixed effects control for changes in beliefs over the survey waves. However, it is possible that individuals learned about their infection and disease severity risks in a way that is systematically correlated with their return horizons over the course of our three-week study, even though this is a short period of time. For this type of learning to be an alternative explanation for our findings, it must be the case that (1) respondents were systematically pessimistic about p_w and optimistic about p_h initially, (2) became more likely to seek information as their return date neared, and (3) the information they obtained decreased p_w and increased p_h. Although there is considerable variation in perceived risk, there is no reason to expect systematic biases in p_w and p_h, especially not in opposite directions. As we argued in Section 3.1, beliefs seem compatible with the findings of other studies at the time and not necessarily different from what a rational Bayesian would have expected given the information available. Even if initial beliefs were biased, it is unlikely that individuals could simultaneously learn that the infection risk at home is worse and the infection risk at work is better than they previously thought after acquiring information. The news coverage in May of 2020 included case and death numbers, CDC and Governor announcements, as well as a variety of opinions that varied depending on the political slant of the news source. The availability of general information about COVID-19 and its associated infection risks was limited due to challenges surrounding testing accessibility and the preliminary nature of research on COVID-19. Moreover, the differential infection risks associated with returning to the workplace relative to staying at home were not known and remain elusive 3 years later. Therefore, it is unclear what respondents could differentially learn about p_w and p_h that would move these beliefs in opposing directions.

Furthermore, if the movements in beliefs were driven by the acquisition of information, we would expect to observe two empirical patterns which we fail to see. First, if the increase in optimism in the beliefs about one's own disease severity and infection risk at work is a response to information acquired, we would similarly expect to see an increase in optimism in beliefs regarding the impact of the pandemic on others as the economy opened up. However, we find no such evidence. In the survey, we asked respondents about their expectations of how many people in the U.S. will die from COVID-19 by July 1, 2020, which is roughly one month after the survey period. We also elicited beliefs about how the pandemic will affect the U.S. economy by asking respondents about their expectations of GDP growth in 2020 as well as the rate of unemployment by July 1, 2020.[32] Table 2 shows that these expectations are similar for respondents who are about to go back to work and those who return in four or more weeks (all p-values > 0.434).[33] Second, consuming a variety of news sources, which should increase the chances of receiving more information, also does not moderate our findings (see Online Appendix Table C.1, Column 6). Therefore, our data do not support the hypothesis that people who acquired general information about COVID-19 update their beliefs in a way that could explain our results.

Of course, agents may not be accessing systematically unbiased information. Thus, a second story about informational confounding is that agents were intentionally accessing biased information

[32] The average expectation was 133,800 deaths by July 1, 2020 (the actual number was 120,954). Respondents also expected an unemployment rate of 15.4% and GDP growth of 1.67%, which were both higher than the actual values of 11.0% and -2.8%, respectively. Detailed statistics for all elicited beliefs are summarized in Online Appendix Table A.5.

[33] Although respondents may have had a better understanding of the overall COVID-19 situation than their own risk of infection after returning to the workplace, this is unlikely to explain the lack of movement in general COVID-19 beliefs. We asked participants to predict future realizations of COVID-19 deaths, unemployment rate, and GDP growth, which introduced a significant amount of subjective uncertainty about these outcomes. This is reflected in the coefficient of variation (CV) of these beliefs, which is substantially lower for p_w than for GDP and similar to that of total deaths and unemployment rate. Furthermore, the CVs do not decrease over time, which corroborates the lack of convergence of beliefs to a known target. Finally, we observe systematic differences in general COVID-19 beliefs across individual characteristics, such as political ideology (see Online Appendix Table A.7). This further underscores the malleability of these beliefs.

to support desired beliefs, while also failing to account for the biased nature of the information. Such behavior, where individuals access information sources that almost always tell them the desired states of the world, while failing to account for the fact that this implies the source is relatively uninformative (see, e.g., Masatlioglu et al., 2023, for a discussion of this tradeoff for Bayesians) is tantamount to engaging in motivated optimism.

A more nuanced version of this story is that individuals were more likely to acquire information as their return date approached and were learning from news sources they typically consulted, while being naive about the strength of the information. In this case, we would expect politically more conservative individuals to update their beliefs more optimistically than individuals with more liberal political views. This is because news sources targeted to conservatives were systematically more optimistic about the pandemic (e.g., Ash et al., 2023).[34] However, we do not find that politically more conservative individuals exhibit a stronger shift towards optimistic beliefs as their work return date approaches (see Online Appendix Table C.1, Column 8). Similarly, individuals who typically consult Fox News do not show a different pattern of belief movements as a function of return horizon compared to those who typically consume more liberal news outlets (see Online Appendix Table C.1, Column 7). Therefore, a learning story based on news consumption from individuals' typical news sources also cannot explain our results.

A third potential alternative explanation is that individuals were more likely to receive positive news about workplace precautions (e.g., personal protective equipment or social distancing practices) as they approached their return to work. This specific learning hypothesis assumes that workers systematically underestimate the extent to which their employers would implement precautions. It is not clear, however, why such a systematic bias should exist in the first place. Even if we entertain the possibility of systematic pessimism about workplace precautions, this explanation would need to account for several other patterns we observe. First, this account cannot explain individuals' increased pessimism regarding p_h. Second, the lack of change in overall expectations about COVID-19 (number of deaths, unemployment and GDP growth rates) suggests that this account would have to assume that individuals are systematically pessimistic about workplace precautions, but do not update their beliefs about other employers' precautions once they learn about their own workplace. Third, this account cannot explain why high-risk individuals become more optimistic about their infection risk at work than low-risk individuals. Fourth, this account cannot

[34] Congruent with relying on these news to form opinions, prior work documents substantial and persistent partisan differences in risk perceptions (e.g., Allcott et al., 2020; Fan et al., 2020). Similarly, we find partisan differences in both news consumption patterns and the levels of subjective risk predictions (i.e., infections risks, disease severity, total U.S. deaths, GDP growth, and unemployment; see Appendix Tables A.6 and A.7).

Table 2: Differences in general COVID-19 beliefs across return-to-work horizons

	GDP		COVID-19 Deaths		Unemployment Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Main Effects						
This or next week	0.727	0.029	0.285	-0.134	-0.018	-0.044
	(0.929)	(1.371)	(2.688)	(3.637)	(0.486)	(0.670)
Two or three weeks	0.903	0.589	-5.049	-7.644	-0.974	-0.695
	(0.872)	(0.931)	(2.450)	(2.577)	(0.466)	(0.505)
Controls						
Wave FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓
Return Week FE	-	✓	-	✓	-	✓
N	3312	3312	3312	3312	3312	3312

Note: Each column reports estimated coefficients (and associated standard errors) from a regression of the dependent variable indicated in column heading on the main regression specification plus indicated controls. Beliefs about GDP and the unemployment rate are measured in percentage points; beliefs about COVID-19 deaths are reported in thousands.

explain why individuals become more optimistic about the severity of symptoms, since precautions are unlikely to affect the likelihood of needing hospitalization or ICU treatment.

A final possibility to consider is that individuals might have perceived the reopening of an industry as a signal of its relative safety. A belief that safer industries reopen earlier could lead to a positive association between the perceived risk of infection at work and return horizon. Similarly, the reopening of an industry could be interpreted as a positive signal of local transmission rates, resulting in a positive relationship between the perceived risk of infection at home and return horizon. However, this signaling explanation is inconsistent with several findings. First, a positive signal about the risk within a particular community should lead to more optimistic beliefs regarding the infection risk associated with staying at home, rather than the observed less optimistic beliefs. It should also not influence individuals' beliefs about the likelihood of severe illness if infected. Second, if the reopening of an industry serves as a signal of its safety, we would expect individuals to update their beliefs once, right upon learning the reopening date, and independently of when they are surveyed (τ).[35] That said, we may worry that individuals may update their beliefs about workplace infection risk differently depending on the reopening date (T) announced. For example, they may think that an industry that is allowed to reopen soon is safer than an industry that

[35]We thank an anonymous reviewer for this observation about the timing of the belief updating. Focusing only on respondents (N = 2,378) who knew when the state will reopen their industry with certainty, we replicate our findings (Columns 4 and 8 in Online Appendix Table B.2).

is allowed to reopen later. Such inferences regarding industry safety could lead to a spurious correlation between p_w and return horizons $(T - \tau)$. To account for this, we also estimate a model that controls for the variation in return horizon due to different reopening dates (by including reopening-week fixed effects). These regressions only exploit the temporal variation across survey waves, therefore eliminating the potential informational impact that different return dates might have. While the coefficient estimates are smaller in magnitude, our conclusions remain unchanged (see columns (4) to (6) in Table 1).

In summary, an alternative explanation based on information acquisition or signaling would have difficulty accounting for all the patterns in the data.

3.6.2 Examining the role of planned precautions in belief movements

We also examine the possibility that as individuals approach their return to work, they may think more carefully and concretely about what preventive actions to take at the workplace, and such planning might be responsible for the increased optimism in $\hat{p}_w$.[36] In waves 2 to 4, the survey included questions about the preventive actions workers planned to undertake upon returning to work, including wearing masks while working indoors, wearing a mask when working outdoors, wearing gloves when touching common surfaces, washing and sanitizing hands frequently, and disinfecting their own working surface once a day. In Online Appendix B.1, we present results of an extended specification 1 that includes planned preventive actions as control variables. If the increased optimism regarding workplace risk primarily stems from the precautions workers planned to take upon returning to work, we would expect the relationship between return horizon and changes in perceived workplace risk to be substantially smaller or even eliminated when controlling for planned preventive actions. However, as shown in Appendix Figure B.1, the movements in perceived infection risks remain materially unchanged and are not muted after incorporating planned preventive actions. Therefore, planned precautions cannot be a significant driver for the increased optimism regarding workplace risk.

3.6.3 Robustness to specification choices

In Section B.2 of the Online Appendix, we additionally present results that show the robustness of our results to: (i) a log-likelihood transformation of beliefs to account for their truncated nature, (ii) accounting for outliers in dependent variables by winsorizing 5% of the tails, (iii) including all participants who were admitted to our survey, and excluding (iv) 140 respondents who return with

[36] We thank an anonymous reviewer for raising this point about increased salience.

a delay due to exogenous reasons, (v) 248 respondents who suspect they have already been infected with the virus, and (6) 934 respondents who are not sure about when the state will reopen their industry and are therefore placed in the LATER group. Overall, our conclusions do not change.

4 Discussion

Our results raise the normative question of whether distorted beliefs are "optimal" in terms of welfare. Is there potential scope for interventions that could improve the well-being of individuals who motivate their beliefs? To answer this question, it is useful to consider various aspects of welfare. To what extent do motivated beliefs influence behavior? What is their impact on emotional well-being? How do these potential gains or losses compare to psychological costs of distorting beliefs? To the best of our knowledge, prior research has not addressed these fundamental questions. To shed some light on these matters, our survey's first wave collected information on workers' level of worry regarding the health and economic well-being of themselves, their partners, children, and extended family members. In subsequent waves, the survey elicited precautionary measures workers planned to take upon returning to work, including wearing masks while working indoors and outdoors, wearing gloves when touching common surfaces, washing and sanitizing hands frequently, and daily disinfection of their workspaces. The following discussion provides a general discussion of the challenges in identifying the causal impact of motivated beliefs on emotions or actions. Furthermore, we present supplementary results from our context, which we hope will stimulate further thought and research on the implications of motivated optimism for welfare.

How do motivated beliefs impact emotional well-being? The motivated beliefs literature frequently posits that individuals distort their beliefs to manage the psychological cost of anticipatory emotions, such as anxiety (e.g., Molnar and Loewenstein, 2021; Engelmann et al., 2019; Akerlof and Dickens, 1982; Caplin and Leahy, 2001; Loewenstein, 1987). Longstanding research in psychology suggests that higher levels of optimism are associated with improved subjective well-being during times of adversity or difficulty (e.g., Carver et al., 2010). However, we are not aware of any causal evidence that increased optimism leads to decreased levels of anxiety or increased levels of emotional well-being. Establishing a causal relationship between belief distortions and emotional well-being is challenging due to the circular nature of negative anticipatory emotions (e.g., anxiety), which act as both an antecedent and a managed target outcome of optimism. This circular relationship makes it difficult to interpret observational data. For example, our survey data reveals that individuals with more optimistic risk perceptions also tend to experience lower overall levels of worry (see details in Online Appendix C.2). While this correlation may suggest that belief distortions may help with anxiety, it does not establish a causal effect, because individuals who distort their beliefs are likely more anxious to begin with. To illustrate, consider the case of Anna and Bob. Anna, being more anxious than Bob because she is about to return to work, distorts her beliefs to hold more optimistic $\hat{p}_w$ and experiences less anxiety than she otherwise would have felt. However, even after distorting her beliefs, Anna may still have higher anxiety levels than Bob if the motivated belief formation does not fully offset the initial anxiety difference. In other words, we can only observe the net effect of belief distortion on anxiety, but we cannot compare it to the worry levels that people would have experienced if they had not engaged in motivated optimism. To address this inference problem, one would need to compare two people with the same level of anxiety when confronted with an anxiety-producing future event, and (experimentally) prevent one person from engaging in motivated optimism, then compare their resulting anxiety levels.[37] We are not aware of any experimental interventions that effectively vary the ease with which individuals engage in motivated belief formation while keeping anxiety levels constant.[38] We hope that future research will identify innovative ways to examine whether belief distortions effectively regulate negative anticipatory emotions.

How do motivated beliefs influence behavior? In Appendix C.3, we explore how precautionary action intentions vary with temporal distance to the work-return date by estimating equation 1, where the dependent variable captures the extent to which a worker plans to take a specific precaution. Our findings reveal that workers who are closer to returning to the workplace are slightly more likely to plan on wearing masks and gloves compared to those returning a month or more later. However, we do not observe statistically significant differences in intentions to regularly sanitize hands or routinely clean their own working surfaces (Online Appendix Table C.6).[39] These results provide limited evidence that individuals not only exhibit greater optimism regarding infection risks as their return to work approaches but also tend to be more likely to plan taking preventive actions.[40] While one might expect the need to take preventive actions to decrease as

[37]Collecting time-series data for a before/after comparison is not helpful either because it is difficult to pinpoint the exact moment when a person starts to distort their beliefs.

[38]Studies that manipulate motivated belief formation typically achieve this by manipulating the antecedent motivation to distort beliefs, such as the degree of anxiety (e.g., Engelmann et al., 2019).

[39]We also elicited the willingness to pay for hypothetical health insurance in the event of being hospitalized with COVID-19, information demand for COVID-19 research findings, and the degree to which people engaged in other risky behaviors. We find no significant changes in these actions as the return to work approaches (see Online Appendix Table C.7).

[40]However, unlike the belief elicitation, we did not fix the time frame for the questions about preventive actions. This could introduce a confound as respondents may have had different time horizons in mind when answering the preventive actions questions. For example, people might have expected COVID-19 risks to be lower in the summer. Therefore, people returning to work in the summer, which corresponds to the time period "4 weeks or later" in our study, might rationally expect to need fewer precautions. Consequently, the results should be treated with caution.

optimism increases, it is worth noting that different models of motivated beliefs generate different predictions regarding the relationship between beliefs and such actions. For example, in Brunnermeier and Parker (2005), agents first distort their beliefs and then choose an action based on these distorted beliefs. If preventive actions generate a lower marginal benefit when beliefs about staying healthy are already high (i.e., beliefs and actions are substitutes), this model predicts that more optimistic beliefs are associated with a reduction in preventive actions. In contrast, in Caplin and Leahy (2019), where agents choose beliefs and actions simultaneously, beliefs and actions may move in the same direction. Furthermore, when these models are extended to multiple periods, the predicted relationship between beliefs and actions can reverse. Depending on the length of time under consideration and levels of risk perceptions, either individuals with relatively optimistic or pessimistic beliefs will find it more valuable to take preventive actions.[41] It is crucial to recognize the difficulty in interpreting empirical relationships between beliefs and actions, including the ones presented here, as favoring or opposing a particular model.[42] Consequently, we emphasize the need for future research testing the causal impact of motivated beliefs on actions within a fully-specified theoretical framework.

Although our study cannot provide conclusive evidence for the welfare question, it can weigh in on one particular formulation of distorted beliefs — that they are cognitive mistakes (e.g., based on a misapplied heuristic, as in Krizan and Windschitl, 2009). Specifically, in models where mistakes can be minimized via costly effort, one would expect individuals with the greatest concerns about health risks to have the strongest incentives to exert effort in order to minimize belief distortions. However, we find that these individuals actually distort their beliefs the most. This aligns with models where anticipatory concerns feature prominently in the utility function, such that higher stakes lead to increased belief adjustments.

[41] To illustrate this, suppose the effectiveness of a preventive action is a concave function of individuals' pre-action beliefs about staying healthy. If there is only one period, individuals who are more optimistic (e.g., they have pre-action beliefs of 0.85 rather than 0.05) about staying healthy will take fewer preventive actions. In contrast, if there are 10 periods, and the decision-maker is deciding whether to take a preventive action in all 10 periods, the change in staying healthy over the 10 periods changes from 0.20 ($= 0.85^{10}$) to 0.35 ($= 0.9^{10}$) for individuals with the high beliefs about staying healthy. In contrast, for individuals with low beliefs, the change is from $10 \cdot 10^{-14} (= 0.05^{10})$ to $6 \cdot 10^{-9} (= 0.15^{10})$, which is a much smaller change. Thus, the marginal benefit of changing behavior (across all periods) is much higher for individuals with the initially optimistic beliefs compared to those with the more pessimistic beliefs.

[42] Other empirical evidence on perceived COVID-19 risks and precautionary actions is also diverse. For example, Bundorf et al. (2021) find that people who believe they face a higher risk of infection also tend to avoid everyday activities like grocery shopping and taking public transport. Similar to our findings, Heffetz and Ishai (2021) find that risk perceptions are weakly but positively correlated with taking preventive actions but the results depend on the risk elicitation method. In contrast, Akesson et al. (2020) find that higher perceived risks lead to fewer protective actions. These studies collectively underscore the multifaceted nature of the relationship between risk perceptions and preventive actions.

5 Conclusion

In this paper, we use a natural experiment to investigate whether individuals exhibit motivated optimism when confronted with a imminent heightened health risk in their work environment. After the initial wave of COVID-19 lockdowns in the U.S. during the spring of 2020, many workers had to resume work at their workplaces despite facing an elevated risk of infection compared to staying at home. We conducted a series of surveys among workers who had to return to their workplaces, and find that they became more optimistic about the risk of infection at the workplace and at the same time less optimistic about the risk at home as their return date approached. These belief distortions are more pronounced among individuals expected to experience more adverse health outcomes if infected, in line with a motivated optimism account.

The setting we examine allows us to avoid several potential confounds that typically affect research into understanding whether anticipatory concerns can cause individuals to distort their beliefs. First, because we focus on workers who all have to return to work by an exogenously imposed date, we avoid the standard selection bias issues. Second, we also are able to avoid a distinct psychological mechanism that could also lead to motivated optimism: a desire to justify past choices and reduce cognitive dissonance. Demonstrating the impact of anticipatory motives, distinct from justification and cognitive dissonance, is important not only because they are psychologically distinct mechanisms, but also because they suggest different potential interventions. Unlike justification, which merely requires chosen actions to compare favorably to unchosen ones, anticipatory utility implies that individuals prefer to think positively about the future, regardless of past choices. Thus, pathways for debiasing beliefs that focus on past actions, such as reducing the perceived value of foregone alternatives, will be ineffective when anticipatory emotions are the main source for optimism.

Despite the lack of clear welfare criteria in the literature on anticipatory utility, policy-makers may still want to intervene even if belief distortions are individually optimal when such distortions can exacerbate externalities. Unlike cognitive dissonance, which merely requires that chosen actions compare favorably to unchosen ones, anticipatory utility implies that individuals prefer to think positively about the future, regardless of past choices. Thus, pathways for debiasing beliefs that focus on past actions, such as reducing the perceived value of foregone alternatives, will be ineffective when anticipatory emotions are the main source for optimism (but would potentially reduce biased beliefs due to cognitive dissonance). Our results further shed light on when and for whom interventions will be most effective. For example, it may be optimal to correct beliefs shortly before actions must be taken or before individuals transition to a situation with heightened risk.

This approach allows for the benefits from distorted beliefs prior to this time period but prevents individuals from acting in ways that reduce their overall utility.

Our findings raise questions that are relevant for other areas of research. First, distorting beliefs about future risk is just one possible strategy to regulate emotions. A large body of literature in psychology suggests that individuals can learn to control the impact of their emotions through cognitive reappraisal of a situation (e.g., Gross, 2015). In the field of economics, an early example of this is presented by Becker and Rubinstein (2004), who propose a model where individuals can invest in their ability to control their fears and empirically test it in the context of terrorism. Another line of research suggests that individuals may try to regulate their emotions through selective access to information (e.g., Caplin and Leahy, 2001 discuss this point theoretically, while Oster et al., 2013 and Ganguly and Tasoff, 2017 provide evidence in the medical domain). These mechanisms may be viewed as potentially substitutes (because avoiding information reduces the need to distort beliefs) or complements (because avoiding information may make distorting beliefs easier). Although relatively under-powered, our study does not reveal significant differences in information avoidance across individuals with different return horizons (see Table C.7 in Online Appendix C.3). More research is needed to better understand the relative importance and interplay of these distinct emotion regulation strategies.

Second, researchers often use wage differentials across industries with varying health risks to estimate the value of a statistical life (VSL) (see Viscusi, 2018 for a recent survey). However, recent work by Anelli and Koenig (2021) using data from the COVID-19 pandemic shows that using subjective beliefs rather the objective probabilities about workplace risks can lead to significantly different estimates of VSL. Our findings suggest that the issue may run even deeper: individuals may manipulate their subjective beliefs based on their circumstances, such as whether they feel compelled to work in a particular industry rather than choosing between a risky industry and a less risky industry without any current employment. Consequently, we may obtain very different estimates of the VSL depending on the specific details of workers' situations. These different VSL estimates may not necessarily result from preference heterogeneity but rather from the degree of belief distortion about risks across different groups of workers. Understanding how distorted beliefs can impact our estimates of policy-relevant parameters, such as the VSL, is an important and as of yet, unexplored topic.

The COVID-19 pandemic distributed proverbial lemons in the form of severe health risks to people worldwide. Our results suggest that individuals, as they approach a heightened risk, tend to mentally sweeten the lemons (i.e., adjust their beliefs) to make the the world seem safer and more palatable. As highlighted in the preceding discussion, more research is needed to better understand the broader implications of these belief distortions.

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Online Appendix for Motivated Optimism and Workplace Risk

A Summary statistics and cross-sectional differences in beliefs

We provide summary statistics of our control variables in Tables A.1 to A.4. The first two tables highlight the diversity of our sample in terms of race, education, age, income, and political attitudes, and an over-representation of women. The third table shows the wide variation across our sample in the number of local COVID-19 cases and deaths, recent changes in local COVID-19 cases and deaths, and population density. The last table indicates that a substantial number of individuals in our sample faced restrictions on in-person work, while almost all experienced some limitations on gatherings and in-person schooling.

Table A.5 summarizes elicited beliefs about individual risks and expectations of national outcomes, and Tables A.6 and A.7 describe how these beliefs vary with demographics.

In line with Fan et al. (2020) and Allcott et al. (2020), who studied beliefs in a similar time period, we observe that individuals identifying as politically liberal (political view variable < 0) perceive higher infection risks and expect more deaths in the U.S. due to COVID-19. They are also more worried about the pandemic's economic impact in 2020. Note that some of these cross-sectional differences may be influenced by differences in motivated cognition.

Furthermore, we find that women are more worried about the infection risk associated with returning to work. They are also more pessimistic about the total number of COVID-19 related deaths and the national unemployment rate. These differences are consistent with women being more worried about the pandemic in general (Galasso et al., 2020; Fan et al., 2020; Bundorf et al., 2021; Bordalo et al., 2020). However, we do not find a gender difference in the perceived chance of disease severity. On the other hand, women tend to worry less about the pandemic's impact on GDP.

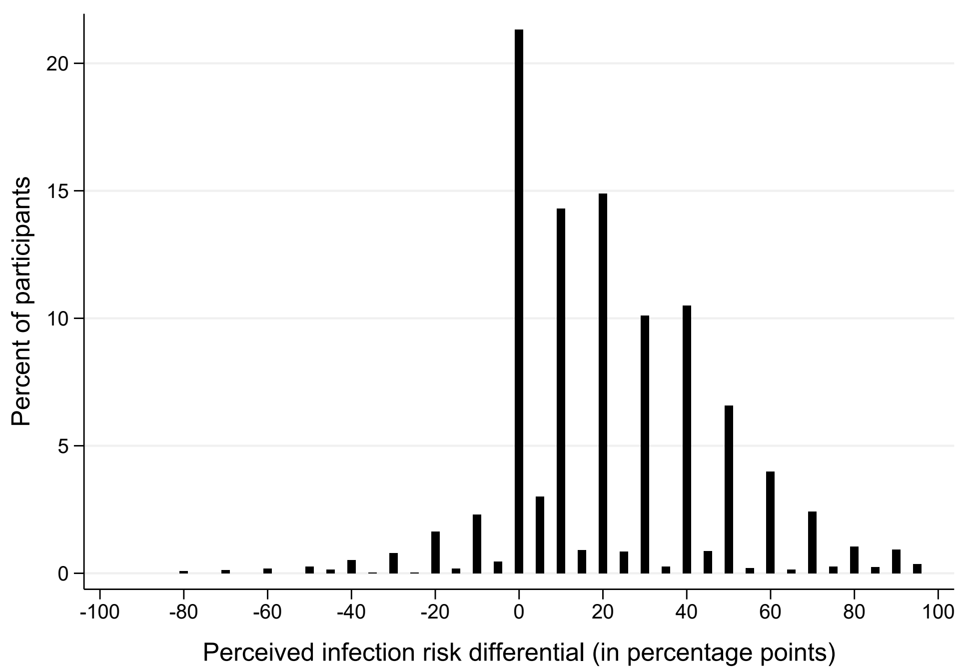
Individuals with annual household income less than $40,000 perceive a lower chance of infection associated with returning to work, predict fewer deaths in the nation, and are less worried about the pandemic's impact on GDP compared to higher income households. On the other hand, individuals with higher education perceive a lower infection risk associated with staying at home, expect a larger increase in infection risk if they go back to work, and, at the same time, expect a more negative impact of the pandemic on GDP.

Similar to Bordalo et al. (2020), we find that younger individuals perceive a higher risk of infection (and in our case, also more deaths nationally), especially after returning to work, even after controlling for political views. The number of confirmed cases accounted for the same proportion of all adult age groups according to the CDC.[43] This perceived difference may be due to several factors. First, young adults are more likely to have asymptomatic and mild cases, and therefore they may

[43] https://web.archive.org/web/20211029013220/https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-age.html Accessed October 29, 2021.

be less likely to get tested and appear in case counts. Second, older people have been reported to adopt more preventive behaviors (Kim and Crimmins, 2020), such as limiting social contact, and therefore, they might perceive a lower risk of infection. Third, as proposed in Bordalo et al. (2020), the pandemic may have made mortality salient for the first time to young people.[44] Importantly, however, older people report higher risks of severe health outcomes that require hospitalization (or worse). In fact, and in line with Bundorf et al. (2021), we find that individuals who are generally at a higher objective risk — older people, individuals who have at least one health-risk factor, and individuals whose annual household income is below $40,000 — realistically expect a higher chance of severe health outcomes conditional on getting infected.[45]

Figure A.1: Distribution of Δ



Notes: Histogram of $\Delta = \hat{p}_w - \hat{p}_h$.

[44]It could also be the case that younger workers have jobs with more customer or employee interaction. To check for this possibility, we ran another specification that included the number of employees and customers the respondent reported engaging with on a typical day as controls. As expected, beliefs about the infection risk at work increase with number of employees and customers. However, the results regarding age differences in perceived risk remain largely unchanged.

[45]We observe heightened perceptions of infection risk and expectations of total deaths in the country among individuals who have at least one health-risk factor, a pattern also documented by Bundorf et al. (2021).

Table A.1: Summary statistics of demographic controls

	%
Race	
White	80.4
Black	8.0
Asian	5.2
Other	6.4
Education	
Less than Bachelor's	34.4
Bachelor's degree	31.1
Graduate degree	25.4
Did not report	9.1
Gender	
Female	69.3
Male	30.7
Household income	
< $40k	16.9
$40 - 75k	32.9
$75 - 100k	17.6
$100 - 150k	18.1
$150k <	10.2
Did not report	4.3
Political Leaning	
Extremely liberal (-3)	7.5
Liberal (-2)	17.2
Slightly liberal (-1)	10.3
Moderate/Middle of the road (0)	22.4
Slightly conservative (1)	15.1
Conservative (2)	17.7
Extremely conservative (3)	9.8
N	3,312

Note: This table presents summary statistics of demographics using self-reported information from survey participants. Each category for each demographic lists the fraction of subjects in that category.

Table A.2: Summary statistics of health risk factors

	%
Age	
18 to 29	24.2
30 to 39	25.5
40 to 49	20.9
50 to 59	17.3
60 and above	12.1
Health conditions on the CDC comorbidity list as of May 2020	
Has none	67.9
Has one or more	32.1
N	3,312

Note: This table presents summary statistics of health risks using self-reported information from survey participants. The top panel provides the fraction of participants in each age category, while the lower panel provides the fraction of individuals either having none, or at least one of the co-morbidities listed by the CDC in May 2020.

Table A.3: Summary statistics of geographic risk factors

	Mean	SD	Median
COVID-19 cases (per 100,000 people)	521.46	642.73	263.80
14 day change in COVID-19 cases (per 100,000 people)	107.12	116.78	65.38
Deaths from COVID-19 (per 100,000 people)	33.90	54.01	11.32
14 day change in deaths from COVID-19 (per 100,000 people)	8.80	13.58	3.20
Natural logarithm of population density (per sq. mile)	6.55	1.64	6.62
N			3,312

Note: This table presents summary statistics of COVID-19 risk factors across the respondents, based on the county they live in. The data is made available by Killeen et al. (2020).

Table A.4: Fraction of respondents facing different restrictions at the time of survey

	%
Stay-at-home order	53.6
Restaurant closure	56.1
Entertainment venues and gym closure	58.6
Gathering limitation (50 people or more)	90.1
Gathering limitation (500 people or more)	96.1
Public school closure	100
N	3,312

Note: This table presents the fraction of respondents experiencing different activity restrictions at the time of survey, based on the county they live in. The data was made publicly available by Killeen et al. (2020).

Table A.5: Summary statistics of elicited beliefs

	Mean	SD	Median
Infection risk associated with staying at home	17.7	19.7	5
Infection risk associated with returning to work	38.8	26.1	35
Chance of severe symptoms	16.5	21	10
GDP growth in 2020	1.67	21.3	.75
Unemployment rate by July 1st, 2020	15.4	10.6	15
U.S. deaths due to COVID-19 by July 1st, 2020 (in 000s)	133.8	60.2	120
N			3,312

Note: This table presents summary statistics of participants' expectations regarding a variety of individual risks and national outcomes. Participants reported most estimates by choosing among intervals (e.g., 10-20% chance or 200,000 - 225,000 deaths). We re-coded their answers as the middle point of the interval. Chances of different possible health outcomes were elicited continuously. Appendix D details elicitation questions.

Table A.6: Individual risk belief variation across respondent characteristics

	(1) Work Beliefs ($\hat{p}_w$)	(2) Home Beliefs ($\hat{p}_h$)	(3) Belief Differental (Δ)	(4) Chance of severe symptoms
Age (*omitted: 18-29 y.o.*)				
30-39	-2.680	-0.318	-2.362	-1.546
	(1.291)	(1.014)	(1.302)	(0.895)
40-49	-3.134	0.392	-3.526	1.024
	(1.365)	(1.048)	(1.320)	(1.000)
50-59	-3.241	-0.808	-2.433	1.385
	(1.423)	(1.095)	(1.349)	(1.098)
60 and above	-7.910	-1.471	-6.439	5.801
	(1.503)	(1.251)	(1.441)	(1.390)
Female	6.672	0.481	6.191	-0.037
	(0.947)	(0.741)	(0.885)	(0.762)
Race (*omitted: White*)				
Black	-2.606	0.532	-3.139	-0.899
	(1.758)	(1.386)	(1.640)	(1.396)
Asian	1.425	3.338	-1.913	-0.114
	(1.941)	(1.788)	(2.158)	(1.352)
Other	1.923	0.813	1.110	2.348
	(1.925)	(1.503)	(1.847)	(1.595)
Household Income (*omitted:* $< \$40k$)				
$\$40-75k$	4.080	-0.009	4.089	-0.771
	(1.377)	(1.137)	(1.347)	(1.089)
$\$75-100k$	3.008	-0.013	3.022	-0.677
	(1.556)	(1.285)	(1.549)	(1.212)
$\$100-150k$	4.883	-0.440	5.323	-0.723
	(1.589)	(1.257)	(1.523)	(1.232)
$> \$150k$	3.277	-0.547	3.823	-1.316
	(1.874)	(1.489)	(1.882)	(1.372)
Did not report	-0.878	-4.085	3.207	-2.505
	(2.446)	(1.775)	(2.460)	(1.808)
Education (*omitted: less than Bachelor's*)				
Has a Bachelor's degree	0.485	-2.665	3.150	0.033
	(1.114)	(0.886)	(1.071)	(0.880)
Has a Graduate degree	4.522	-2.972	7.493	2.122
	(1.247)	(0.955)	(1.213)	(0.968)
Did not report	-2.572	-0.313	-2.259	0.610
	(2.285)	(1.848)	(2.291)	(1.786)
Political View	-1.922	-0.619	-1.304	-0.270
	(0.251)	(0.198)	(0.243)	(0.204)
Has at least one health-risk factor	9.304	4.226	5.078	15.993
	(0.962)	(0.774)	(0.933)	(0.875)
Constant	29.461	21.948	7.513	9.398
	(3.258)	(2.644)	(3.080)	(2.419)
Controls				
Wave FE	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓
N	3312	3312	3312	3312

Note: This table displays results from regressions of individual risk beliefs (column header) on respondent characteristics and other controls included in our main regressions.

Table A.7: Systemic risk belief variation across respondent characteristics

	(1) Change in GDP	(2) Deaths due to Covid	(3) Unemployment rate
Age (*omitted: 18-29 y.o.*)			
30-39	-0.527	-6.032	0.738
	(0.411)	(3.152)	(0.579)
40-49	-1.476	-6.445	1.520
	(0.445)	(3.374)	(0.604)
50-59	-2.702	-2.974	2.306
	(0.502)	(3.490)	(0.629)
60 and above	-3.446	-6.427	2.420
	(0.550)	(3.617)	(0.647)
Female	0.870	3.820	1.909
	(0.321)	(2.154)	(0.397)
Race (*omitted: White*)			
Black	1.128	0.050	0.725
	(0.575)	(4.538)	(0.762)
Asian	-1.541	2.631	0.507
	(0.749)	(5.161)	(0.882)
Other	0.961	1.564	1.325
	(0.660)	(4.682)	(0.829)
Household Income (*omitted:* $< \$40k$)			
$\$40-75k$	-1.268	1.457	-1.115
	(0.462)	(3.385)	(0.630)
$\$75-100k$	-1.852	-0.104	-0.750
	(0.517)	(3.816)	(0.702)
$\$100-150k$	-1.667	2.788	-2.076
	(0.522)	(3.712)	(0.692)
$> \$150k$	-1.658	13.120	-0.645
	(0.652)	(4.934)	(0.835)
Did not report	-0.307	-1.614	-1.167
	(0.805)	(5.297)	(1.056)
Education (*omitted: less than Bachelor's*)			
Has a Bachelor's degree	-1.446	1.905	-0.337
	(0.373)	(2.603)	(0.495)
Has a Graduate degree	-1.858	3.060	-0.625
	(0.407)	(2.793)	(0.535)
Did not report	-1.349	15.674	-0.202
	(0.780)	(5.862)	(0.903)
Political View	0.559	-5.097	-0.481
	(0.087)	(0.595)	(0.108)
Has at least one health-risk factor	0.590	12.230	0.121
	(0.315)	(2.347)	(0.413)
Constant	0.772	126.899	14.444
	(1.074)	(8.019)	(1.447)
Controls			
Wave FE	✓	✓	✓
Geographic Risk Factors	✓	✓	✓
County Interventions	✓	✓	✓
N	3312	3312	3312

Note: This table displays results from regressions of systemic risk beliefs (column header) on respondent characteristics and other controls included in our main regressions.

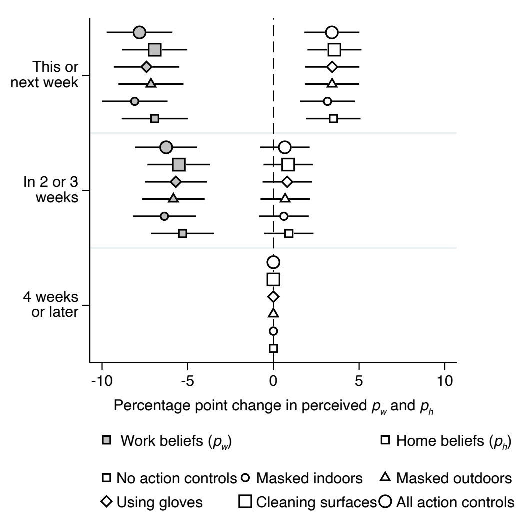
B Robustness Checks

B.1 Robustness to planned precautions

In waves 2 to 4, the survey asked workers about the preventive actions they planned to undertake upon returning to work, including wearing masks while working indoors and outdoors, wearing gloves when touching common surfaces, washing and sanitizing hands frequently, and disinfecting their own work-spaces once a day. We extend specification 1 in the main text to include planned preventive actions as control variables. If the increased optimism regarding workplace risk primarily results from the precautions workers planned to take once they are back at work, we would expect the relationship between return horizon and changes in perceived workplace risk to be substantially smaller or even eliminated when controlling for planned actions.

In Figure B.1 below, we provide the original estimates for $\hat{p}_w$ and $\hat{p}_h$ (denoted with gray and white small squares, respectively), and the results from the same regression when we include dummies for the levels of intention to mask indoors (small circles), mask outdoors (triangles), wear gloves (diamonds), and wipe surfaces (large square) at the workplace, with indicators for each level of intention. The last specification (large circles) includes all planned actions as explanatory variables. As can be seen from the figure, the movements in perceived infection risks are materially unchanged, and are not muted with the inclusion of planned precautionary actions. Therefore, planned precautionary actions cannot be the sole driver for the increased optimism regarding workplace risk.

Figure B.1: Difference in infection risk beliefs across return-to-work horizons, controlling for planned precautions



Notes: This figure provides estimated β_1 and β_2 from equation 1 and their 95% confidence intervals. The small squares indicate our main results. Other estimates add controls for the levels of each planned precaution: to mask indoors (small circles), to mask outdoors (triangles), to wear gloves (diamonds), to wipe surfaces (large square) at the workplace, and all precautionary plans (large circles).

B.2 Robustness to censoring and sample selection

In Table B.1, we repeat the results from our main specification with all controls in Panel (a), and show the robustness of our findings to a log-likelihood transformation of beliefs to account for their censored nature in Panel (b), and to accounting for outliers in the dependent variables by winsorizing 5% of the tails in Panel (c). In Table B.2, we further show the robustness of our results to including all participants who were admitted to our survey (All), excluding 140 respondents who return with a delay due to exogenous reasons (No Exogenous), excluding 248 respondents who suspect they have been infected with the virus (No Infected), and excluding 934 respondents who are not sure about when the state will reopen their industry (Only Certain Open Date). Our conclusions remain the same.

C Additional Results

C.1 Moderation Analysis

One of the key findings of this paper is that belief adjustments are stake-dependent. Individuals who have more to lose from getting sick (i.e., older people or those with certain medical conditions) distort their beliefs more as the time to work return gets closer. Here, we examine other potentially important heterogeneities in belief adjustments. In particular, we explore gender, risk aversion, education, household income, the pandemic's impact on household income, news consumption habits, and political views as potential factors affecting belief adjustments. We report the results for two outcome measures: the difference in beliefs about the infection risk associated with going back to work vs. staying at home (Table C.1), and the perceived probability of severe illness (Table C.2). Each column in the tables examines a different moderator variable, as indicated by the column headers. The regressions include the full set of controls (see section 3.3 in the main text for a description of the control variables). For completeness, we also provide results where we additionally include reopening-week fixed effects (Tables C.3 and C.4). Overall, we do not find moderation effects on temporal differences in risk perceptions by demographics, risk aversion, or news consumption.

Gender (column 1 in each table). Comparing respondents who are about to go back to those who continue to stay at home for at least a month, women change their beliefs about infection risks by 11.9 percentage points, while men alter their beliefs by 9.3 percentage points. This difference of 2.6 percentage points is not significant ($p = 0.198$). We observe a similar yet even smaller difference by gender when we compare respondents who are returning in two or three weeks to those who have a month or longer before they return ($p = 0.553$). We also find relatively small differences by gender in belief adjustments with regard to the probability of severe illness. In that case, men tend to adjust their beliefs more than women, but the interaction effects are not significant ($p = 0.181$ and 0.656).

Risk aversion (column 2 in each table). We measured risk aversion using an experimentally-

Table B.1: Robustness of main results to log-transformed beliefs and winsorization

	Work Beliefs ($\hat{p}_w$)		Home Beliefs ($\hat{p}_h$)		Belief Differental (Δ)		Chance of severe symptoms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel (a): Main Effects								
This or next week	-8.467	-5.554	2.626	2.053	-11.093	-7.607	-1.425	-0.417
	(1.089)	(1.476)	(0.890)	(1.252)	(1.032)	(1.438)	(0.837)	(1.158)
Two or three weeks	-5.918	-5.261	0.304	0.223	-6.223	-5.484	0.055	0.010
	(1.044)	(1.138)	(0.802)	(0.901)	(1.014)	(1.083)	(0.850)	(0.931)
Panel (b): Log-Ratio Transformed								
This or next week	-0.479	-0.275	0.175	0.160			-0.104	-0.008
	(0.066)	(0.089)	(0.064)	(0.090)			(0.073)	(0.100)
Two or three weeks	-0.280	-0.241	0.030	0.021			0.060	0.083
	(0.062)	(0.068)	(0.060)	(0.067)			(0.071)	(0.077)
Panel (c): Winsorized								
This or next week	-8.226	-5.463	1.949	1.449	-10.088	-7.079	-1.221	-0.419
	(1.052)	(1.428)	(0.752)	(1.043)	(0.898)	(1.231)	(0.722)	(0.996)
Two or three weeks	-5.790	-5.174	0.307	0.204	-5.773	-5.076	0.093	-0.045
	(1.007)	(1.101)	(0.702)	(0.776)	(0.893)	(0.960)	(0.727)	(0.791)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
Return Week FE	-	✓	-	✓	-	✓	-	✓
N	3312	3312	3312	3312	3312	3312	3312	3312

Note: Panel (a) replicates the results from our main specification with all controls (dependent variable y indicated in column header) in odd columns and results from a specification that adds return week fixed effect in even columns. Panel (b) reports results from the same specifications with a transformed dependent variable $\tilde{y} = log(.01 + \frac{y}{100-y})$. Because $\hat{\Delta}$ can have negative values, we omit the transformation of that variable. Panel (c) reports results from the same regressions as in Panel (a) after winsorizing the dependent variables (5% of the tails). Estimated coefficients are followed by associated standard errors in parentheses.

Table B.2: Estimates for different sub-samples

	Belief Differental (Δ)				Chance of severe symptoms			
	(1) All	(2) No Exogenous	(3) No Infected	(4) Only Certain Open Date	(5) All	(6) No Exogenous	(7) No Infected	(8) Only Certain Open Date
Panel (a) Main Effects								
This or next week	-11.176	-11.339	-10.927	-12.491	-2.096	-1.553	-0.957	-1.075
	(0.993)	(1.047)	(1.059)	(1.208)	(0.814)	(0.847)	(0.879)	(0.953)
Two or three weeks	-6.715	-5.964	-6.582	-8.361	-0.360	0.120	0.213	0.653
	(0.901)	(1.053)	(1.043)	(1.310)	(0.779)	(0.889)	(0.890)	(1.081)
Panel (b) Moderation								
This or next week	-9.291	-9.594	-9.705	-11.190	0.459	0.464	0.783	0.667
	(1.247)	(1.303)	(1.317)	(1.503)	(0.823)	(0.864)	(0.900)	(0.936)
Two or three weeks	-6.731	-5.792	-7.078	-9.859	0.835	1.156	1.144	1.087
	(1.142)	(1.348)	(1.315)	(1.676)	(0.739)	(0.866)	(0.855)	(1.034)
High Stakes	-2.667	-2.611	-3.098	-3.562	-4.309	-3.018	-3.461	-4.104
	(2.258)	(2.557)	(2.596)	(3.045)	(3.027)	(3.380)	(3.416)	(4.024)
This or next week	-4.548	-4.239	-3.019	-3.177	-6.133	-4.904	-4.282	-4.186
× High Stakes	(1.981)	(2.073)	(2.102)	(2.347)	(1.758)	(1.834)	(1.922)	(2.022)
Two or three weeks	-0.004	-0.487	1.257	3.701	-3.007	-2.631	-2.378	-1.060
× High Stakes	(1.799)	(2.089)	(2.083)	(2.581)	(1.713)	(1.945)	(1.991)	(2.329)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
N	3877	3172	3064	2378	3877	3172	3064	2378

Note: Results are from the main regression, including all controls, with dependent variables indicated in column headings. Column headings also indicate which set of the subjects are included in the regression: all participants who were admitted to our survey (All), excluding respondents who return with a delay due to exogenous reasons (No Exogenous), excluding respondents who suspect they have been infected with the virus (No Infected), excluding respondents who are not sure about when the state will reopen their industry (Only Certain Open Date). Standard errors are in parentheses.

validated survey question developed by Falk et al. (2018). Respondents were asked how willing they are to take risks on a scale from 0 (completely unwilling to take risks) to 10 (very willing to take risks). We created a median split to identify individuals who are relatively more risk tolerant and should thus be less likely to engage in motivated optimism. Indeed, when we compare respondents who are going back soon to those who stay at home for a little longer, we see that individuals who are more risk tolerant adjust their beliefs about infection risks less than others. However, the difference of 3.1 percentage points is not significant (p = 0.120). We also do not find a significant difference by risk preferences when we compare respondents who return in two or more weeks to those who return later (p = 0.866). Moreover, there is no clear pattern across respondents with different risk preferences when we look at beliefs about the chance of getting severely ill (p = 0.598 and 0.140).

Education (column 3 in each table). We split the sample by whether respondents have at least a bachelor's degree (almost 38% do not have a bachelor's degree). Since we do not have information on education for 300 respondents, our analysis is based on a reduced sample. Among respondents with higher education, those who are about to return to work adjust their beliefs about infection risks by 12.1 percentage points relative to those returning in a month or later, while the beliefs of less educated individuals differs by 9.9 percentage points across time-to-return. The difference of 2.2 percentage points between the two groups is not significant (p = 0.312). The results are similar when we compare respondents who return in two to three weeks to those who return in four or more weeks. More educated individuals tend to distort their beliefs more as they get closer to returning to work, but the interaction effect is not significant (p = 0.413). We also do not find that education moderates belief distortions with regard to the chance of getting severely ill. Respondents with a bachelor's degree or higher tend to adjust their beliefs more than others, but the differences are again not significant (p = 0.249 and 0.963).

Income (column 4 in each table). Our theoretical framework predicts that individuals with larger differences in payoffs between being healthy and being sick will distort their beliefs more, as they have a higher marginal return to distorting beliefs. However, it remains unclear whether high- or low-income individuals had more to lose financially if they got sick, as there was little clarity for workers regarding their entitlements if they contracted COVID-19. Indeed, surveys indicate that many people were unaware about possible legal protections, which also varied, e.g., by state and company size. Nonetheless, we examine whether income affects the strength of belief distortions by dividing the sample into two groups based on a median split on income (annual household income of less than $75,000 vs. $75,000 or more). Since income information is missing for 144 respondents, we conduct the analysis with a reduced sample. We do not find that income moderates how people adjust their beliefs about infection risks. Both interaction effects are close to zero and not significant (p = 0.719 and 0.969). Moreover, we do not find a systematic pattern across respondents with different income levels when examining beliefs about the chance of getting severely ill. The interaction effects have opposite signs, with one effect being significant at the 10%-level (p = 0.095 and 0.183).

Economic impact of pandemic on household (column 5 in each table). We asked respondents whether the pandemic has already had an impact on their household income. For the analysis, we divide the sample into two groups: those who experienced some loss in income and those who did not. We find a tendency that respondents who did not experience a loss of income since the beginning of the pandemic adjust their beliefs about infections risk more than others, but only one of the interaction effects is significant at the 10%-level (p = 0.082 and 0.258). In contrast, the same individuals tend to be less optimistic about the probability of getting severely ill (p = 0.350 and 0.119). Thus, the data do not provide a clear picture of whether financial concerns amplify belief distortions.

News consumption (columns 6 and 7 in each table). We examine how news consumption affects belief adjustments in two ways. First, we divide the sample based on a median split on the number of news sources that people say they usually rely on (less than three vs. three or more). Then, we examine whether Fox News viewers (about 30% of the sample) have a stronger or weaker tendency to distort beliefs given the network's controversial coverage of the pandemic. Diversity in news consumption has no influence on the extent to which people distort their beliefs as a function of time to return, neither with regard to infection risks (p = 0.679 and 0.866) nor with regard to the chance of severe illness (p = 0.549 and 0.988). We also do not find clear evidence that Fox News viewers adjust their beliefs differently than others. Comparing respondents who return within a week to those who return in four or more weeks, Fox News viewers change their beliefs about infection risks by 2.2 percentage points less than non-viewers, but the difference is not significant (p = 0.322). The difference gets larger when we compare respondents who go back in two to three weeks to those who return later (p = 0.041). On the other hand, temporal adjustments of beliefs about getting severely ill do not differ by viewership (p = 0.474 and 0.360).

Political views (column 8 in each table). Lucid provided us with information about respondents' political leaning on the spectrum of "extremely liberal" to "extremely conservative." To examine the role of politics, we use a median split which conveniently divides the sample into liberals vs. conservatives. Politically more conservative respondents distort their beliefs about infection risks by 2.5 and 1.5 percentage points, respectively, less than others, but those differences are not significant (p = 0.224 and 0.460). We also do not find that political views affect how people distort their beliefs about outcome severity (p = 0.368 and 0.428).

In sum, we do not find strong evidence for heterogeneity in belief adjustments across a number of variables that could potentially play a role. The interaction effects tend to be small and imprecisely estimated. The results also do not change meaningfully when we control for reopening-week fixed effects, as shown in Tables C.3 and C.4.

Table C.1: Moderation by other factors: Infection risk differential

	(1) Female	(2) High risk tolerance	(3) Has atleast a Bachelor's	(4) Household income > $70k	(5) No negative pandemic related change in income	(6) Follows at least three news networks	(7) Watches Fox News	(8) Identifies as conservative
This or next week	-9.252	-12.780	-9.932	-11.650	-9.735	-10.769	-11.546	-12.184
	(1.645)	(1.540)	(1.676)	(1.475)	(1.318)	(1.315)	(1.245)	(1.384)
Two or three weeks	-5.362	-6.052	-5.454	-6.262	-5.399	-6.137	-7.433	-6.834
	(1.689)	(1.501)	(1.776)	(1.393)	(1.272)	(1.322)	(1.195)	(1.371)
Moderator	6.708	-4.522	6.480	3.925	0.371	3.242	-5.370	-0.570
	(1.306)	(1.254)	(1.557)	(2.094)	(1.280)	(1.280)	(1.421)	(1.866)
This or next week × Moderator	-2.651	3.142	-2.166	0.738	-3.572	-0.846	2.154	2.453
	(2.058)	(2.023)	(2.143)	(2.050)	(2.053)	(2.045)	(2.173)	(2.016)
Two or three weeks × Moderator	-1.234	-0.333	-1.780	-0.080	-2.322	-0.336	4.516	1.471
	(2.077)	(1.983)	(2.173)	(2.045)	(2.054)	(1.991)	(2.206)	(1.989)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
N	3312	3312	3012	3168	3312	3312	3312	3312

Note: The dependent variable is Δ, the difference between subjective beliefs about infection risks associated with staying at home and infection risks associated with returning to the workplace. The table reports estimated coefficients (and associated standard errors) from Equation 2. Column headers correspond to the particular (binary) moderator variable being tested.

Table C.2: Moderation by other factors: Severe illness probability

	(1) Female	(2) High risk tolerance	(3) Has atleast a Bachelor's	(4) Household income > $\$70k$	(5) No negative pandemic related change in income	(6) Follows atleast three news networks	(7) Watches Fox News	(8) Identifies as conservative
This or next week	-3.088	-1.918	-0.477	-0.224	-2.083	-1.032	-1.018	-2.078
	(1.522)	(1.286)	(1.475)	(1.235)	(1.060)	(1.089)	(1.023)	(1.117)
Two or three weeks	-0.507	1.401	0.123	-0.968	-0.984	0.016	-0.487	-0.514
	(1.484)	(1.319)	(1.492)	(1.206)	(1.049)	(1.149)	(0.991)	(1.069)
Moderator	-0.941	-0.996	2.586	-0.967	-1.425	1.594	0.100	-0.909
	(1.139)	(1.027)	(1.267)	(1.597)	(1.033)	(1.029)	(1.180)	(1.505)
This or next week × Moderator	2.397	0.883	-2.055	-2.795	1.615	-0.982	-1.244	1.491
	(1.791)	(1.677)	(1.784)	(1.671)	(1.726)	(1.641)	(1.739)	(1.655)
Two or three weeks × Moderator	0.798	-2.493	-0.084	2.294	2.769	0.026	1.702	1.355
	(1.792)	(1.690)	(1.820)	(1.725)	(1.777)	(1.663)	(1.858)	(1.710)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
N	3312	3312	3012	3168	3312	3312	3312	3312

Note: The dependent variable is the subjective probability of being sick enough to be hospitalized or needing treatment in the ICU conditional on getting infected. The table reports estimated coefficients (and associated standard errors) from Equation 2. Column headers correspond to the particular (binary) moderator variable being tested.

Table C.3: Moderation by other factors: Infection risk differential, incl. return week fixed effects

	(1) Female	(2) High risk tolerance	(3) Has atleast a Bachelor's	(4) Household income > \$70k	(5) No negative pandemic related change in income	(6) Follows at least three news networks	(7) Watches Fox News	(8) Identifies as conservative
This or next week	-6.049	-9.222	-6.628	-8.404	-6.307	-7.344	-7.957	-8.616
	(1.911)	(1.824)	(1.920)	(1.754)	(1.654)	(1.664)	(1.622)	(1.730)
Two or three weeks	-4.899	-5.313	-5.131	-5.599	-4.634	-5.442	-6.747	-6.130
	(1.718)	(1.545)	(1.776)	(1.451)	(1.346)	(1.367)	(1.246)	(1.436)
Moderator	6.480	-4.345	5.854	3.992	0.247	3.212	-5.261	-0.387
	(1.306)	(1.253)	(1.561)	(2.090)	(1.275)	(1.274)	(1.419)	(1.864)
This or next week	-2.279	2.880	-1.509	1.077	-3.349	-0.688	1.861	2.265
× Moderator	(2.061)	(2.019)	(2.147)	(2.053)	(2.053)	(2.040)	(2.171)	(2.014)
Two or three weeks	-0.830	-0.444	-1.144	0.087	-2.376	-0.217	4.517	1.540
× Moderator	(2.074)	(1.977)	(2.147)	(2.035)	(2.048)	(1.983)	(2.197)	(1.985)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
Return Week FE	✓	✓	✓	✓	✓	✓	✓	✓
N	3312	3312	3012	3168	3312	3312	3312	3312

Note: The dependent variable is Δ, the difference between subjective beliefs about infection risks associated with staying at home and infection risks associated with returning to the workplace. The table reports estimated coefficients (and associated standard errors) from Equation 2 plus return-week fixed effects. Column headers correspond to the particular (binary) moderator variable being tested.

Table C.4: Moderation by other factors: Severe illness probability, incl. return week fixed effects

	(1) Female	(2) High risk tolerance	(3) Has atleast a Bachelor's	(4) Household income > $70k	(5) No negative pandemic related change in income	(6) Follows atleast three news networks	(7) Watches Fox News	(8) Identifies as conservative
This or next week	-2.191	-0.963	0.789	0.521	-1.130	-0.034	0.044	-1.063
	(1.699)	(1.536)	(1.672)	(1.453)	(1.326)	(1.345)	(1.310)	(1.391)
Two or three weeks	-0.543	1.378	0.293	-1.075	-1.048	-0.046	-0.524	-0.623
	(1.518)	(1.385)	(1.549)	(1.298)	(1.112)	(1.201)	(1.058)	(1.145)
Moderator	-0.960	-1.016	2.428	-1.090	-1.510	1.561	0.022	-0.853
	(1.141)	(1.029)	(1.273)	(1.599)	(1.034)	(1.029)	(1.183)	(1.507)
This or next week	2.594	0.934	-1.931	-2.629	1.743	-0.948	-1.193	1.456
× Moderator	(1.786)	(1.674)	(1.789)	(1.673)	(1.731)	(1.642)	(1.737)	(1.656)
Two or three weeks	0.778	-2.588	0.144	2.363	2.789	0.091	1.783	1.486
× Moderator	(1.789)	(1.687)	(1.824)	(1.725)	(1.779)	(1.664)	(1.856)	(1.713)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
Return Week FE	✓	✓	✓	✓	✓	✓	✓	✓
N	3312	3312	3012	3168	3312	3312	3312	3312

Note: The dependent variable is the subjective probability of being sick enough to be hospitalized or needing treatment in the ICU conditional on getting infected. The table reports estimated coefficients (and associated standard errors) from Equation 2 plus return-week fixed effects. Column headers correspond to the particular (binary) moderator variable being tested.

C.2 Distorted Beliefs and Worries

In the initial wave of our survey, we included questions about respondents' level of worry regarding the health and economic well-being of various individuals, including themselves, their partners, children, and extended family members. Respondents rated their level of worry on a scale ranging from "Not at all worried" (1) to "Extremely worried" (5) with an option to indicate N/A if the participant did not have the person mentioned in their lives. Since these questions were only asked in the initial wave of the survey, we have 583 responses and only cross-sectional variation in the return horizon.

We explore the correlation between worries and risk perceptions.[46] We find positive and significant correlations between worries and beliefs about one's infection risk and disease severity (see Table C.5). As expected, the correlation of infection and disease severity risk perceptions with health worries is stronger than their correlation with economic well-being worries. Overall, these results indicate that individuals with more optimistic risk perceptions also tend to experience lower levels of worry. If we interpret the degree of worry as an indicator of anxiety, these findings suggest that individuals with more optimistic risk perceptions also tend to experience lower levels of anxiety. It is also worth noting that reported worries do not respond to differences in return horizons across individuals. We estimate specification 1 with worries as the dependent variable and find that individuals who are on the verge of returning to work do not exhibit significantly different levels of health worries compared to those who have a month or more before their return (see Figure C.1). This evidence can be seen as supportive of the notion that by distorting their perceptions of infection risk associated with both remaining at home and returning to work, individuals were able to maintain a similar level of anxiety about their health throughout. However, for reasons discussed in Section 4 of the main text, these results do not provide causal evidence of the impact of motivated beliefs on anxiety regulation.

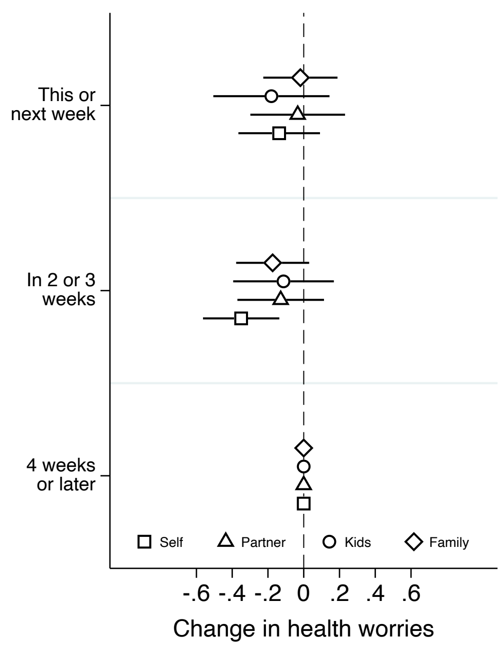
[46] We thank an anonymous reviewer for this suggestion.

Table C.5: Correlation between Worries and Subjective Risk Beliefs

	Work Beliefs ($\hat{p}_w$)	Home Beliefs ($\hat{p}_h$)	Belief Differental (Δ)	Chance of severe symptoms
Worry about health				
Self	0.319	0.304	0.426	0.079
	(0.000)	(0.000)	(0.000)	(0.057)
Partner	0.320	0.297	0.284	0.082
	(0.000)	(0.000)	(0.000)	(0.080)
Kids	0.367	0.320	0.268	0.126
	(0.000)	(0.000)	(0.000)	(0.016)
Family	0.361	0.316	0.288	0.107
	(0.000)	(0.000)	(0.000)	(0.011)
Worry about economic conditions				
Self	0.193	0.146	0.174	0.077
	(0.000)	(0.000)	(0.000)	(0.063)
Partner	0.192	0.199	0.184	0.033
	(0.000)	(0.000)	(0.000)	(0.481)
Kids	0.251	0.162	0.227	0.130
	(0.000)	(0.002)	(0.000)	(0.015)
Family	0.268	0.268	0.222	0.054
	(0.000)	(0.000)	(0.000)	(0.201)

Note: This table presents the correlation between worry levels and subjective risk perceptions (p-values are in parentheses).

Figure C.1: Differences in the degree of health worries across return-to-work horizons



Notes: This figure provides the coefficient values and 95% confidence intervals for the effect of time horizon on the degree of health and economic well-being worries (scale range 1 to 5), estimating equation 1 in the main text with each set of worries (self, partner, kids, family) as the dependent variable.

C.3 Distorted Beliefs and Actions

Preventive actions. In waves 2 to 4, we asked respondents about the preventive actions they plan to take upon returning to work. In particular, we asked about wearing masks when working indoors/outdoors, wearing gloves when touching common surfaces, washing and sanitizing hands frequently, and disinfecting the own work surface once a day. Each preventive action was measured on a five-point scale from 1 = "Definitively not" to 5 = "Definitively yes." We chose these preventive actions because they were commonly discussed in the popular press as potentially effective measures, and they represent the precautions that people were engaging in.

We estimate our main specification (with the full set of controls) with preventive actions as the dependent variable. Table C.6 presents the results. The even columns display the results after adding reopening-week fixed effects. Column 1 shows that respondents who return within a week or within two to three weeks have 0.3 points higher expectations to wear a mask when working indoors compared to those who return later ($p < 0.001$). Similarly, as shown in column 3, respondents who return sooner are more likely to think they will wear a mask when working outdoors ($p = 0.034$). We also observe some differences in the willingness to wear gloves at work. For example, column 5 shows that compared to those who return in four or more weeks, respondents who return immediately expect to be 0.1 points more likely to wear gloves upon returning to work ($p = 0.032$). However, we do not find any significant differences regarding the intention to regularly wash hands (or use hand sanitizer) or routinely cleaning high-touch work surfaces (all p-values > 0.050). We also obtain similar results using a specification that binarizes the dependent variable (=1 if probably or definitely yes, =0 otherwise). Overall, although there is some evidence that individuals who go back to work sooner plan to take more preventive actions, the differences are relatively small in magnitude considering that the answer scale goes from 1 to 5. It is important to note that unlike the belief elicitation, the survey did not fix the time frame for the questions about preventive actions. This could introduce a confound as respondents may have had different time horizons in mind when answering those questions. For example, people might have expected COVID-19 risks to be lower in the summer. Therefore, individuals returning to work in the summer, which corresponds to the time period "4 weeks or later" in our study, might rationally expect to need fewer precautions. Consequently, the results should be treated with caution.

Risky behaviors. In waves 2 to 4, we asked respondents whether they had undertaken (or were planning to do) activities in the past (next) week that carry a certain level of infection risk. We then identified activities that were considered as relatively risky during the early stages of the pandemic (Benzell et al., 2020). These activities include: eating at a restaurant (sit-down), visiting a coffee shop, visiting a bar/pub, going to the grocery store, shopping for non-food items, going to the gym, meeting up with a friend, meeting up with an extended family member, and being part of a gathering with more than 10 people (e.g., church, school, demonstrations, meetings, etc.). On average, respondents indicated that they had engaged (or were planning to engage) in about two risky activities in the week before (after) the survey. In Table C.7, we report the results from

Table C.6: Preventative Actions

	Mask indoors		Mask outdoors		Wear gloves		Sanitize surfaces		Wash hands	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Main Effects										
This or next week	0.310	0.325	0.135	0.256	0.138	0.173	-0.039	-0.025	-0.036	-0.031
	(0.060)	(0.086)	(0.064)	(0.088)	(0.064)	(0.091)	(0.039)	(0.055)	(0.027)	(0.033)
Two or three weeks	0.280	0.249	0.212	0.201	0.104	0.048	0.027	0.016	0.003	-0.004
	(0.058)	(0.064)	(0.061)	(0.067)	(0.064)	(0.070)	(0.036)	(0.040)	(0.022)	(0.025)
Controls										
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Work Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Return Week FE	-	✓	-	✓	-	✓	-	✓	-	✓
N	2725	2725	2725	2725	2725	2725	2725	2725	2725	2725

Note: The table reports estimated coefficients (and associated standard errors) from Equation 1 in odd columns, and the specification with return-week fixed effects in even columns. The dependent variable in each column pair is a different binary action-intent, as indicated by the headers and detailed in Appendix C.3.

Table C.7: Risky behaviors, insurance, information avoidance

	Risky activities in past week		Risky activties next week		Willingness to pay for insurance		Info Acquisition: Covid19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Effects								
This or next week	0.112	0.050	0.056	-0.097	-0.231	-0.310	-0.000	0.017
	(0.086)	(0.117)	(0.095)	(0.130)	(0.284)	(0.390)	(0.023)	(0.033)
Two or three weeks	0.027	0.016	0.158	0.116	-0.253	-0.298	0.027	0.036
	(0.085)	(0.092)	(0.097)	(0.109)	(0.283)	(0.313)	(0.023)	(0.025)
Controls								
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
Geographic Risk Factors	✓	✓	✓	✓	✓	✓	✓	✓
County Interventions	✓	✓	✓	✓	✓	✓	✓	✓
Return Week FE	-	✓	-	✓	-	✓	-	✓
N	1580	1580	1580	1580	1580	1580	2725	2725

Note: The table reports estimated coefficients (and associated standard errors) from Equation 1 in odd columns, and the specification with return-week fixed effects in even columns. The dependent variable in each column pair is indicated by the header and detailed in Appendix C.3.

estimating our main specification (with the full set of controls), where the dependent variable is the number of risky activities. Column 1 examines activities in the past week, and column 3 focuses on activities in the week following the survey. The even columns display the corresponding results with reopening-week fixed effects. Overall, we do not find any significant differences in past or planned engagement in risky activities across respondents who are going back to work sooner vs. later (all p-values > 0.050).

Health insurance. In waves 2 to 4, they survey also featured a hypothetical choice scenario where respondents were asked to indicate their "willingness to pay" for health insurance that would cover part of the out-of-pocket expenses in case they were hospitalized for COVID-19. We used a multiple price list to elicit respondents' valuation of such health insurance. Respondents were told to imagine that the insurance costs \$10 and were then asked to state whether they would be willing to take up the insurance if it pays an amount X $\in \{\$50, \$75, \ldots, \$300\}$ for hospitalization services. Participants had to indicate for each amount whether they would be willing to pay \$10 for the insurance. The payment amounts were listed in ascending order. Thus, we use the switching point from not taking the insurance to opting in as a measure of respondents' willingness to take up the insurance (with larger values indicating a lower willingness to get the insurance). The median response is to pay \$10 in order to get \$200 back if hospitalized. We estimate our main specification (with the full set of controls) using the switching point as the dependent variable. The results are shown in column 5 of Table C.7. Column 6 additionally includes reopening-week fixed effects. We do not find any meaningful differences in the willingness to pay for a fictive health insurance across respondents with shorter and longer time horizons to work return ($p = 0.416$ and 0.372).

Information avoidance. An often-discussed consequence of belief-based utility is that people avoid information that would make them feel bad, even it it means making sub-optimal choices (e.g., Golman et al., 2017). In waves 2 to 4, we included a measure of information avoidance presented as a choice between reading a short summary of a research article about the potential long-term health effects of COVID-19 or about sleep deprivation. We estimate our main specification (with the full set of controls) using a dummy variable for whether respondents chose to read the COVID-19 related article as the dependent variable. The results are shown in column 7 of Table C.7. Column 8 additionally includes reopening-week fixed effects. A majority of respondents (61%) actually preferred to read about the potential long-term health consequences of COVID-19. We also do not find that respondents who are temporally closer to returning to work were more likely to refuse reading the COVID-19 related article ($p = 0.991$ and 0.234).

D The survey instrument

Consent Form

You are invited to participate in a research study about COVID-19. This is a 10 minute long survey that will ask about your perceptions, expectations and feelings about the disease, its effects on you and on our nation. If you agree to be part of the research study, you will be asked to provide your opinions on policies, risks, and will be asked to answer questions related to your current situation. Please pay attention to all questions. We will include several attention checks.

Benefits of the research to the public stem from your participation and honest answers. Using this survey data, we hope to be able to provide guidelines for assessing and responding to differences across communities. Risks and discomforts: Thinking about COVID-19 and its impact may induce negative emotions, like anxiety or fear. These risks and discomforts are minimal for most people.

Participating in this study is completely voluntary. Even if you decide to participate now, you may change your mind and stop at any time. You may choose not to continue with the survey at any time and for any reason.

There is no deception or false information in this survey.

We will protect the confidentiality of your research records by not publishing any information that may identify you. Information collected in this project may be shared with other researchers, and may be connected to other aggregate datasets at the county level. We will not share any information that could identify you. All results will be reported in aggregate.

Principal Investigator: Yesim Orhun, Associate Professor, University of Michigan. If you have questions about this research study, please contact Prof. Yesim Orhun by emailing aorhun@umich.edu. The University of Michigan Institutional Review Board Health Sciences and Behavioral Sciences has determined that this study is exempt from IRB oversight (HUM00181725).

By clicking to proceed, you are confirming that you read this page and are providing consent to participate.

The survey began with participants electronically accepting participation after reading the consent form. The survey proceeded with the following questions:

Risk Tolerance

Thinking about yourself, in general, how willing or unwilling are you to take risks? Please use the scale below, ranging from 0 to 10, where 0 means "completely unwilling to take risks" and a 10 means you are "very willing to take risks." You can also use any number between 0 and 10 to indicate where you fall on the scale. [Scale: 0 to 10, choose one.]

– Page Break –

Employment and Economic Impact

- What's your current employment status? [Choose one: Employed full time; Employed part time; Furloughed; Unemployed (before the coronavirus); Unemployed (after the coronavirus); Retired; Student; Prefer not to answer.]

- Please think of everyone in your household who was earning an income before the coronavirus crisis. What was the economic impact of the coronavirus situation on the income of your household? [Choose one: Greatly negative; Very negative; Somewhat negative; No change; Somewhat positive; Very positive; Greatly positive.]

– Page Break –

Personal Experience with COVID-19

Have you been infected with the coronavirus? [Choose one: Yes, I tested positive; No, I tested negative; Probably yes, but I did not get tested; Probably not, but I did not get tested.]

Attention check, Screening

Please think of everyone in your community who has been affected by the coronavirus crisis. It is important that you pay attention to this survey. Please check greatly positive below. [Choose one: Greatly negative; Very negative; Somewhat negative; No change; Somewhat positive; Very positive; Greatly positive.]

– Page Break –

Occupation and State Restrictions on Work

- What type of work do you do? Please mention your industry and your role or position. [Fill in.]
- In your state, is the industry you work in being allowed to return to work? [Choose one: Definitely yes, already allowed; Definitely yes, next week; Definitely yes, within 2 weeks; Definitely yes, within 3 weeks; Definitely yes, in 4 weeks or more; Maybe soon, unclear; Definitely not yet.]
- When do you think you will return to working outside the home? If you are not sure, give us your best guess at this time [Choose one: By this weekend; This coming week (last week of May); First week of June; Second week of June; Third week of June; Fourth week of June; First week of July; Second week of July; Second half of July; Some time in August; Some time in September; October or later.][47]

– Page Break –

[47] The options were updated in each wave based on the survey time

Worries[48]

How worried are you feeling for the health of the following people? (If you don't have the people mentioned in some statements (partner, kids, extended family), please click "Not Applicable") Items: My own health, My partner's health, My kids' health, My extended family's health. [Not at all worried (1), Slightly worried (2) Moderately worried (3), Very worried (4), Extremely worried (5).]

Q4.2 How worried are you feeling for the economic well being of the following people? (If you don't have the people mentioned in some statements (partner, kids, extended family), please click "Not Applicable") Items: My own economic well being, My partner's economic well being, My kids' economic well being, My extended family's economic well being. [Not at all worried (1), Slightly worried (2) Moderately worried (3), Very worried (4), Extremely worried (5).]

– Page Break –

Beliefs About Infection Risk

- As of May 15, 2020, CDC (Centers for Disease Control and Prevention) is reporting 1,412,121 confirmed coronavirus cases and 85,990 deaths in the U.S. Many cases go undetected.[49] Of course, infection rates depend on the community and the protection measures each person takes.

  What are the chances that you will get infected with the coronavirus in the next three months if your current living/working conditions did not change? [Choose one: 0% chance; 1-10% chance; 11-20% chance; 21-30% chance; 31-40% chance; 41-50% chance; 51-60% chance; 61-70% chance; 71-80% chance; 81-90% chance; 91-100% chance.]

The next question was displayed to those respondents who indicated that they are currently not working outside their home.

- What would your infection chance be if you went back to working outside the home next week? [Choose one: 0% chance; 1-10% chance; 11-20% chance; 21-30% chance; 31-40% chance; 41-50% chance; 51-60% chance; 61-70% chance; 71-80% chance; 81-90% chance; 91-100% chance.]

– Page Break –

[48] These questions were only part of the survey administered in the first wave.

[49] The date and these two numbers were updated to the applicable information of two days prior to the survey time

Beliefs About Health Outcomes Conditional on Being Infected

According to the CDC (Centers for Disease Control and Prevention) report, about 7% of people diagnosed with the coronavirus are hospitalized, but do not need intensive care. About 1.5% of people are hospitalized and need intensive care. It is also suspected that a large percentage of people are symptom free and/or have mild versions of the disease.

Most importantly, the chances are person-specific. The progression of the disease can be very different based on your age, health, pre-existing condition, living conditions, how much of the virus you are exposed to, etc. Although it's hard to know without data, you probably have a better understanding of your situation than anyone else. Therefore, we ask you to predict how the coronavirus is likely to affect you, should you get infected:

Please make sure numbers add up to 100. Allocate points according to how big you think your chances are for each possibility. [Chances that I will be symptom free are: (fill in, numerical); Chances that I will have a mild version of the disease are: (fill in, numerical); Chances that I will have a moderate version (without hospitalization) are: (fill in, numerical); Chances that I will have a severe version that requires hospitalization (but no further interventions) are: (fill in, numerical); Chances that I will have a severe version that requires intensive care at the hospital are: (fill in, numerical).]

– Page Break –

Pre-existing health conditions.

The CDC (Centers for Disease Control and Prevention) released the list of underlying medical conditions that put people of all ages at higher risk for severe illness resulting from the coronavirus infection. We list them below.

Which of these apply to you? Please click all that apply. [Choose all that apply: Moderate to severe asthma; COPD or other chronic lung disease; Serious heart conditions; Diabetes; Conditions that can cause a person to be immunocompromised, including cancer treatment, smoking, bone marrow or organ transplantation, immune deficiencies, poorly controlled HIV or AIDS, and prolonged use of corticosteroids and other immune weakening medications.; Severe obesity (BMI of 40 or higher); Chronic kidney disease and currently undergoing dialysis; Liver disease; I do not want to answer; None of them apply to me.]

– Page Break –

Beliefs About Systemic Health Risk (Total Number of Deaths in the U.S.)

As of May 15, 2020, CDC (Centers for Disease Control and Prevention) is reporting 85,990 deaths in the U.S.[50] How many people do you think will die from a coronavirus infection in the U.S by July 1, 2020? [Choose one: 75,000 - 90,000; 90,000 - 110,000; 110,000 - 130,000; 130,000 - 150,000; 150,000 - 175,000; 175,000 - 200,000; 200,000 - 225,000; 225,000-250,000; 250,000-275,000; 275,000-300,000; 300,000-350,000; more than 350,000.][51]

Beliefs About Economic Outcomes

- The U.S. gross domestic product (GDP) grew about 2.3% in 2019. How much GDP growth do you expect in 2020? [Choose one: more than 10% growth; 5%-10% growth; 2.5%-5% growth; 0%-2.5% growth; 0% to -2.5% growth (negative growth means contraction); -2.5% to -5% growth (negative growth means contraction); -5% to -10% growth (negative growth means contraction); -10% to -20% growth (negative growth means contraction); -20% to -30% growth (negative growth means contraction); worse than-30% growth (negative growth means contraction).]
- In the last quarter of 2019, unemployment rate in the U.S. was 3.6%. How much unemployment do you expect in the U.S. by July 1, 2020? [Choose one: less than 3%; 3-5%; 5-10%; 10-15%; 15-20%; 20-25%; 25-30%; 30-35%; 35-40%; more than 40%.][52]

– Page Break –

Preventive Actions at Work[53]

When you return to work, will you want to take the following precautions personally (regardless of whether it is required or not)? [Precautions: Wear a mask when working indoors; Wear a mask when working outdoors; Wear gloves when touching common surfaces (door knobs, bathroom, kitchen, cabinets, etc.); Wash/sanitize hands frequently; Sanitize own working surface every day.] [Choose one: Definitely not; Probably not; Might or might not; Probably yes; Definitely yes.]

– Page Break –

[50] The date and the number of deaths were updated to the applicable information of two days prior to the survey time.

[51] The options were updated at the lower end to reflect the increasing number of deaths between the different survey times

[52] The options, 30-35%; 35-40%; more than 40%, were added in wave 2, replacing the option more than 30%

[53] These questions were only part of the survey administered in and after the second wave.

Activities outside of Work[54]

- Please indicate the activities you engaged in during the last 7 days. Please click all that apply. [Choose all that apply: Ate at a restaurant (outside seating); Ate at a restaurant (inside seating); Went into a coffee shop; Went into a bar/pub; Ordered food-to-go (curbside pick up); Ordered food delivery to my door; Went grocery shopping; Ordered grocery delivery to my door; Met up with a friend; Met up with an extended family member; Went shopping for non-food items (at the mall, hardware store, etc.); Went to a gym or other sports facility; Was part of a gathering with more than 10 people (church, school, demonstrations, meetings, etc.); None of the above.]

– Page Break –

- Please indicate the activities you plan to engage in the next 7 days. Please click all that apply. [Choose all that apply: Ate at a restaurant (outside seating); Ate at a restaurant (inside seating); Went into a coffee shop; Went into a bar/pub; Ordered food-to-go (curbside pick up); Ordered food delivery to my door; Went grocery shopping; Ordered grocery delivery to my door; Met up with a friend; Met up with an extended family member; Went shopping for non-food items (at the mall, hardware store, etc.); Went to a gym or other sports facility; Was part of a gathering with more than 10 people (church, school, demonstrations, meetings, etc.); None of the above.]

– Page Break –

Willingness to pay for Insurance[55]

Even if you are insured, you may have to pay out of pocket costs if you are hospitalized. Would you be willing to pay $10 now to receive the following amounts of cash in the case you had to be hospitalized due to COVID-19? [Insurance payouts: pay $10 now, receive $50 if hospitalized; pay $10 now, receive $75 if hospitalized; pay $10 now, receive $100 if hospitalized; pay $10 now, receive $125 if hospitalized; pay $10 now, receive $150 if hospitalized; pay $10 now, receive $175 if hospitalized; pay $10 now, receive $200 if hospitalized; pay $10 now, receive $225 if hospitalized; pay $10 now, receive $250 if hospitalized; pay $10 now, receive $275 if hospitalized; pay $10 now, receive $300 if hospitalized.][Choose one: Yes; No]

– Page Break –

[54] These questions were only part of the survey administered in and after the third wave.
[55] These questions were only part of the survey administered in and after the third wave.

Information Acquisition: Choice[56]

Even conditions that occur for a short time can have important long-term impacts. For example, research has shown that sleep deprivation can have serious long-term effects on health, effects that can reduce people's quality of life even after they have sufficient sleep. Similarly, doctors have begun to find that having a COVID-19 infection can also cause serious long-term health effects. These effects may reduce people's quality of life for many years after they have recovered from the virus.

We have collected recent research articles about the potential long-term negative effects of sleep deprivation and COVID-19. At the end of the survey, we will ask you to read a summary on the long-term effects of either sleep deprivation or COVID-19. Regardless of the option you choose, the number of sentences on the next page will be equal. Also, in both cases, you will be asked a question to check that you read the text.

Which of the two would you like to read at the end of the survey? [Choose one: Findings on the long-term health effects of having COVID-19; Findings on the long-term health effects of sleep deprivation.]

– *Page Break* –

Exposure at Work

The questions on this page refer to a typical day in your workplace before the pandemic.

- Which of the following spaces best describes where you work? Click all that apply. [Choose all that apply: Outdoor; Indoor, in an office space; Indoor, other.]
- At your workplace, how many other employees do you come into contact with on a typical day? (e.g., physical contact, sharing the same space) [Choose one: I work alone; 1-2; 3-5; 6-10; more than 10.]
- At your workplace, how many customers/patrons/patients do you come into contact with on a typical day? [Choose one: I do not interact with any patrons at my work; 1-2; 3-5; 6-10; more than 10.]

– *Page Break* –

[56] These questions were only part of the survey administered in and after the second wave.

Return to Work

The next question embedded the response from a previous question.

- You indicated that you expect to return to work: [the week or month by which the respondent indicated they expected to return to work]. If you had it your way, when would you like to return to work? [Choose one: I would have liked to be already back by now; This coming week (last week of May); First week of June; Second week of June; Third week of June; Fourth week of June; Some time in July; Some time in August; Some time in September; October or later.]

The next two questions were displayed to those respondents who indicated that their state had allowed work in-person for the industry they worked in prior to the survey time.[57]

- You stated that your industry is allowed to go back to work already, but that you are not working at your workplace yet. Which describes the most accurate reason? [Choose one: My employer did not call back any employees to the workplace; My employer called back other employees, but not me (yet).]
- Why? [Choose one: Business is too slow; The workplace cannot be effectively prepared for limiting the risk of exposure to COVID-19; My employer is worried about COVID-19 risks, even though the workplace can be effectively prepared to limit exposure; Other (fill in).]
- Overall, how effective do you expect your workplace to be in reducing workers' risk of exposure to the coronavirus? [Choose one: Extremely effective; Very effective; Moderately effective; Slightly effective; Not effective at all.]

– Page Break –

- Think about how well your work environment will be able to implement the following infection prevention measures when you return to work. Please rate your workplace's probable precautions based on your best guess at this time. [Precautions: Limiting number of customers/other patrons (outside of workers); Modifications to allow for social distancing among employees; Providing masks; Providing gloves; Providing supplies that promote hygiene (soap, disposable wipes, hand sanitizers, disinfectants, etc.); Providing and enforcing guidelines regarding social distancing and hygiene; Modifications to limit sharing of physical resources among employees; Routine cleaning and disinfection of surfaces, equipment, etc.; Prompt isolation of sick workers.] [Choose one: Extremely good; Moderately good; Slightly good; Neither good nor bad; Slightly bad; Moderately bad; Extremely bad.]

[57] They were not part of the survey administered in the first wave.

– Page Break –

- Each industry is different in how they are mandated by the state to return to work. Please choose the one that applies in the case of your workplace. [Choose one: Only curbside pickup/delivery/takeout, no in-store customers; State mandated capacity restrictions within the workplace (number of employees and/or customers); No restrictions, but operating with social distancing guidelines and other hygienic precautions; Business as usual.]

– Page Break –

News sources

- Which news sources do you usually rely on? [Choose all that apply: ABC News; CNN; Fox News Channel; Local news; NBC/MSNBC; NPR (Public Radio); Huff Post; The New York Times; The Wall Street Journal; Washington Post; Other: (fill in); I don't follow any news.]
- What other sources of information do you mostly pay attention to? [Other sources: My friends; My family members; My pastor and/or our spiritual community; The President and his administration; Our Governor; Scientists/researchers; CDC (Center for Disease Control); People I follow on Twitter; People I follow on Facebook.] [Choose one: Not at all; A little bit; Somewhat; Mostly; Very much so; Not applicable.]

– Page Break –

Attention check, screening

What question was asked on the page immediately before this one? [Choose one: Which news sources do you usually rely on?; How many confirmed coronavirus deaths are there in the US?; Has your state introduced any social distancing measures?; Which of the following changes have you made to protect yourself from the coronavirus infection?]

– Page Break –

Information Acquisition: Text and Attention check

The following text and question was displayed to those respondents who indicated a preference for reading about the long-term health effects of COVID-19

> When asked, you indicated a preference for reading about the long term health effects of COVID-19.
>
> In one study, 66 of 70 hospitalized patients had some amount of lung damage in CT scans, and more than half had the kind of lesions that are likely to develop into scars. Doctors in Los Angeles found that chronic cardiac complications (i.e. heart issues) could arise in COVID-19 patients even after recovery as a result of persistent inflammation. This can include an increased risk of blood clots and thus strokes and heart attacks. Another study found that over a third of COVID-19 patients had neurological issues, although there isn't enough data yet to determine the long-term consequences of these issues.
>
> Click to proceed to the next page when you are done reading.
>
> Sources:
>
> 1. https://www.bloomberg.com/news/articles/2020-05-12/covid-19-s-health-effects-can-last-long-after-virus-is-gone
> 2. https://www.healthline.com/health-news/what-we-know-about-the-long-term-effects-of-covid-19#COVID-19-might-affect-the-brain-stem
> 3. https://www.vox.com/2020/5/8/21251899/coronavirus-long-term-effects-symptoms

– Page Break –

- Which of the following issues was NOT addressed in the text you just read? [Choose one: Neurological issues; Heart issues; Dementia; Lung damage.]

The following text and question was displayed to those respondents who indicated a preference for reading about the long-term health effects of sleep deprivation

> When asked, you indicated a preference for reading about the long term health effects of sleep deprivation.
>
> Researchers have found that insufficient sleep may lead to type 2 diabetes. Sleep deprivation can lead to higher chance of cardiac problems such as stroke and heart attacks. Not sleeping enough can lead to an increase of 33% in risk of dementia.
>
> Click to proceed to the next page when you are done reading.
>
> Sources:

1. http://healthysleep.med.harvard.edu/healthy/matters/consequences/sleep-and-disease-risk
2. https://www.hopkinsmedicine.org/health/wellness-and-prevention/the-effects-of-sleep-deprivation
3. https://www.webmd.com/sleep-disorders/features/10-results-sleep-loss#1

– Page Break –

- Which of the following issues was NOT addressed in the text you just read? [Choose one: Diabetes; Heart issues; Dementia; Lung damage.]

The study ended with inviting comments, if respondents had any, about the survey.

E Proofs of Propositions

Proof of Propositions 1 and 2: Proposition 2 immediately implies Proposition 1. Thus, we prove Proposition 2. To do so, we focus on the case of $t = 0$, i.e., how beliefs are distorted in the current period (since this is what we measure). The payoff for determining current period beliefs can be written as:

$$\overbrace{\alpha\left[\frac{1}{1-\delta(1-\hat{p}_{h,0})} - \frac{\delta^T(1-\hat{p}_{h,0})^T}{1-\delta(1-\hat{p}_{h,0})} + \frac{\delta^T(1-\hat{p}_{h,0})^T}{1-\delta(1-\hat{p}_{w,0})}\right]}^{\text{Anticipatory utility}} \underbrace{-c_h(p_h,\hat{p}_{h,0}) - c_w(p_w,\hat{p}_{w,0})}_{\text{Cost of adjusting beliefs}}$$
$$+\overbrace{\left[\frac{1}{1-\delta(1-p_h)} - \frac{\delta^T(1-p_h)^T}{1-\delta(1-p_h)} + \frac{\delta^T(1-p_h)^T}{1-\delta(1-p_w)}\right]}^{\text{Realized utility}}$$

Because we focus on $t = 0$ beliefs, we drop the subscript in beliefs indicating the time period. Thus, the payoff function for $T = 0$ (i.e., NOW) is:

$$\alpha\left[\frac{1}{1-\delta(1-\hat{p}_w)}\right] + \left[\frac{1}{1-\delta(1-p_w)}\right] - c(p_h,\hat{p}_h) - c(p_w,\hat{p}_w)$$

The second order conditions are not necessarily globally negative, so we cannot simply analyze the first order conditions. Instead, our analysis will focus on deriving comparative statics in a way that does not rely on first-order conditions. Because there is no benefit to distorting beliefs about the risk at home if $T = 0$, $\hat{p}_{h,NOW} = p_h$. In contrast, $\hat{p}_{w,NOW} \leq p_w$.

As T gets large (for LATER), utility converges to:

$$\alpha[\frac{1}{1-\delta(1-\hat{p}_h)}] + [\frac{1}{1-\delta(1-p_h)}] - c(p_h, \hat{p}_h) - c(p_w, \hat{p}_w)$$

Thus, we have the opposite situation from before $\hat{p}_{w,LATER} = p_w$ and $\hat{p}_{h,LATER} \leq p_h$. □

Proof of Proposition 3: We will show that $\hat{p}_{w,NOW} \leq \hat{p}_{w,LATE} \leq \hat{p}_{w,LATER}$. The case that $\hat{p}_{h,NOW} \geq \hat{p}_{h,LATE} \geq \hat{p}_{h,LATER}$ follows analogously. By construction $\hat{p}_{w,LATE} \leq \hat{p}_{w,LATER}$. Thus, we just need to ensure that $\hat{p}_{w,NOW} \leq \hat{p}_{w,LATE}$. Consider the portion of the utility payoff that depends only on the selection of $\hat{p}_w$:

$$\alpha\frac{\delta^T(1-\hat{p}_h)^T}{1-\delta(1-\hat{p}_w)} - c_w(p_w, \hat{p}_w)$$

Observe that the first term represents the benefit of distortion, and the second the cost. Suppose $\hat{p}^*_{w,NOW}$ is optimal at $T = 0$. Then $\alpha\frac{1}{1-\delta(1-\hat{p}^*_{w,NOW})} - c_w(p_w, \hat{p}_w) \geq \alpha\frac{1}{1-\delta(1-\hat{p}_w)} - c_w(p_w, \hat{p}_w)$ for all $\hat{p}_w \in [0, 1]$.

Now consider what happens to payoffs when we move to $T > 0$. Observe that the benefits at all $\hat{p}_w \in [0, 1]$ fall, since $\delta^T(1-\hat{p}_h)^T < 1$, but that they fall greatest for lower levels of p_w (one can easily confirm this by looking at the cross partial derivative of $\frac{z}{1-\delta(1-\hat{p}_w)}$ with respect to z and $\hat{p}_w$). Moreover, the costs of distortion do not change. Thus, if $\hat{p}_w < \hat{p}^*_{w,NOW}$, then $\hat{p}_w$ cannot be optimal for any $T > 0$. Therefore, $\hat{p}_{w,NOW} \leq \hat{p}_{w,LATE}$. □

Proof of Proposition 4: Notice that answering which of the two beliefs moves more boils down to asking the optimal solution for $\hat{p}_w$ at NOW, i.e., the argmax of:

$$\alpha\frac{1}{1-\delta(1-\hat{p}_w)} - \gamma(|.5-p_w|)k(p_w-\hat{p}_w)^2$$

is larger or smaller than the solution for $\hat{p}_h$ at LATER, i.e., the argmax of:

$$\alpha\frac{1}{1-\delta(1-\hat{p}_h)} - \gamma(|.5-p_h|)k(p_h-\hat{p}_h)^2.$$

Since we assume $p_h < p_w$, another way of answering our question is to see whether the optimum (with respect to $\hat{p}$) of:

$$\alpha\frac{1}{1-\delta(1-\hat{p})} - \gamma(|.5-p|k(p-\hat{p})^2$$

is increasing more than one-for-one or less than one-for-one with p.

First, we note that the first order condition is

$$\gamma(|.5-p|)k(p-\hat{p}) - \alpha\frac{\delta}{(1-\delta(1-\hat{p}))^2} = 0$$

which is a third-order polynomial in $\hat{p}$. Moreover, at $\hat{p} = p$ the first order condition is negative. This immediately implies that there are at most two local maxima for $\hat{p}$ between 0 and p; up to one interior one, and a potential edge case at $\hat{p} = 0$. By assumption we rule out the edge case, so we just need to consider the interior solution which satisfies the first order condition. Thus, we just need to ask how any solution to the equation[58]

$$\gamma(|.5 - p|)k(p - \hat{p}) - \alpha\frac{\delta}{(1 - \delta(1 - \hat{p}))^2} = 0$$

changes with p (with $p < \frac{1}{2}$); and, in particular, if it increases more or less than one for one. Taking the derivative of the FOC with respect to p gives:

$$\gamma(|.5 - p|)k - \gamma'(|.5 - p|)k(p - \hat{p}).$$

Taking the derivative of the FOC with respect to $\hat{p}$ gives:

$$-\gamma(|.5 - p|)k + \alpha\frac{2(1 - \delta(1 - \hat{p}))\delta^2}{(1 - \delta(1 - \hat{p}))^3}.$$

Thus, the change in $\hat{p}$ with respect to p is:

$$\frac{\gamma(|.5 - p|)k - \gamma'(|.5 - p|)k(p - \hat{p})}{\gamma(|.5 - p|)k - \alpha\frac{2(1-\delta(1-\hat{p}))\delta^2}{(1-\delta(1-\hat{p}))^3}}.$$

The first term in the numerator and denominator are the same. Thus, the question becomes whether the second term in the numerator is larger or smaller (in absolute value) than the second term in the denominator. So long as γ' is large enough, the former is larger (in absolute value) than the latter. Therefore, $\hat{p}$ increases less than one for one with p. This means that $p_h - \hat{p}_h$ is smaller than $p_w - \hat{p}_w$ since $p_h < p_w$.□

Proof of Proposition 5: Denote the flow payoff of not being sick for HS people as $H > 1$ so that they face a bigger gap between payoffs. We will prove that $\hat{p}_{w,LATER,HS} = \hat{p}_{w,LATER,LS} > \hat{p}_{w,NOW,LS} > \hat{p}_{w,NOW,HS}$. The analogous results follow for $\hat{p}_h$. The proposition follows since we know that $\hat{p}_{h,LATER,HS} + \hat{p}_{w,NOW,HS} < \hat{p}_{h,LATER,LS} + \hat{p}_{w,NOW,LS}$, which is equivalent to $\Delta_{NOW,HS} - \Delta_{LATER,HS} < \Delta_{NOW,LS} - \Delta_{LATER,LS}$.

The utility for LATER does not depend on $\hat{p}_w$, and the maximization problem is equivalent to:

$$\alpha\frac{H}{1 - \delta(1 - \hat{p}_h)} - c_h(p_h, \hat{p}_h)$$

Thus, $\hat{p}_{w,LATER,HS} = \hat{p}_{w,LATER,LS}$.

[58] Note that although there is only one interior maximum, there may also be an interior minimum (i.e., there may be two local extrema, one a maximum and one a minimum). Our result shows that in both cases the comparative static result holds.

The payoff for NOW is:

$$\alpha \frac{H}{1-\delta(1-\hat{p}_w)} - c_w(p_w, \hat{p}_w)$$

Suppose $\hat{p}^*_{w,NOW,LS}$ is optimal for LS individuals (where the payoff to being healthy is H). Then, $\alpha\frac{1}{1-\delta(1-\hat{p}^*_{w,NOW,LS})} - c_w(p_w, \hat{p}^*_{w,NOW,LS}) \geq \alpha\frac{1}{1-\delta(1-\hat{p}_w)} - c_w(p_w, \hat{p}_w)$ for all $\hat{p}_w \in [0,1]$.

Now consider what happens to payoffs when we move the payoffs to being healthy to $H' > H$ and thus consider HS individuals. Observe that the benefits at all $\hat{p}_w \in [0,1]$ increase, but they increase greatest for lower levels of p_w (one can easily confirm this by looking at the cross partial derivative of $\frac{z}{1-\delta(1-\hat{p}_w)}$ with respect to z and $\hat{p}_w$). Moreover, the costs of distortion do not change. Thus, if $\hat{p}_w > \hat{p}^*_{w,NOW,LS}$, then $\hat{p}_w$ cannot be optimal at $H' > H$. Therefore, $\hat{p}_{w,NOW,HS} \leq \hat{p}_{w,NOW,LS}$. $\square$

F Joint Distortions of Chance and Severity of Illness

In this subsection we extend the model in the body of the paper in order to accommodate beliefs about the anticipated severity of illness, conditional on catching COVID-19. In the model we presented in the body of the paper, conditional on being sick, only a single expected payoff could be realized.[59] In this appendix, we allow for two payoffs based on degrees of the severity of illness, conditional on catching COVID-19. Moreover, we allow for the individual to distort these beliefs, distinct from their distortion of their beliefs about catching COVID-19.

In particular, suppose that conditional on being ill, two states may realize — a severe infection, or a mild infection. Suppose that, conditional on being sick, the mild infection realizes with chance q, and the severe illness with chance $1-q$. We will normalize the present discounted payoff the severe illness to be 0, the present discounted payoff for the mild illness to be m, where $0 < m < 1$, and the flow payoff for staying healthy to be 1. Thus, when moving from time period t to $t+1$, first the agent faces a random draw determining whether they are sick or not. If at work, this happens with chance p_w, if at home, with chance p_h. Then, conditional on illness being realized, with chance q they have a mild case, and with chance $1-q$ they have a severe case. Notably, we assume that the true chance of mild or severe illness does not depend on whether the illness was contracted at h or w.

We will, for simplicity, focus on agents who either return NOW or LATER. As before, we allow individuals to distort their work and home chances of infection to $\hat{p}_w$ and $\hat{p}_h$ at cost c. We similarly allow for distortions of q to $\hat{q}$, at cost $\tilde{c}$ (which has the same assumptions as c). Notice that the cost function of distortion may differ depending on whether the belief is about getting sick or about the severity of the disease.

For the moment, consider individuals who return NOW. In order to simplify our presentation,

[59] One may think of the model in the body of the paper as having multiple degrees of severity, each with a different payoff, but where the probability of severity, conditional on being infected, cannot be distorted. Thus, the expected payoff conditional on being sick is fixed, and this is what we define as the payoff if COVID-19 is caught.

we will suppress the timing subscripts in our notation. In any given period at w, one of three things can happen. With chance $(1-p_w)$ the agent is healthy and receives flow payoff of 1 (and proceeds to the next period). With chance $p_w q$ the agent gets mildly sick and gets a lump sum payoff of m (and no additional payoffs). And with chance $p_w(1-q)$ the agent gets severely sick and receives a lump sum payment of 0 (and no additional payoffs). Recall they discount the future at rate δ (and that they are healthy in the initial period). The agent perceives p_w as $\hat{p}_w$, and q as $\hat{q}$.

The true present discounted value of the problem is thus

$$\frac{1}{1-\delta(1-p_w)} + \frac{\delta p_w q m}{1-\delta(1-p_w)}$$

where the first term captures the expected PDV flow payoffs from staying healthy, and the second captures the expected PDV of getting mildly ill. The expected PDV of being severely ill is 0.

Thus, the utility function for an agent is thus

$$\alpha[\frac{1+\delta\hat{p}_w\hat{q}m}{1-\delta(1-\hat{p}_w)}] + [\frac{1+\delta p_w q m}{1-\delta(1-p_w)}] - c_w(p_w,\hat{p}_w) - c_h(p_h,\hat{p}_h) - \tilde{c}(q,\hat{q})$$

Similarly, for those returning LATER the utility function is

$$\alpha[\frac{1+\delta\hat{p}_h\hat{q}m}{1-\delta(1-\hat{p}_h)}] + [\frac{1+\delta p_h q m}{1-\delta(1-p_h)}] - c_w(p_w,\hat{p}_w) - c_h(p_h,\hat{p}_h) - \tilde{c}(q,\hat{q})$$

As in the body of the paper, we will suppose that A2 holds — which says that there is a higher (true) chance of catching COVID-19 at work compared to being at home.

In order to ensure that our results are not being driven by distinct functional forms of costs for distorting home versus work beliefs, we will impose symmetry:

X1: $c_h = c_w$

Moreover, we will make several assumptions in order to simplify the exposition of our result and the analysis. The first is simply that there is a unique local interior maximum. Although this is not without loss, it is satisfied by many common functional forms, such as quadratic costs like those used in the body of the paper (as in A1).

X2: *There exists a unique local interior maximum.*

The second assumption says that at this interior maximum the optimization problem is strictly concave in the relavant variables. This assumption is for expositional simplicity, as it allows us to the use the implicit function theorem to derive our results. That said, again many common functional forms on costs, such as quadratic costs, are consistent with this assumptions.

X3: *At the interior maximum the utility function is strictly concave in $\hat{p}_w, \hat{q}$ for NOW and $\hat{p}_h, \hat{q}$ for LATER.*

Given these assumptions, we find that individuals will downweight the severity of their illness, conditional on getting sick, more if they have to return to work earlier. The intuition is fairly simple. Given A2, individuals face a higher objective chance of getting sick at work. Under our mild assumptions, X1 and X2, we can show that an increase in the objective risk translates into an increase in the perceived risk. If individuals perceive it is more likely that they will get sick, the marginal benefit of distorting their beliefs about the severity of the illness increases, leading to an increase in the chance of a mild illness.

Proposition 6 *If A2 and X1-X3 hold, and agents subjectively believe there is a non-zero chance of them becoming ill, then* $\hat{q}_{NOW} > \hat{q}_{LATER}$.

Proof of Proposition 6: Given the assumptions we know the solution for agents must be an interior maxima. We will consider an arbitrary agent trying to maximize

$$\alpha\left[\frac{1+\delta\hat{p}\hat{q}m}{1-\delta(1-\hat{p})}\right]+\left[\frac{1+\delta pqm}{1-\delta(1-p)}\right]-c(p_w,\hat{p})-\tilde{c}(q,\hat{q})$$

and show that $\hat{q}$ increases when when p increases. This will prove the result (recall that NOW agents simply set $\hat{p}_h = p_h$, and LATER agents set $\hat{p}_w = p_w$), because we assume that $p_w > p_h$.

First, note that the following first order conditions must equal 0 (the first is the condition for $\hat{p}$ and the second for $\hat{q}$).

$$-\alpha\frac{\delta(1-(1-\delta)m\hat{q})}{(1-\delta(1-\hat{p}))^2}-c_2(p,\hat{p})$$

$$\alpha\frac{\delta m\hat{p}}{1-\delta(1-\hat{p})}-\tilde{c}_2(q,\hat{q})$$

Call the former expression K, and the latter H. Recall that because this is a maximum, it must be the case that the determinate of the Hessian is negative semi-definite. By assumption X2 we can strengthen this to negative definite. Thus, $K_{\hat{p}}H_{\hat{q}} - K_{\hat{q}}H_{\hat{p}} = K_{\hat{p}}H_{\hat{q}} - K_{\hat{q}}^2 > 0$

Using the (3 variable) Implicit Function Theorem, we can compute how $\hat{p}$ changes as an implicit function of p:

$$\hat{p}'(p) = -\frac{K_pH_{\hat{q}} - K_{\hat{q}}H_p}{K_{\hat{p}}H_{\hat{q}} - K_{\hat{q}}H_{\hat{p}}}$$

Notice that $H_p = 0$. Moreover, the denominator of the fraction is positive. Notice that K_p and $H_{\hat{q}}$ have opposite signs (because they are simply the derivative of the marginal cost function with either the true belief or the choice variable). Thus, $\hat{p}'(p) > 0$.

Now we know when p increases, $\hat{p}$ increases. Next we show that this causes $\hat{q}$ to increase. Recall that we know the solution to $\hat{q}$ must solve $\alpha\frac{\delta m\hat{p}}{1-\delta(1-\hat{p})} - \tilde{c}_2(q,\hat{q}) = 0$. p does not appear, but if $\hat{p}$ increases, it must be the case that $\hat{q}$ must increase as well. To see this, observe that $H_{\hat{p}} = \frac{(1-\delta)\delta m}{(1-\delta(1-\hat{p}))^2} > 0$, and the claim immediately follows. □

Just as in the body of the paper we considered heterogeneity across individuals in the degree of distortion of p, we can also think about heterogeneity in the degree of belief distortion of q. In particular, we can ask whether individuals who face more concerns about getting sick are those who distort their beliefs about getting severely (vs. mildly) ill the most.[60] Such an exercise would involve simply replicating the methods developed in the paper, so we will simply summarize the intuitions here.

We want to note that there are now two ways to think about the high risk group. The first is that the payoff to being severely sick is lower.[61] Then, replicating the argument of Proposition 5, we obtain the same result — that the gap between the true probability and the distorted probability is larger for the high-risk group.[62]

Of course, if we think of being severly ill as potentially death, then it is hard to conceive of that payoff as differing across groups. Instead, it might be that the probability of being severely ill, conditional on being sick, is higher for those at high risk. So long as this probability is still less than $\frac{1}{2}$ it is the case that we can replicate the assumptions and arguments used for Proposition 4 (in particular, we now assume that $\tilde{c}$ also obeys the functional form restrictions used in that proposition) and show that high-risk individuals will distort their beliefs about being severely relative to mildly ill more.[63]

[60] Recall that in our empirical work it is precisely those who are in our "high risk" group who drive the results on the distortions in beliefs about the severity of infection.

[61] In an environment with three potential states of the world, and payoffs, we need to be careful in how they change when thinking about this comparative static. In the body of the paper we did a comparative static on changing the payoff conditional on being healthy. With only two states, this is equivalent to changing the payoff conditional on getting infected. But changing the payoff conditional on being healthy does not directly change the marginal benefit of belief distortion conditional on becoming ill, and so this would not generate the result we seek here. If, instead, we change the payoff of being mildly sick by making it higher for the high risk group, so that, conditional on being sick, they face a larger payoff gap between severe and mild infection, then there are two countervailing effects. One is that individuals want to distort their belief more, conditional on being sick. The other is that they want to distort their beliefs less about the chance of being sick (which goes against our findings). In contrast, if we reduce the lowest payoff, then we get that the high-risk individuals both want to distort their beliefs more about getting sick, and conditional on getting sick, in accordance with the empirical findings.

[62] At the same time, under mild restrictions the high-risk group will still have a lower expected payoff conditional on getting sick, and so we would also still expect them to distort their beliefs more about the probability of getting sick.

[63] Note that under mild restrictions it will still be the case that the high-risk group will have a lower expected payoff, conditional on getting sick, and so Proposition 5 will still hold.