# Vaccine Progress, Stock Prices, and the Value of Ending the Pandemic*

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**Abstract**

We estimate the value of ending the COVID-19 pandemic using the joint behavior of stock prices and a vaccine progress index during 2020. In an equilibrium model of repeated pandemics, the market response to vaccine news serves to identify the expected loss of wealth from the pandemic, which determines the welfare gain attributable to returning to non-pandemic life. In our calibrated model, ending the pandemic would have been worth 5-15% of total wealth. This value rises with greater exposure externality in labor choice. With uncertainty about pandemic parameters, resolving the uncertainty can be as valuable as resolving the pandemic itself.

**JEL Codes**: G12, D5, I1, Q54
**Keywords** : vaccine development, COVID-19, welfare cost, asset pricing, parameter uncertainty

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# 1 Introduction

Quantifying the economic consequences of pandemics is a crucial step in assessing policy responses along social, medical, fiscal, and monetary dimensions. This paper builds on the hypothesis that stock markets contained salient information for gauging the value of resolving or mitigating the COVID-19 pandemic during 2020. Specifically, the market's reaction to news about progress in development of vaccines impounded information about the value of shortening the anticipated duration of the pandemic. In the context of an economic model, the private value reflected in the stock market can be related to social welfare more broadly. The gain in social welfare attributable to a given shortening in the expected duration can, within the model, be expressed in units of wealth. The same calculation can give us the social value of immediately ending the pandemic (i.e., shortening its duration to zero), which is one way of summarizing the *ex-ante* expected cost of the episode. Effectively, we estimate the willingness-to-pay of a representative agent for a return to non-pandemic life. Empirically, the key inputs are measures of the expected duration of the pandemic, and of the market reaction to changes in that expectation. In the calibrated model, ending the pandemic would have been worth 5-15% of total wealth, as the expected duration evolved over the sample period.

Our exercise can be viewed as complementary to the standard approach in health economics of computing the cost/benefits of interventions (including vaccines) via combining their forecasted effects on infections and deaths with some estimates of (or assumptions about) the monetary value of these outcomes. Our approach does not require us to either model the global epidemiology of the pandemic or to take a stand on the monetary value of a life. Instead, we need to model the vaccine development process and the evolution of the underlying economy in pandemic and non-pandemic states. In calibrating the model using stock market reactions to vaccine news, a maintained hypothesis is that the effect of COVID-19 on the rate of growth of all wealth – encompassing human and social dimensions – is the same as its effect on the rate of growth of private capital, as reflected in stock prices.

The welfare calculation we undertake is directly analogous to the seminal work of Lucas (1987) in assessing the costs associated with business cycle risk. Just as that paper provides a framework for assessing the consequences of policy responses to mitigate con-

sumption volatility, our work speaks to the cost-benefit analysis in alleviating the threat of current and future pandemics. Uniquely to the literature studying the welfare cost of disasters, we exploit novel information within the crisis itself to identify the key quantities in the model. Going beyond our baseline estimate for the welfare gain, our work can also shed light on how extensions to the economy affect that gain. The value of mitigating the pandemic risk rises with greater exposure externality in labor choice. With uncertainty about the stochastic parameters governing pandemic frequency and duration, resolving the uncertainty can be as valuable as resolving the pandemic itself.

The paper's analysis proceeds as follows.

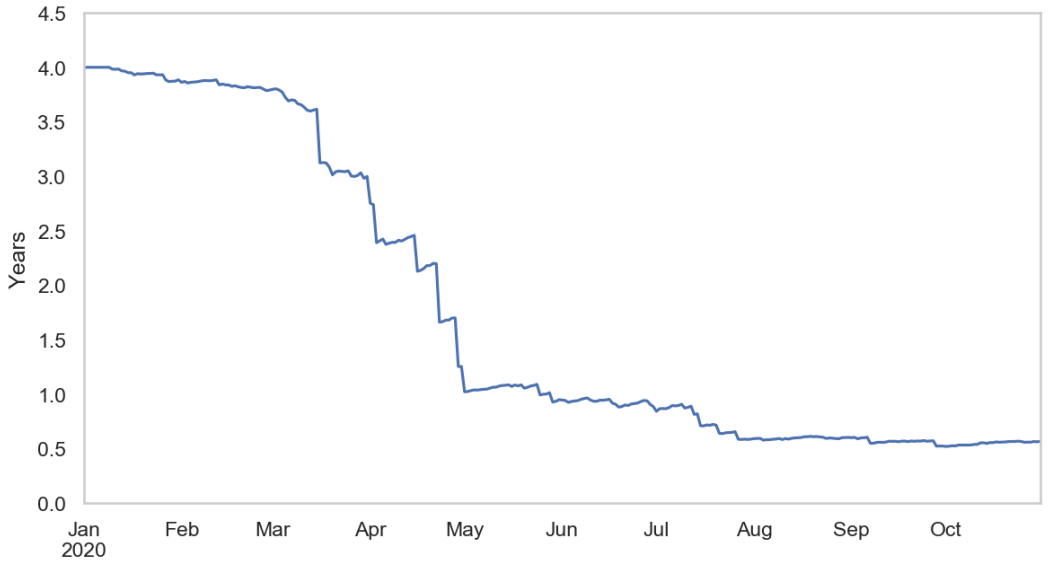
The first step is to construct a time-series within 2020 of forecasts for the expected time to the widespread deployment of a successful vaccine. Our vaccine progress indicator (VPI) is based on the chronology of stage-by-stage progress of individual vaccine candidates (obtained from the Vaccine Centre at the London School of Hygiene & Tropical Medicine) and related news (obtained from FactSet). Each day, as described in Section 3, we assign probabilities to each active candidate's future transition across developmental phases, or to failure. We then simulate these future transitions for all of the candidates, and each simulation produces a first-to-succeed candidate.[1] Averaging across simulations gives us that day's forecast for the expected time remaining until vaccine deployment.

The evolution of our forecast during 2020 is shown in Figure 1. Note that we do not claim that the VPI is a sufficient statistic for the state of the pandemic at each point in time, nor even for the state of vaccine development. However, it captures one dimension – the anticipated time to deployment – that was the subject of intense interest at the time.Moreover, this forecast becomes a first important determinant of the welfare gain to resolving the pandemic.

We then relate stock market valuations to the expected time to vaccine deployment by regressing returns on changes in our vaccine progress indicator. Controlling for large moves attributable to release of other macroeconomic news, and allowing for some lead-lag structure in the relationship, we estimate that a reduction in the expected time to deployment of a vaccine by one year results in an aggregate stock market return of from 4 to 8%. The joint relationship exhibits the right cross-sectional properties, with the co-

[1] An analogy from credit risk literature is that of a first-to-default basket in which several correlated firms are part of a basket and the quantity of interest is the expected time to a first default.

**Figure 1: Expected Time to Vaccine Deployment**




**Note:** Figure shows our estimate of the expected time to widespread deployment of a COVID-19 vaccine in years.

movement between returns and changes in the vaccine progress indicator being stronger for sectors most affected by the onset of COVID-19 (see Figure 5). The stock market sensitivity to changes in the VPI is the second crucial empirical quantity in our welfare calculation.

Armed with these estimates, we next build and calibrate a general equilibrium regime-switching model of repeated pandemics. The state of the economy can be either in a pandemic or not. In keeping with a common modeling assumption in the rare disaster literature (see (Barro, 2006; Gabaix, 2012; Gourio, 2012; Tsai and Wachter, 2015)), the nature of a pandemic is that agents are exposed to a shock that destroys forever a part of the economy's stock of wealth.[2] Within the pandemic, we model sub-regimes corresponding to observable progress towards resolution of the pandemic. The economy transitions probabilistically across these states. The value of a claim to the economy's output responds to these transitions, and the magnitude of this response identifies the parameters determining the severity and intensity of the pandemic.

[2]In the present case, the loss can be viewed as due to a variety of factors including mortality, attrition of human capital in working from home amidst closures of schools and lack of child care, deadweight losses in asset value due to default, and reallocation frictions in the labor market.

In the context of 2020, widespread deployment of an efficacious vaccine was considered a necessary condition to lay the foundation for a robust economic recovery.[3]During our sample period there was little progress on treatments, and natural (herd) immunity was not in sight. Moreover, with optimistic views at the time about distribution and uptake, widespread vaccine availability was also seen as a sufficient condition for return to normalcy. This is a key observation that we exploit. It allows us to interpret the vaccine deployment forecasts computed in Section 3 as effectively forecasts for the duration of the pandemic.[4] We can therefore map our VPI to the expected transition time across the sub-regimes in the model. Most importantly, we can use the stock market's sensitivity to VPI changes to calibrate the equivalent sensitivity within the model. We show that, given an expected time to the pandemic's end, the market sensitivity is essentially a sufficient statistic for computing the welfare gain due to curtailing the pandemic.

We report the welfare gain to interventions that transition the economy between intermediate sub-regimes within the pandemic. With standard parameters employed in the literature for preferences and output dynamics in the non-pandemic state, the value of shortening the pandemic by a year is approximately 5% of wealth. Our VPI forecasted an expected remaining duration of about a year in late April 2020. Hence the calibration implies ending the pandemic immediately at that point would have been worth 5% of wealth. At the begining of March, the analogous number is approximatley 15%. These values are in line with estimates from similar exercises in the literature to assess the welfare cost of rare disasters. We discuss interpretation of our finding and relate it to other estimates of the cost of COVID-19 in Section 5.

The paper then extends the model in several directions.[5] A first extension endogenizes the real option to invest in vaccine research so that the speed of progress is an equilibrium outcome. Although we do not attempt to estimate a production function for

[3]As Federal Reserve Chairperson Jay Powell remarked to CBS News in May 2020: "For the economy to fully recover, people will have to be fully confident. And that may have to await the arrival of a vaccine".

[4]We acknowledge that we are attributing to investors what have turned out to be incorrect beliefs. It is straightforward to relax the assumption that, during 2020, the market anticipated that vaccine deployment would be tantamount to resolving the pandemic. Note that our baseline assumption biases our estimate of the value of ending the pandemic downward because a more skeptical market would react less strongly to vaccine news. So, holding the observed response fixed, the less success a vaccine is expected to have, the greater must be the value of complete success.

[5]To our knowledge, these extensions have not previously been examined in the literature on the welfare cost of disasters or business cycle risk.

pharmaceutical R&D, it is clear *a priori* that the more powerful the available technology the smaller the welfare cost of a pandemic. Nonetheless, we show that given the observed market response to vaccine progress, and the observed expected duration of the pandemic, our welfare calculation would not be significantly altered under this version of the model.

The next generalization endogenizes the magnitude of health shocks via labor choice in order to study the role of exposure externalities. We assume labor augments agent's capital stock in production; however, it also exposes the agent to the pathogen. The agent thus optimally withdraws labor in the pandemic states, and the magnitude of the labor withdrawal then determines the equilibrium severity of the shocks to output. However, agents' privately optimal labor choice does not fully internalize the exposure created for other agents.

Using our empirical estimates of the COVID-19 severity, and estimates in the literature of the withdrawal of labor in Spring 2020, we compute the difference in the welfare gain with individually optimal labor choice versus that by a central planner. Since the planner imposes a stricter labor contraction (or lockdown) and thus subjects the economy to less damage, the welfare gain is approximately 15% lower than under the representative agent's policy. This difference rises with the severity of the externality as measured by the increased degree of lockdown under central planning.

Finally, given the extreme uncertainties during 2020, we relax the assumption that agents in the economy fully understand the (stochastic) properties of the pandemic.[6] Specifically, we assume that agents do not know the regime switching probabilities that govern the expected duration and frequency of pandemics. Using parameter values from the calibration with endogenous labor, we find that the welfare gain rises sharply relative to the full-information model. This effect is stronger – not weaker – when agents have a preference for later resolution of uncertainty (formally, an elasticity of intertemporal substitution that is lower than the inverse coefficient of relative risk aversion). Indeed, we find that the representative agent would be willing to pay as much for resolution of this parameter uncertainty as for resolving the pandemic itself. An important policy implica-

[6]Such uncertainty is natural given the rare nature of pandemics and the evolving understanding of connections between various pandemics (SARS, H1N1, COVID-19, etc.). See, for example, "COVID-19 Is Bad. But It May Not Be the 'Big One'", Maryn McKenna, Wired, June 17, 2020, and "The next pandemic: where is it coming from and how do we stop it?", Leslie Hook, Financial Times, October 29, 2020.

tion is that understanding the fundamental biological and social determinants of future pandemics, may be as important as resolving an on-going pandemic.

To summarize, the contribution of the paper is to bring novel data observed during 2020 to bear on the important question of the *ex-ante* cost of such pandemics. We show that two key quantities that we estimate – the expected duration of the crisis and the stock market response to vaccine progress – are effectively sufficient to identify the welfare gain to interventions curtailing the pandemic.

As in any such exercise, there are inherent limitations in interpreting the results. The model provides only a reduced form depiction of the pandemic, of the economy, and of the stock market. We acknowledge that, in reality, the value of ending the pandemic depends on factors that we omit, including the state of the population (as in SIR-type models), the infectiousness of the virus and its variants, and the stance of fiscal and monetary policy. Without adding more state variables, our theory cannot provide a complete account of stock market behavior during 2020. (Roughly speaking, our calibration implies that the arrival of the pandemic explains about two-thirds of the market drop to the lows in March, and that unexpected clinical trial success explains about one-third of the rebound through October.) In focussing solely on the (average) stock market reponse to vaccine progress, our aim is to tease out one thread of a complex tapestry of economic forces.

The rest of the paper is organized as follows. Section 2 relates our work to the existing literature. Section 3 describes the construction of vaccine progress indicator and estimates its covariance with stock market returns during 2020. Section 4 contains our main results: we calibrate a model of recurring pandemics to the empirical evidence and deduce the implied value of returning to non-pandemic life. Section 5 discusses interpretation and validity of our baseline finding. Section 6 develops the extensions described above. Section 7 summarizes and concludes.

## 2 Related Literature

As noted in the introduction, our approach to quantifying the cost of the pandemic parallels that of Lucas (1987) in assessing the cost of business cycles. While Lucas (1987) finds small welfare improvements to reducing consumption uncertainty, Tallarini Jr (2000) shows

that this conclusion is overturned in models with recursive utility when calibrated to match asset pricing moments. Echoing this finding and foreshadowing our own, Barro (2009) reports that, in a model with rare disasters, moderate risk aversion, and an elasticity of intertemporal substitution greater than one, society would willingly pay up to 20% of permanent income to eliminate disaster risk. A number of papers, including Pindyck and Wang (2013), explore the welfare costs associated with climate risk. The latter work addresses the issue of how much should society be willing to pay to reduce the probability or impact of a catastrophe.

A different approach to determining agent's valuation of alternative consumption paths is presented by Alvarez and Jermann (2004) who define the "marginal cost" of business cycles as the ratio of a market price of a claim to the true consumption process to that of an alternative path with the same mean but lower uncertainty. While this approach has the advantage of being preference-free, it is not obvious how to attain the required market prices. (It may well be applicable in the future if pandemic insurance becomes widely traded.)

Our model is related to Ai (2010) and Gourio (2012). We share many of features of each, but differ by offering a setting that allows us to connect to our unique empirical data. Both of those papers feature shocks to the stock of productive capital, with endogenous consumption. Like Ai (2010), our model is in continuous time and allows for frictionless adjustment to capital. That paper also studies the effect of parameter uncertainty, although not in a setting with rare disasters. We differ from Gourio (2012) in modelling *extended* disasters, like pandemics, whose *expected duration* is a crucial and evolving feature of the economy.

While the literature studying the economic impact of COVID-19 has exploded in a short period of time, there is relatively little focus on the role played by vaccine development and its progress. We first relate to the theoretical literature in asset pricing that is closest to our model; we then relate to the empirical literature on observed contraction in employment and consumption during the pandemic.

Hong et al. (2020b) study the effect of pandemics on firm valuation by embedding an asset pricing framework with disease dynamics and a stochastic transmission rate, equipping firms with pandemic mitigation technologies. Similar to our paper, they model vaccine arrival as a Poisson jump process between pandemic and non-pandemic states.

Hong et al. (2020a) combine the model of Hong et al. (2020b) with pre- and post-COVID-19 analyst forecasts to infer market expectations regarding the arrival rate of an effective vaccine and to estimate the direct effect of infections on growth rates of earnings. In particular, they develop a regime-switching model of sector-level earnings with shifts in their first and second moments across regimes.

In both of these papers, the pricing kernel is exogenously specified for the pandemic and the non-pandemic states. In contrast, our model is general equilibrium in nature with the representative agent optimally choosing labor and consumption (and, in turn, investment in capital) to mitigate health risk. Deriving asset prices from first principles in a regime-switching framework of pandemics – which allows for several sub-states in a pandemic relating to vaccine progress – is an important theoretical contribution of our paper. We build upon this setup further to introduce learning when there is parameter uncertainty about pandemic parameters.[7]

For empirical work, Hong et al. (2020b) fix expected pandemic duration around one year but show in comparative statics that asset prices show considerable sensitivity to the arrival rate of the vaccine. Hong et al. (2020a) use their model to infer the arrival rate of the vaccine. In contrast, we provide a vaccine progress indicator in the form of an estimated time to vaccine deployment using actual data and related news on the progress of clinical trials of vaccines for COVID-19. We relate this vaccine progress indicator to stock market returns to infer the loss in economic wealth in the pandemic state relative to the non-pandemic state.

Elenev et al. (2020) incorporate a pandemic state with low, disperse firm productivity that recurs with low probability for studying government intervention in corporate credit markets. While we do not model credit markets in our setup, our differentiating novel features are: construction of a vaccine progress indicator and estimation of its joint relationship with stock markets, and mapping it into a general equilibrium regime-switching model of pandemics with asset prices in order to derive an estimate of the value of a vaccine in alleviating a pandemic.

Kozlowski et al. (2020) model learning effects that lead to long-term scarring after the

[7]On a technical front, Hong et al. (2020b,a) consider aggregate transmission risk into a SIR-style model, whereas our model of health risk arising from a pandemic is closer to the literature on rare disasters cited in the Introduction.

pandemic is over as policy responses relating to debt forgiveness in the current pandemic can lead to lower leverage and consumption post-pandemic. Through the learning channel in our model, there can also be scarring effects wherein agent's consumption upon exit from a pandemic does not revert to the pre-pandemic levels due to the increase in updated probability of future pandemics. This, however, is not the focus of our paper.

Collin-Dufresne et al. (2016) show that learning can amplify the pricing of macroeconomic shocks when the representative agent has Epstein-Zin preferences and Bayesian updating. Our results on learning and the impact of parameter uncertainty on welfare are related to the findings of both these papers; our model can generate both long-term scarring in consumption due to updated probability of pandemics and significant contraction of labor and consumption when parameter uncertainty is high, when the elasticity of intertemporal substitution (EIS) is low. Interestingly, expected time to deployment of a vaccine can be considered as a "macroeconomic shock" in our model that affects asset prices and depends crucially on parameter uncertainty in a manner that interacts with deep preference parameters.

# 3 Vaccine Progress Indicator and its Covariance with Stock Returns

As described in the introduction, the paper's hypothesis is that during 2020 the stock market may have conveyed information about the social value of resolving the pandemic. This section explains our empirical steps towards extracting that information. First, we construct a method for summarizing the state of vaccine research. Second, we estimate the stock market response to its changes.

## 3.1 Measuring Vaccine Progress

Throughout 2020, the unprecedented global effort to develop a vaccine for COVID-19 involved dozens of candidates under study as they made their way through pre-clinical work and clinical trials. On any given day, the state of the entire enterprise was a high-dimensional object consisting of multiple pieces of information about all of the projects. Our goal is to reduce that high dimensional object to a single number summarizing beliefs at the time. Perhaps the single most discussed aspect of the development effort during

that year was the anticipated time until widespread availability of a proven candidate. We therefore construct an estimator of that quantity using a stochastic model of vaccine progress.

As described in more detail in 3.1.1 below, each day, the model simulates the future progress of each candidate in order to forecast the time until the first candidate successfully deploys. Each run of the simulation takes the current stage of each candidate, then simulates forward the entire clinical timeline through pre-clinical trials, clinical trials, application submission, regulatory approval and vaccine deployment.[8] Each clinical stage is characterized by an expected duration and a probability of failing. We update these probabilities as news arrives about individual candidates: preliminary results or more complete information about earlier trials may be published, released to the press, or leaked. At each simulated stage, each candidate can either fail (and that candidate's run ends) or advance onto the next stage (and the simulation continues). The model then records the time to deployment among candidates successfully reaching deployment, and the average time across a large number of runs is that day's estimate of the expected time until a successful deployment.

Note that vaccine deployment is a final stage with a non-zero probability of failure. That is, an approved vaccine possibly still could not attain widespread deployment, e.g., due to manufacturing and distribution difficulty, emergence of serious safety concerns, mutation of the virus, or adoption hesitancy. In other words, observers at the time were aware that the approval of a vaccine would not necessarily correspond to a "magic bullet" that instantly terminates the spread of COVID-19 and ends the pandemic.

The forecast incorporates the expectation that the success and failure of candidates is positively correlated. This positive dependence arises most obviously because all vaccines were targeting the same pathogen, and would succeed or fail largely due to its inherent biological strengths and weaknesses. Candidates also shared one of a handful of strategies (or platforms) for stimulating immunological response,[9] relied on common

[8]This is a simplification. Candidate vaccines will actually undergo multiple overlapping trial sequences with different patient populations, delivery modalities, or medical objectives (endpoints). One sequence could fail while others succeed. Trials can also combine phases I and II or II and III. In our empirical implementation we focus on the most advanced trial of a candidate. This follows Wong et al. (2018).

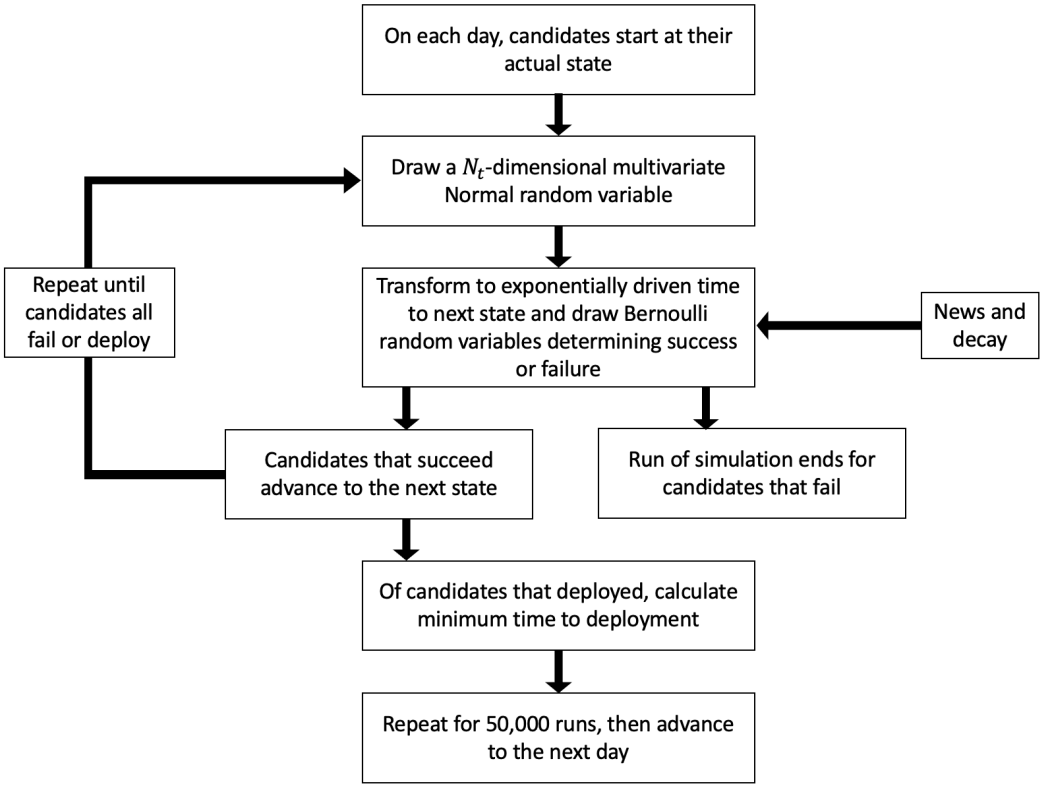
[9]For example, if an RNA-based platform proves to be safe and effective, then all candidates in this family would have a higher likelihood of success. In October 2020, two candidate vaccines had their trials paused due to adverse reactions: both were based on adenovirus platforms.

technological components, resources or abilities, and some research teams concurrently developed several candidate vaccines. The model incorporates correlation among candidates by assuming the stochastic durations of each stage are generated by a Gaussian copula with positive correlation matrix.

The next subsection provides details on the data and the each step in the construction of the forecast time-series and discusses some of the underlying assumptions.

### 3.1.1 Forecast Construction

**Figure 2: Simulation Flow Chart**

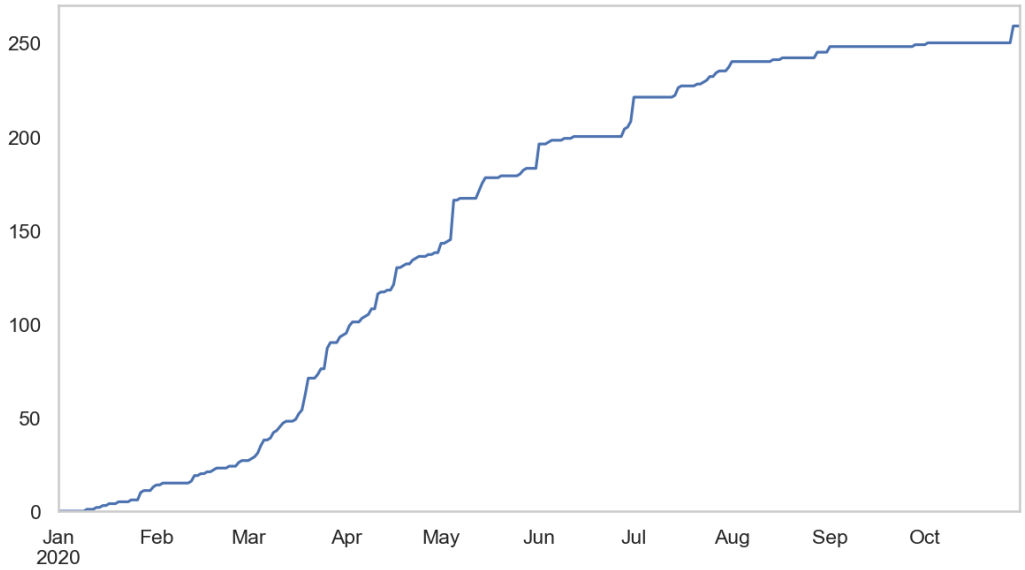



**Note:** Figure shows the simulation that estimates the expected time until vaccine deployment.

Figure 2 outlines the simulation procedure. We start with $N$ positively correlated vaccine candidates, with correlation matrix $\mathcal{R}$. Each candidate $n$ is in a state $s \in S$, where

$$S = \{\text{failure}, \text{preclinical}, \text{phase 1}, \text{phase 2}, \text{phase 3}, \text{application}, \text{approval}, \text{deployment}\}$$

**Figure 3: Number of Active COVID-19 Vaccine Projects**




**Note:** Figure shows the number of active COVID-19 vaccine candidates. Data as of November 2020.

and each state has expected duration $\tau_s$ and baseline probability of success $\Pi_s^{\text{base}}$.

Next we augment the state-level, baseline probability of successes with candidate-specific news. Let $\omega_{n,t} \in \Omega$ denote news published at time $t$ about candidate $n$. For example, $\Omega$ could span positive data releases, negative data releases, next state announcements, etc. Then let $\Delta\pi :\to [-1,1]$ be a mapping from news to changes in probabilities. For each candidate, we cumulate the changes in probabilities from all news from the beginning of our sample $t_0$ up to time $t$,

$$\Delta\pi_{n,t}^{\text{news}} = \sum_{t'=t_0}^{t} \Delta\pi\left(\omega_{n,t'}\right).$$

Finally, we combine it with the baseline probability of success, resulting in a candidate-specific probability of success that potentially varies over time, even within the same state,

$$\pi_{n,s,t}^{\text{total}} = \frac{\exp \Upsilon_{n,s,t}}{1 + \exp \Upsilon_{n,s,t}}$$

where $Y_{n,s,t} = \log \frac{\pi_s^{\text{base}}}{1-\pi_s^{\text{base}}} + 2\Delta\pi_{n,t}^{\text{news}}$.

We simulate stage-by-stage progress of each candidate and generate the expected time to first vaccine deployment, similar to a first-to-default credit model. Specifically, on each day, one run of the simulation repeats steps one and two until candidates have all failed or deployed:

1. We model each state transition as a 2-state Markov chain with exponentially distributed times. Draw an $N$-dimensional multivariate normal random variable

$$z_t = [z_{1,t}, \ldots, z_{N,t}]' \sim \mathcal{N}(0, \mathcal{R})$$

and for each candidate, transform to exponential time with intensity $\lambda_{n,s,t} = \frac{\pi_{n,s,t}}{\tau_s}$

$$t_{n,s,t} = -\frac{\log \Phi(z_{n,t})}{\lambda_{n,s,t}}.$$

2. Then draw a success or failure Bernoulli random variable with parameter $\pi_s$. If failure, then that candidate's run is over. Else if success, then that candidate advances states and the run continues.

3. Calculate each candidate's time to vaccine deployment as

$$T_n = \begin{cases} \sum_s t_{n,s,t} & \text{, if candidate deploys} \\ \infty & \text{, if candidate fails} \end{cases}$$

4. Then calculate minimum time to vaccine deployment across candidates, $\min_n T_n$.

That finishes one run of the simulation. We repeat for $50{,}000$ runs and take the cross-run average as $T^D$, before advancing to the next day. On each day across runs, we calculate the average

$$\mathbb{E}[T^*] = (1-\mu)T_t^D + \mu T^{ND},$$

where some fraction, $\mu$, of simulations will result in all candidates not reaching deployment, so we incorporate $T^{ND}$, an estimated expected time to deployment by a project

outside of our sample.

We obtain the pre-clinical dates and trial history of vaccine candidates from publicly available data collated by the London School of Hygiene & Tropical Medicine (LSHTM). We observe the start dates and durations of each pre-clinical and clinical trial, along with their vaccine strategy. We augment the LSHTM timeline with news pertinent to vaccine progress from FactSet StreetAccount. We classify vaccine related stories into seven positive types and six negative types. The Online Appendix includes more detail on the number of candidates and breakdown of strategies, the news types and corresponding probability adjustments, and our choices of parameters, also presenting evidence that our assumptions are reasonably consistent with the (small) set of observed trial outcomes. We will validate our choices both by examining robustness to reasonable variations and by comparing them to other actual *ex ante* forecasts published during the sample period.

Our indicator of vaccine progress aims to capture expectations about deployment principally in the U.S. since this is likely to be the primary concern of U.S. markets. Because of political considerations, we believe that observers at the time judged it to be very improbable that vaccines being developed in China and Russia would be the first to achieve widespread deployment in the U.S. Our base case construction for this reason omits candidates coded in the LSHTM data as originating in Russia or China, retaining candidates coded as multi-country projects including these two countries. We will also verify that including them in our index does not change our primary results.

In focusing on the scientific advancement of the individual candidates, our measure does not attempt to capture general news about the vaccine development environment and policy. News about the acquisition and deployment of delivery infrastructure by governments (or the failure to do so) could certainly affect estimates of the time to availability. We also do not capture the news content of government financial support programs or pre-purchase agreements. News about regulatory approval standards could have affected forecasts as well. While we could alter our index based on some assessment of the impact of news of this type, we feel we have less basis for making such adjustments than we do for modeling clinical trial progress.

Figure 1 shows the model's estimation of the expected time to widespread deployment from January through October of 2020, and Figure 3 shows the number of active vaccine projects. The starting value of the index, in January, is determined by our choice

of the parameter $T^{ND}$ because, with very few candidates and none in clinical trials, there was a high probability that the first success would come from a candidate not yet active. However this parameter effectively becomes irrelevant by March when there are dozens of projects.

### 3.1.2 Validation

We are aware of two datasets that contain actual forecasts of vaccine arrival times, as made in real-time during 2020. As a validation check, we compare our index to these.[10]

The two data sets are surveys, to which individuals supplied their forecasts of the earliest date of vaccine availability. Comparisons between these pooled forecasts and our index require some intermediate steps and assumptions. In both cases, the outcomes being forecast are given as pre-specified date ranges. Thus, on each survey date, we know the percentage of respondents whose point forecast fell in distinct bins. For each survey we estimate the median response, assuming a uniform distribution of responses within the bin containing the median. Under the same assumption, we can also tabulate the percentage of forecasters above and below our index.

The first survey is conducted by Deutsche Bank and sent to 800 "global market participants" asking them when they think the first "working" vaccine will be "available". The survey was conducted four times between May and September. The second survey is conducted by Good Judgement Inc., a consulting firm that solicits the opinion of "elite superforecasters." Their question asks specifically "when will enough doses of FDA-approved COVID-19 vaccine(s) to inoculate 25 million people be distributed in the United States?" (Information about the number of responders is not available.) Responses are tabulated daily, starting from April 24th. For brevity, we examine month-end dates. Table 1 summarizes the comparison.

Our forecasts align well with those of the Deutsche Bank survey, though ours are more optimistic than the median. The optimism is more pronounced when compared to the superforecasters early in the pandemic. Although we are within the interquartile range of forecasts after May, the earlier dates see us in the left-tail of the distribution. A possible reason is the particular survey question, which specifies an exact quantity of the vaccine

[10] We do not employ these in our empirical work because the forecasters may condition their views on contemporaneous stock market reactions, whereas our measure does not employ any financial market information.

being distributed in the United States. Respondents may have more skeptical of feasible deployment than we have assumed. We will examine robustness of our results below to increasing the probability of an approved vaccine failing in the deployment stage.

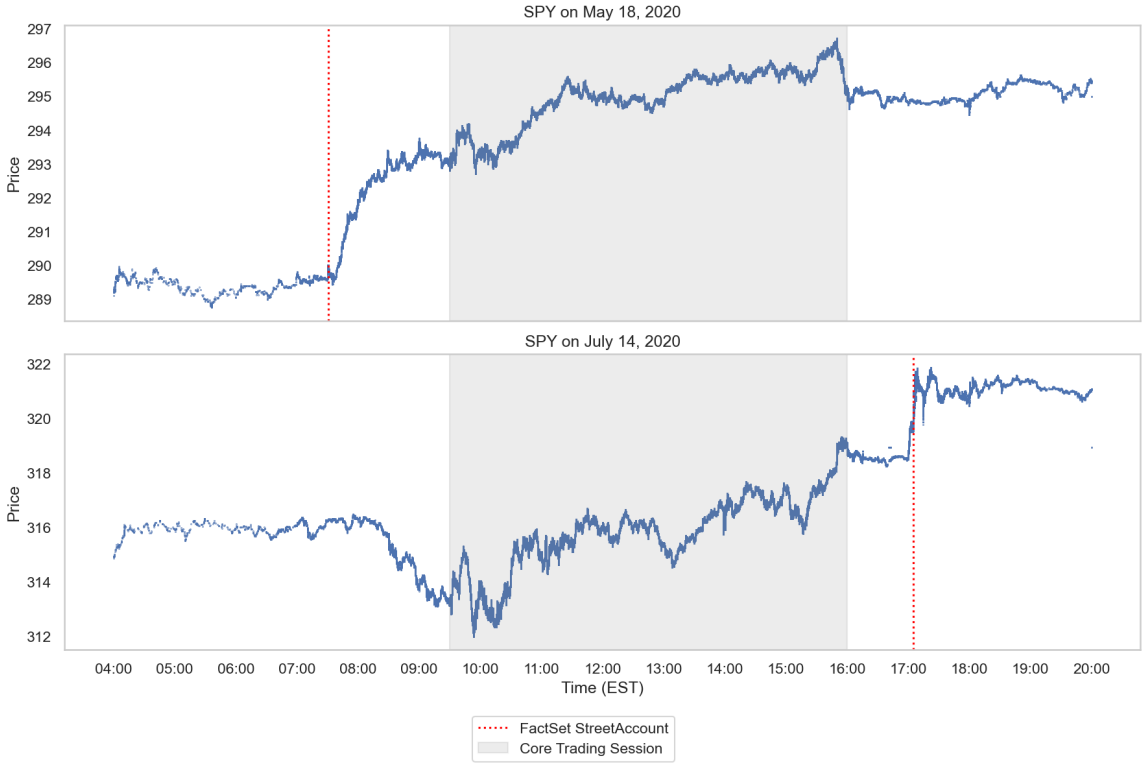
## 3.2 Stock Market Response

We now turn to assessing the stock market's response to vaccine news. The primary methodology is straightforward: we regress market returns on changes in the VPI. Our index construction does not involve any stock market information. Its changes are therefore exogenous in the regression context. A relevant consideration, however, is controlling for other exogenous news, of which there was a great deal during 2020. To motivate the salience of vaccine news, consider two events: On May 18 and July 14, 2020, *Moderna*, announced good news relating to the progress in its Phase I clinical trials and scheduling of the next stage of trials.[11] The real-time stock market responses are shown in Figure 4, where the timing of the news releases in the FactSet data is indicated by vertical bars. In each case the market's immediate reaction was to rally strongly. In the spirit of the high-frequency identification literature in emprical macroeconomics, the precise timing of the news releases (as well as the fact that both occurred outside of normal market hours) make it very unlikely that the market was responding to non-vaccine news. Note that, while both events conveyed positive clinical trial information, they concerned only intermediate stage results of one of several candidates. Thus, the responses are consistent with a large sensitivity of market valuation to vaccine progress.

Returning to the full sample, our approach to the issue of controlling for non-vaccine news is to exclude days with large stock market moves that were reliably judged to be due to other sources. Specifically, we employ the classification of Baker et al. (2020) for causes of market moves greater than 2.5% in absolute value. Those authors enlist the opinion of three analysts for each such day and ask them to assign weights to *types* of causes (e.g., corporate news, election results, monetary policy, etc). Under their classification, research on vaccines falls under the category"other". We view market returns as very unlikely to have been driven by vaccine news if none of the three analysts assigns more than 25% weight to this category, or if the return was more negative than -2.5%. The latter exclusion

[11] See Matt Levine, Money Stuff, May 19, 2020, and Matt Levine, Money Stuff, July 16, 2020 in the internet appendix.

## Figure 4: Vaccine Progress: High Frequency Identification




**Note:** The figure plots the price of the SPDR S&P500 ETF (SPY) on two dates during 2020. The vertical bars show the time of release of positive news relating to clinical trials of Moderna's vaccine.

is based on the fact that there were no significant vaccine setbacks prior to the end of our data window,[12] and on the assumption that positive vaccine progress cannot have been negative news. We then include dummies for all of the non-vaccine large-news days. There are 28 such days, 17 of which were in March. While the approach is imperfect, it avoids putting (endogenous) financial variables on the right hand side of our regressions. And, at a minimum we are limiting the ability of our estimation to misattribute the largest market moves to vaccine progress.

Table 2 shows the resulting regression estimates of market impact. These regression specifications include changes in the vaccine progress indicator in a five day window

[12] As of the time of this draft, Baker et al. (2020)'s website had classified days through June 2020. We append September 3 and September 23 as two dates with negative jumps that arguably were driven by non-vaccine progress related news.

around each day, $t$, on which stock returns are measured. Including changes on days other than the event day-$t$ guards against our imperfect attribution of the date of news arrival. *A priori* we suspect it is more likely that, if anything, markets have information before it is reflected in our index, meaning the relevant reaction would correspond to the $t+1$ or $t+2$ coefficients. On the other hand, given the sheer volume of news being processed during this period, we do not rule out delayed incorporation of information, which would show up in the $t-1$ or $t-2$ coefficients. The specifications also include two lags of the dependent variable to control for short-term liquidity effects. Specifically, the regression is

$$R^e_{m,t} = \alpha + \sum_{h=-2}^{2} \beta_h \Delta \text{VPI}_{t+h} + \gamma_1 R^e_{m,t-1} + \gamma_2 R^e_{m,t-2} + \sum_{j=1}^{28} \delta_j \mathbb{1}_{\text{jump } j} + \epsilon_t \tag{1}$$

where $\Delta \text{VPI}_t$ is the change in vaccine progress indicator, and $\mathbb{1}_{\text{jump } j}$ is a dummy equal to one on the $j$th jump date from Baker et al. (2020). The dependent variable is the return to the value-weighted CRSP index from January 1 through October 31, 2020.

The first column of the table shows results using our baseline vaccine progress indicator. The coefficient pattern shows the largest negative responses on the $t-1$ and $t+2$ index changes. Focusing on the cumulative impact, the sum of the $\beta$s is statistically significant at the 1% level. The point estimate implies a stock market increase of 8.6 percent on a decrease in expected time to deployment of one year.

Returning to Table 2, the second and third columns implement the methodology of Kogan et al. (2017) (hereafter KPSS). Those authors use an empirical Bayes procedure to estimate the market value of patents using the stock returns to the patenting firm in an event window surrounding patent publication date. As in our case, economic logic rules out a negative response: vaccine progress cannot be unfavorable news just as the value of a patent must be positive. KPSS employ a truncated normal prior distribution for the unobserved true response. Conditional on knowing the return standard deviation, the posterior mean estimate of the response coefficient is then also distributed as a truncated normal. The estimation methodology generalizes naturally to a multivariate regression setting (O'hagan (1973)). We follow KPSS in assuming a zero mean under the prior for the pre-truncated normal distribution, assuming returns are normally distributed, and

in using the regression residual to estimate the return standard deviation. Note that the estimation still includes dummy variable for market jump days making the normality assumption plausible. The table reports posterior mean and standard deviations for the individual response coefficients and for their sum.[13] The methodology is sensitive to the specification of the prior variance of the coefficient distribution. Both column 2 and column 3 assume that the pre-truncated normal distribution for $\beta_t$ has standard deviation equal to 1, which, after truncation, implies that 84% of the distribution mass is below 1.0. We regard this as a conservative choice. Results in the second column use the same (independent) prior for all the response coefficients. The third column uses a smaller prior mean for the lead and lag coefficients. Specifically, the assumption is that pre-truncated standard deviations are 0.7 for the first lead and lag and 0.5 for the second lead and lag. Both priors produce posterior means for the sum of the five response coefficients that are lower than the OLS estimate: -6.4% in column 2 and -4.1% in column 3. The calibrations in the next section will adopt the range of these conservative estimates.

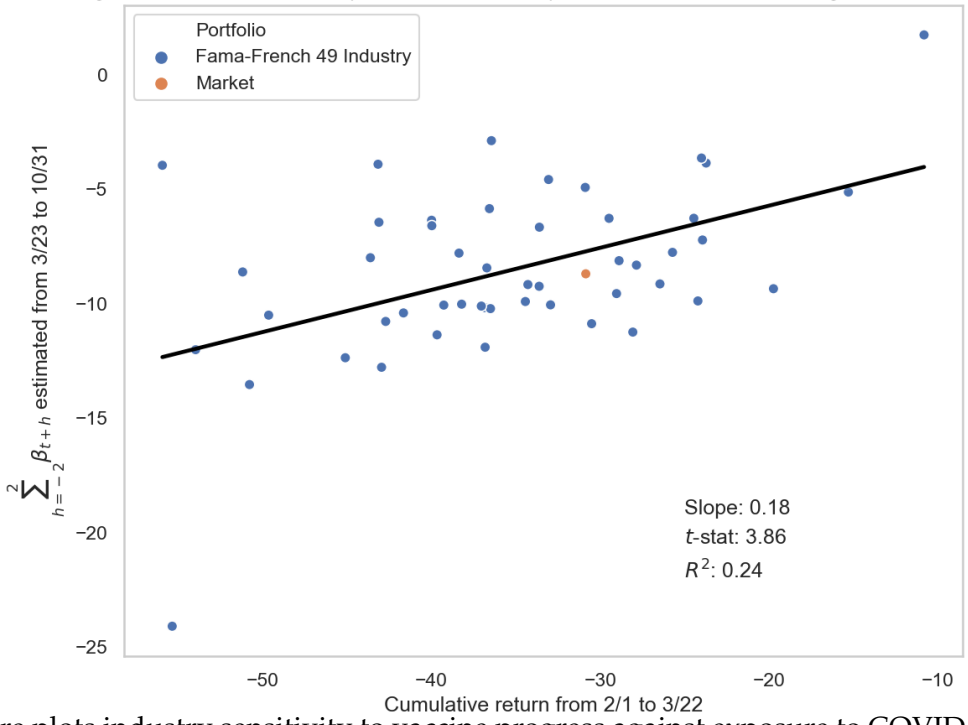
To examine the robustness of the response estimates to the assumptions built into the vaccine progress index, we repeat the OLS specification estimation with five variants. These results are shown in Table 3. The first column repeats the original specification from the prior table. The next two columns vary the assumptions about the effect of news to phase success probabilities. (Column 2 includes no news adjustments. Column 3 applies the news adjustments to only the current trial phase, as opposed to all future phases, and increases the $\Delta\pi$ from news on positive data releases, positive enrollment and dose starts to 15%, 5% and 5%, respectively) The fourth column increases the base copula correlation from 0.2 to 0.4. The fifth column lowers the assumed probability of successful deployment following regulatory approval. As mentioned above, a lower probability of successful deployment may accommodate real-life set backs such as distribution difficulty, emergence of safety concerns, mutations of the virus, or adoption hesitancy. Finally the sixth column includes vaccine candidates whose research program is based in Russia or China. In all of these cases the sum of the response coefficients is highly statistically significant and the point estimates are in the same range as those in Table 2.

[13] Moments of the truncated multivariate normal posterior are computed using the algorithm of Kan and Robotti (2017) using software provided by Raymond Kan. http://www-2.rotman.utoronto.ca/~kan/research.htm.

### 3.3 Industry Responses

As a validity check for our primary findings, we examine the price impact of vaccine progress in the cross-section of industries. We first gauge each industry's exposure to COVID-19 by its cumulative return from February 1, 2020 to March 22, 2020. This period captures the rapid onset of COVID-19 in the US, with a public health emergency being declared on January 31, 2020and a national emergency declared on March 13, 2020.Importantly, this period precedes the Federal Reserve's announcement of the Primary Market Corporate Credit Facility and Secondary Market Corporate Credit Facility on March 23, 2020,helping us pin down industry covariances with COVID-19 itself, separate from covariances with policy responses.

**Figure 5: Industry Sensitivity to Vaccine Progress**




**Note:** Figure plots industry sensitivity to vaccine progress against exposure to COVID-19 as measured by cumulative returns. Cumulative returns are from February 1, 2020 to March 22, 2020. Sensitivity to vaccine progress is estimated from March 23, 2020 to October 31, 2020 as in (2).

We then estimate industry sensitivity to vaccine progress over the non-overlapping

sample from March 23, 2020 to October 31, 2020, by re-estimating (1) sector-by-sector,

$$R^e_{i,t} = \alpha + \sum_{h=-2}^{2} \beta_{h.i} \Delta \text{VPI}_{t+h} + \gamma_{1,i} R^e_{i,t-1} + \gamma_2 R^e_{i,t-2} + \sum_{j=1}^{28} \delta_{j,i} \mathbb{1}_{\text{jump } j} + \epsilon_{i,t} \tag{2}$$

where $R^e_{i,t}$ is value-weight excess returns on the 49 Fama-French industry portfolios.

Figure 5 presents the results. Each industry's sensitivity to vaccine progress is plotted against its exposure to COVID-19. The relationship is negative and statistically significant – industries that were more exposed to COVID-19 subsequently saw more positive price impact as the vaccine was expected to deploy sooner. The industries also exhibit notable variation. Oil, fabricated products and recreation were among those with higher COVID-19 exposure and vaccine progress sensitivity, while pharmaceutical products, food products and computer software had lower exposure and sensitivity. The association of industry exposure to COVID-19 with its subsequent sensitivity to our index lends confidence to the construction and interpretation of the index as, in fact, measuring vaccine progress.

In another validation of the importance of vaccine progress in accounting for asset dynamics, Lars Lochstoer has shown (in private communication) that market volatility (as captured by the VIX index) is positively related to the conditional second moment of the VPI estimated from an EGARCH specification during our sample period.

# 4 Markov State Model of Pandemics

In this section, we introduce a regime-switching model of pandemics in order to compute the welfare cost in terms of the economy's primitive objects. In order to connect the theory to our empirical exercise, we need a model with four attributes: a description of pandemics; a well-defined notion of the value of ending a pandemic; a depiction of progress towards that objective; and a stock market that is sensitive to that progress. Our fundamental view of a pandemic is as a process that destroys household wealth, as in Gourio (2012), with consumption and other policies potentially responding endogenously. For this reason, we work with a production-based framework rather than an endowment economy.

## 4.1 Pandemic Dynamics

We consider the state of the economy to be either in a "non-pandemic" regime or in a "pandemic" regime. Within the pandemic regime, there can be several sub-states that correspond to observable progress to returning to normal life.We denote the state as $s \in \{0,1,\ldots,S-1,S\}$, where for ease of notation both state 0 and state $S$ are the same non-pandemic states, and the others are pandemic states. We assume that the economy switches between these states based on a Markov-switching or transition matrix. The transition probabilities are given as follows:

$$Pr(s_{t+dt} = 1 | s_t = 0 \text{ or } S) = \eta dt \tag{3}$$

$$Pr(s_{t+dt} = s_t | s_t = 0 \text{ or } S) = 1 - \eta dt \tag{4}$$

$$Pr(s_{t+dt} = s - 1 | s_t = s \in [1, S-1]) = \lambda_d(s) dt \tag{5}$$

$$Pr(s_{t+dt} = s + 1 | s_t = s \in [1, S-1]) = \lambda_u(s) dt \tag{6}$$

$$Pr(s_{t+dt} = s_t | s_t = s \in [1, S-1]) = 1 - \lambda_d(s) dt - \lambda_u(s) dt. \tag{7}$$

That is, $\eta$ is the probability of switching from the non-pandemic regime to the pandemic regime, and $\lambda_d$ and $\lambda_u$ are the respective probabilities in a pandemic state to move "down" or "up" to the adjacent states. Given this specification, a straightforward Markov chain calculation yields $\mathbb{E}_t[T^\star | s]$ where $T^\star$ is the time at which the state $S$ is attained and the pandemic is terminated.

The model's depiction of the pandemic consists of a state-specific stochastic process for the accumulation of wealth. Specifically, let $q$ denote the quantity of productive capital of an individual household (which should be viewed as both physical and human capital, the latter reflecting health as well as intangible capital). We assume that the stock of $q$ is freely convertible into a flow of consumption goods at rate $C$ per unit time. Then our specification is that $q$ evolves according to the process

$$dq = \mu(s) q dt - C dt + \sigma(s) q dB_t - \chi(s) q dJ_t \tag{8}$$

where $B_t$ is a standard Brownian Motion and $J_t$ is a Poisson process with intensity $\zeta(s)$. We set $\chi(0) = \chi(S) = 0$ and $\chi(s) > 0$ for pandemic states. Hence we interpret the Poisson shock as capturing the risk of an economic loss when the household is hit by a "health dis-

aster". In non-pandemic states, $\mu(0) = \mu(S)$ and $\sigma(0) = \sigma(S)$ are the percentage growth rate (before consumption) and volatility of the wealth stock. In Section 6.2, we generalize the model to include a production function with optimal labor choice, thus endogenizing the difference between pandemic and non-pandemic output. To connect to our empirical work, however, we can work with the model in reduced-form.

Although the specification allows for arbitrary parameter differences across the pandemic states (hence potentially capturing diverse aspects of the pandemic), our intention is rather to interpret the states as differing *only* in so far as advances in the state reduce the expected time to exit the pandemic, since the latter is the quantity that we attempt to measure in the data. Hence, for $0 < s < S$, we will take $\mu(s) = \mu(1)$, $\sigma(s) = \sigma(1)$, and $\chi(s) = \chi, \zeta(s) = \zeta$ to all be constants.

For parsimony, model does not include state variables that represent the dynamics of an infectious disease within the population, as in standard SIR-type models. Obviously the severity of the pandemic matters for households and investors, and hence affects the value of ending the pandemic. Likewise, the stance of fiscal and monetary policy, also not incorporated in the model, affects the economic consequences of a pandemic. In abstracting from these features, our aim is to capture the impact of variation we measure empirically, namely, clinical trial progress.

Another assumption worth highlighting concerns the long-run effects of the pandemic. Our specification is pessimistic in the sense that loss of wealth due to the health shocks is permanent. Productive capital $q$ does not get restored when the pandemic ends. On the other hand, the model is optimistic in the sense that the productive *process*, $dq$, does fully revert to pre-pandemic dynamics. After the pandemic, the world looks stochastically the same as it did before. In particular, there are no scarring effects, e.g., on the economy's growth rate, $\mu$. Both assumptions are important for tractability.

## 4.2 Agents

We assume the economy has a unit mass of identical agents (households). Each agent has stochastic differential utility or Epstein-Zin preferences (Duffie and Epstein, 1992; Duffie

and Skiadas, 1994) based on consumption flow rate $C$, given as

$$\mathbb{J}_t = \mathbb{E}_t \left[ \int_t^\infty f(C_{t'}, \mathbb{J}_{t'}) dt' \right] \tag{9}$$

and aggregator

$$f(C, \mathbb{J}) = \frac{\rho}{1 - \psi^{-1}} \left[ \frac{C^{1-\psi^{-1}} - [(1-\gamma)\mathbb{J}]^{\frac{1}{\theta}}}{[(1-\gamma)\mathbb{J}]^{\frac{1}{\theta}-1}} \right] \tag{10}$$

where $0 < \rho < 1$ is the discount factor, $\gamma \geq 0$ is the coefficient of relative risk aversion (RRA), $\psi \geq 0$ is the elasticity of intertemporal substitution (EIS), and

$$\theta^{-1} \equiv \frac{1 - \psi^{-1}}{1 - \gamma} \tag{11}$$

The use of recursive preferences is standard in macrofinance models because of their ability to match financial moments. We recognize the limitations of using a utility specification driven by consumption goods, particularly within a crisis when other considerations (e.g., health, social interaction, the safety of others) so strongly affect well-being. However, using a familiar formulation ensures that our findings are not driven by nonstandard assumptions about utility. Another potentially restrictive assumption, given the myriad of uncertainties during 2020 about the coronavirus itself, is that agents have complete knowledge of the stochastic properties of the pandemic. In Section 5, we will consider uncertainty about the transition probabilities for a two-state version of the model.

The representative agent's problem is, in each state $s$, to choose optimal consumption $C(s)$ that maximizes the objective function $\mathbb{J}(s)$. Section 5 will examine another extension in which the agent possesses a vaccine research technology and optimally chooses the rate of research expense.

#### 4.2.1 Solution

We now characterize the solution to the optimization problem.

**Proposition 1.** *Denote*

$$g(s) \equiv \frac{(1-\gamma)\rho}{(1-\psi^{-1})} - (1-\gamma)\left(\mu(s) - \frac{1}{2}\gamma\sigma(s)^2\right) - \left([1-\chi(s)]^{1-\gamma} - 1\right) \tag{12}$$

*Let $H(s)$'s denote the solution to the following system of $S$ recursive equations:*

$$g_0 \equiv g(0) = \frac{(1-\gamma)}{(\psi-1)}\rho^{\psi}\left(H(0)\right)^{-\psi\theta^{-1}} + \eta\left[\frac{H(1)}{H(0)} - 1\right] \tag{13}$$

$$g_1 \equiv g(1) = \frac{(1-\gamma)}{(\psi-1)}\rho^{\psi}\left(H(s)\right)^{-\psi\theta^{-1}} + \lambda_d\left[\frac{H(s-1)}{H(s)} - 1\right] + \lambda_u\left[\frac{H(s+1)}{H(s)} - 1\right], \tag{14}$$

*for $s \in \{1,\ldots,S-1\}$.*

*Assuming the solutions are positive, optimal consumption in state $s$ is*

$$C(s) = \frac{\left(H(s)\right)^{-\psi\theta^{-1}} q}{\rho^{-\psi}}, \tag{15}$$

*and the value function of the representative agent is*

$$\mathbb{J}(s) \equiv \frac{H(s)q^{1-\gamma}}{1-\gamma} \tag{16}$$

*Note: All proofs appear in the appendix.*

The recursive system is straightforward to solve numerically.[14] Henceforth we implicitly assume the parameters are such that a unique solution vector $H(s)$ exists and is strictly positive.[15] An important observation for our calibration exercise is that the pandemic parameters only affect the system (and hence its solution) through the constant $g_1$. More generally, the solution depends on the relative values of $g_0$ and $g_1$. The lower is $g_1$ relative to $g_0$, the lower is the value function in pandemic states relative to the non-

[14] In the Appendix, we work out in detail the solution to the 2-state regime-switching model in which the pandemic regime consists of just one state. Besides illustrating the detailed solution to the model (Hamilton-Jacobi-Bellman (HJB) equations, labor and consumption choices, and system to determine the value function), it also serves as the benchmark case for developing the model further with parameter uncertainty.

[15] A necessary and sufficient condition for this in the two-regime case is that $g_1 < g_0$.

pandemic state. This difference in welfare values is the basis for our quantification of the value of a vaccine in alleviating a pandemic.

### 4.2.2 Value of Exiting the Pandemic

We define the value of ending the pandemic as the certainty equivalent change in the representative agent's lifetime value function upon a transition from state $s$ to state 0 (or to state $S$):

$$V(s) \equiv 1 - \left(\frac{H(s)}{H(0)}\right)^{\frac{1}{1-\gamma}} \tag{17}$$

This is the percentage of the agent's stock of wealth $q$ that, if surrendered, would be fully compensated by the utility gain of reverting to the non-pandemic state. This willingness-to-pay definition is standard in the literature, since Lucas (1987). In Section 5.1 we compare our findings to work using the same definition to quantify the value of averting other types of disasters. Using the optimal consumption characterized above, we also obtain that

**Proposition 2.** *The value ending the pandemic in state s is determined by the ratio of marginal propensity to consume* $(c \equiv dC/dq)$ *in the pandemic state s relative to that in the non-pandemic state, adjusted by the agent's elasticity of intertemporal substitution (EIS):*

$$V(s) = 1 - \left(\frac{c(s)}{c(0)}\right)^{-\frac{1}{\psi-1}} = 1 - \left(\frac{C(s)}{C(0)}\right)^{-\frac{1}{\psi-1}} \tag{18}$$

We will estimate this quantity below, under standard assumptions about the non-pandemic parameters, utilizing the information from our empirical exercise to restrict the set of pandemic parameters.

## 4.3 Asset Pricing

Our next step is to examine the model's counterpart to the sensitivity that we estimated in Section 3.2. We begin by interpreting "the market portfolio" within the model as a

claim to the economy's output.[16] Output is the net new resources per unit time, which is implicitly defined by two endogenous quantities: the change in the cumulative wealth plus consumption, or $dq + Cdt$. Denote the price of the output claim as $P = P(s,q)$. By the fundamental theorem of asset pricing, the instantaneous expected excess return to holding this claim is equal to minus the covariance of its returns with the pricing kernel. Under stochastic differential utility, and with the value function solution above, the pricing kernel in our economy is given by

$$\Lambda_t = \exp\left\{\int_0^t \left[\rho^\psi(\theta/\psi)H(s_u)^{-\psi/\theta}\right] du\right\} q_t^{-\gamma} H(s_t)$$

From this, we derive the value of the market portfolio in the following proposition.

**Proposition 3.** *The price of the output claim is $P = p(s)q$ where the the constants $p(s)$ solve a matrix system $Y = Xp$ where $X$ is an $S+1$-by-$S+1$ matrix and $Y$ is an $S+1$ vector both of whose elements are given in the appendix.*

Henceforth we assume the model parameters are such that the matrix $X$ defined in the proposition is of full rank. The behavior of the price-capital ratio, $p(s)$, accords with economic intuition: it declines sharply on a move from state $s = 0$ to $s = 1$, and then gradually (and approximately linearly) recovers as $s$ advances. Thus, the quantity $\Delta \log P = \log p(s+1) - \log p(s)$ is positive for $s > 0$ and, in practice, varies little with $s$.

Next, define $T^\star$ as the time at which the state $S$ is attained and the pandemic is terminated. It is straightforward to show that its time $t$ expectation, $\mathbb{E}_t[T^\star]$ is again given by a linear system, which we omit for brevity. Moreover, for large $S$, the difference

$$\Delta \mathbb{E}[T^\star] = \mathbb{E}[T^\star|s+1] - \mathbb{E}[T^\star|s] \sim \frac{1}{\lambda_u} \tag{19}$$

is effectively constant as well.

[16] Note that this is not the same as a claim to aggregate consumption. As is well known (see Ai (2010)), in an economy where the capital stock can be costlessly converted to consumption goods, the consumption claim's price is equal to the capital stock, $q$. However, any wedge between consumption and payouts to equity will result in a nonconstant price-capital ratio. Our assumption here is that the expected cash flow to the market portfolio mirrors the expected impact of the pandemic on wealth. In Appendix G we describe a decentralization of the economy in which this cash flow is the net payout of the corporate sector to households.

Combining the above two results, we can readily define the model's analogue of the sensitivity that we empirically estimated as

$$\frac{\Delta \log P}{\Delta \mathbb{E}[T^\star]}. \tag{20}$$

For our purposes the crucial property of this quantity, as we explain below, is it allows us to approximately pin down the pandemic parameters that determine the welfare gain, $V$, to returning to the non-pandemic state.

## 4.4 Calibration and Estimation of $V$

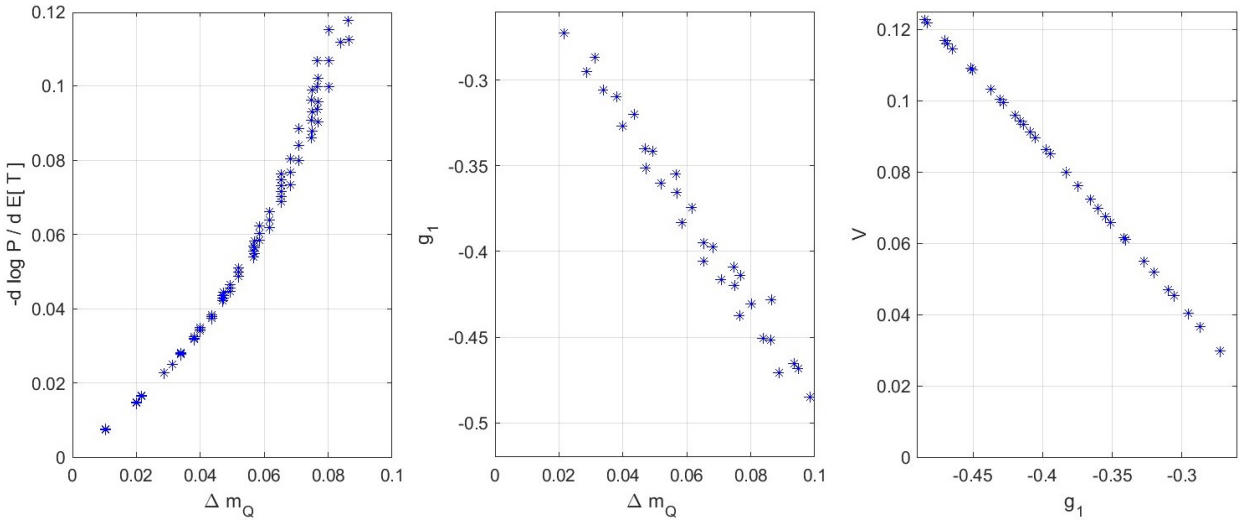
In this section and the next, we present comparative static results exploring the determinants of the value of ending the pandemic, $V$, as defined in Section 4.2.2. In doing this, our approach is to fix the preference and non-pandemic output parameters, and infer the parameters governing the pandemic from the implied quantity (20).

The former set are taken to be relatively standard values, whose effects on the non-pandemic economy are well understood. Unless otherwise stated, we will fix the these to be the values shown in Table 4. The preference parameters are broadly consistent with the macro-finance literature under stochastic differential utility, although we use a relatively low level of risk aversion. The growth rate and volatility parameters for the wealth stock are chosen to approximately match the growth rate and volatility of aggregate dividends in normal times, consistent with our interpretation of a claim to this stream as representing the market portfolio.

The crucial quantity for our calibration is the *relative* loss of output during the pandemic. Specifically, asset markets are highly informative about the decline in the expected growth rate of the stock of wealth, $dq/q - Cdt$, under the risk-neutral measure. This rate of loss, which we denote $\Delta m_Q$, is driven primarily by the difference $\mu(1) - \mu(0)$ and by the expected intensity, $\chi\zeta$, of the Poisson health shocks. (The level of risk aversion and the Gaussian volatility play smaller roles, via the change of measure.) This is illustrated by the left panel in Figure 6, which plots the sensitivity of market returns to vaccine progress, (20), for a wide range of model solutions that differ in their values of the pandemic parameters. The plot shows that there is effectively a one-dimensional relationship between the market sensitivity and $\Delta m_Q$. Further, the middle panel shows that $\Delta m_Q$ is itself tightly

linked to the model parameter $g_1$, which we showed above was a sufficient statistic for the value of $V$, given the non-pandemic parameters. This latter relationship is shown in figure's right hand panel.

## Figure 6: Stock Market Sensitivity Pins Down the Value of Exiting the Pandemic




**Note**: Figure shows how the market reaction to vaccine progress, $-\Delta \log P / \Delta \mathbb{E}[T^\star]$, helps pin down the value $V$ through the decline in expected growth rate of capital $q$ in pandemic states, $\Delta m_Q$, $g_1$ as defined in (14), and other pandemic parameters. Each $\star$ corresponds to a different set of pandemic parameters. The left panel shows the range of $\Delta m_Q$ for a given value of $-\Delta \log P / \Delta \mathbb{E}[T^\star]$. The middle panel shows the range of $g_1$ for a given value of $\Delta m_Q$. And the right panel shows the range of $V$ for a given value of $g_1$. In all three panels, the unconditional expected duration of the pandemic is 4 years, the current expected time to exit is 2 years, intensity of switching to the pandemic state $\eta = 0.03$, and number of pandemic states $S = 12$. The pandemic parameters being varied are the expected output growth ($\mu(1)$), output volatility ($\sigma(1)$), and the size of the health shock ($\chi(1)$).

Our estimated values for the market sensitivity in Table 2 using the KPSS methodology ranged from 0.041 to 0.064.Using this range, the plots in Figure 6 imply a range of $\Delta m_Q$ of approximately 0.045 to 0.065, implying $g_1$ in the range of -0.41 to -0.33. This, in turn, implies $V$ in the range of 6.5 to 9.0 percent of wealth.

The above calculations assume specific values for the timing parameters. In particular, consistent with our empirical work, Figure 6 fixes the unconditional expected duration of the pandemic to be 4 years, and the current expected time to exit to be 2 years, corresponding to our estimate of the actual value in the early spring of 2020. The figure also takes the pandemic frequency parameter to be $\eta = 0.03$. These timing choices have

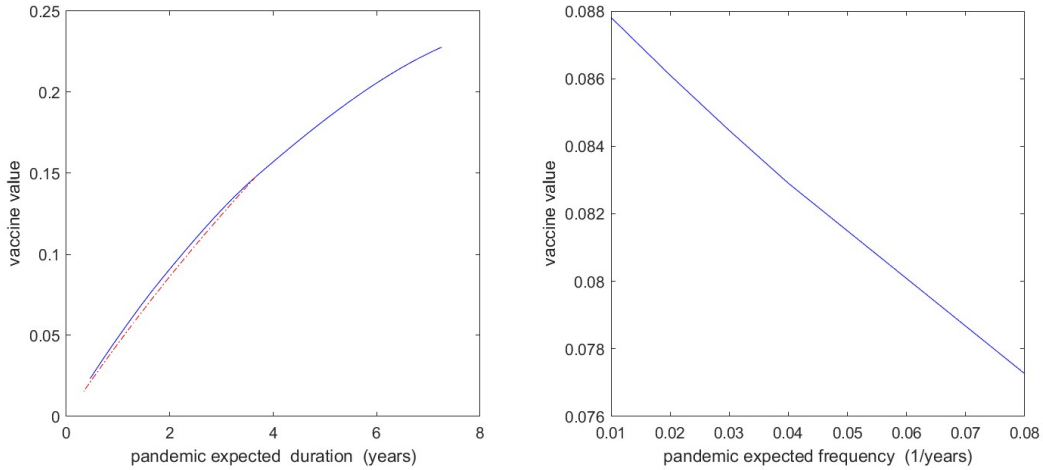
little effect on the identification plot in the left panel and none at all on the relationship in the middle plot. But they do affect $V$, given the pandemic parameters. We also note that the solutions in this section will take the number of states to be $S = 12$, which is arbitrary. Our results are not sensitive to the choice of the number of states, given the total expected duration of the pandemic. Hereafter we will denote $\lambda_u/S$ as $\lambda$ without a subscript. We also set the intensity of regress to be $\lambda_d = 0$, which limits vaccine related volatility. This choice accords with actual experience: the research setbacks through the Fall of 2020 were few and had insignificant impacts on our empirical measure of progress.

Figure 7 plots $V$ as a function of $\eta$ and $\lambda$, fixing the pandemic parameters consistent with the above identification: specifically, $\zeta = 1, \chi = 0.0475, \mu_1 = \mu_0, \sigma_1 = \sigma_0$, which imply $g_1 = -0.367$ and $\Delta m_Q = 0.0577$. The left panel plots $V$ against $1/\lambda$ the expected duration of the pandemic, while the right panel uses the pandemic frequency $\eta$ on the horizontal axis. (The left panel sets $\eta = 0.03$ and the right panel sets $\lambda = 0.5$. Both panels take the current state as $s = 1$.) The right panel shows that the value of ending the pandemic is actually lower when pandemics are more frequent. Recall that a exercise here only computes the gain to ending the current pandemic. This is less valuable when a new pandemic will arise sooner.

Comparing the panels, the model implies a much more important role for the expected duration of the pandemics than for their frequency. Intuitively, the output loss $\Delta m_Q$ is a rate, and $V$ depends critically on how long that rate is expected to be experienced. The dashed line in the left-hand plot varies the expected duration by fixing $\lambda$ and varying the current state, $s$. This line is almost identical to the sold one that fixes $s$ and varies $\lambda$, verifying that the precise combination of parameters is not important, given the forecast mean time, which is the quantity our VPI measures.

From the plot, agents in the economy would be willing to give up as much as 15% of their wealth to return to normal life when the pandemic is expected to last a little less than four years, as we estimate may have been the case in mid-January 2020. In the crucial months of March and April, with our vaccine progress indicator falling towards one year, the figure implies a value of approximately 5% of total wealth. This 5-15% range – determined primarily by the range of expected duration – is our baseline finding. By November 2020, with less than six months expected until successful vaccine deployment, ending the pandemic immediately would still have been worth over 2% of total wealth.

**Figure 7: Value of Ending the Pandemic**




**Note**: Figure shows the welfare gain, $V$, as a function of the intensity of switching to the pandemic (non-pandemic) state $\eta$ ($\lambda$). The left panel plots $V$ against $1/\lambda$. The right panel plots $V$ against $\eta$. The left panel sets $\eta = 0.03$ and the right panel sets $\lambda = 0.5$. The current state is set as $s = 1$.

We defined $V$ as the value of transitioning immediately to the non-pandemic state. Our method speaks, more generally, to the value of any intervention that shortens the expected duration of the crisis. For example, a partially successful vaccine technology which cuts this duration in half can be associated with its analogous welfare gain. The actual deployment of vaccines in 2021 may have achieved something like this. Using the calibration above, Table 5 shows the fraction of wealth the representative agent would be willing to pay to lower the expected duration from one value to another. The table entries are close to constant along each diagonal, indicating that the welfare gain scales almost linearly with the expected change in duration. A semi-effective vaccine that reduces the duration from four to two years is worth somewhat less but close to one that reduces the duration from two years to zero (7.9% versus 8.6%).

# 5 Discussion

Before considering model extensions in Section 6, this section considers the validity of our findings in two respects. First, we ask how our baseline findings on welfare costs should be interpreted in terms of actual dollars, and argue that the magnitudes are sensible economically. Second, given the model's reduced-form structure, we ask to what

extent can it offer a plausible depiction of the path of the stock market and consumption that was actually experienced during 2020. Although there are challenges, we argue that a consistent interpretation is possible, and discuss the extent to which our conclusions may be affected by the model's shortcomings.

## 5.1 Interpreting magnitude of welfare cost

In assessing our conclusions on the value of ending the pandemic, three natural questions arise. First, is 5-15% of total wealth a reasonable amount to be willing to pay to avoid or curtail a pandemic? Second, how should one think about "five percent of total wealth" in terms of real-world values (e.g., dollars)? Finally, are these magnitudes consistent with other ways of assessing the cost of COVID-19?

Within the context of the model, the welfare gain estimate is intimately tied to the rate of loss of wealth (or lower growth rate) due to the expected health shocks. In Section 3, we found that that an increase in one year in expected duration of the pandemic decreased stock market wealth by approximately five percent. This led to a calibration of the rate of loss of wealth (more broadly defined) of a similar number. So sacrificing five percent of wealth per year of expected duration to avoid this outcome makes sense economically.

As another sanity check, one could compare our estimate to the total drop in stock market wealth – around 36% – at the onset of the pandemic. This is not the same quantity that we are estimating. Within the model, the agent's value function summarizes the anticipated lifetime consumption path. Households use their stock of wealth to buffer output (or dividend) shocks. Hence the output claim (stock market) will, in general, be more sensitive to the arrival of the pandemic than the value function is. However, the two numbers are not unrelated. Any estimate of the cost of COVID-19 substantially less than 36% of stock market wealth would be difficult to reconcile with this observation.

Still another argument for the reasonableness of our estimate is its similarity to the literature that computes the welfare gain of eliminating other types of disasters.[17] Barro (2009) reports that, in a model with rare disasters, moderate risk aversion, and an EIS greater than one, society would be willing to pay up to 20% of permanent income to eliminate disaster risk. Tallarini Jr (2000) finds costs to reducing business cycle risk at

[17] Values are commonly reported as percentage reductions of permanent income. Such percentages are directly comparable to our percentages of (permanent) reductions in $q$ since consumption is proportional to $q$.

13% on the conservative end. And Pindyck and Wang (2013) estimates the willingness to pay to reduce the impact of a disaster to 15% of capital stock at 7%.

Turning to the second question, as a baseline value, total U.S. household wealth at the end of 2019 was approximately $96 trillion, implying that five percent represents about $5 trillion. However, some ambiguity arises in interpretation because of the stylized nature of the model's depiction of wealth. A single state variable, $q$, represents not only household wealth, but the (book) value of the capital stock and the (market) value of a claim to all future dividends. One possibility is to view the magnitude of $q$ through the lens of consumption. Aggregate U.S. nondurable and service consumption in 2019 was approximately $13.4 trillion. In the model calibration, the marginal propensity to consume ($C/q$) is approximately 0.04,[18] which would imply that five percent of $q$ represents $(0.05/0.04)$ times $C$, or $V \approx$ $17 trillion.

Dollar values in this range are plausible, and are not out of line with other estimates of the cost of the pandemic. The decline in U.S. market capitalization – just one component of total wealth – translates into $9 trillion. Moving away from values imputed from financial claims, there is now a substantial literature estimating cost of COVID-19 based on foregone health and economic activity. As discussed in the introduction, a common approach in health economics is to assign values to lives and productivity lost due to the virus. Writing in mid-2020, Cutler and Summers (2020) forecast health losses (including both morbidity and mental health) caused by the pandemic and estimate the total economic cost of COVID-19 to be $16 trillion under the assumption that "it will be substantially contained by the fall of 2021." Implicitly, then, this is an estimate of a rate of loss for one year.[19] The similarity of this estimate to our own – despite the very different inputs and assumptions – lends credence to each.

[18] Our calibration aligns with estimates of Blundell et al. (2008), Souleles (1999) and Souleles (2002), among others.

[19] Focusing just on GDP, CBO (2020) estimates over $7 trillion in lost output through 2030. The IMF's World Economic Outlook (IMF (2021)) estimates the collapse could have been three times as large had policymakers not enacted significant intervention (including $16 trillion in fiscal support). They further estimate the cumulative loss in output relative to the counterfactual without COVID-19 to be $28 trillion over 2020–2025. Further, Agarwal and Gopinath (2021) estimates an additional $50 billion in facilitating vaccine availability would infuse $9 trillion into the global economy through 2025.

## 5.2 Interpreting the COVID-19 experience

For tractability, our baseline model omits many factors that played important roles in 2020. We have not included fiscal or monetary policy, for example. (Recall, though, that our empirical work excluded large market-moving events attributable to non-vaccine news as classified in Baker et al. (2020)). In the next section, we will examine the effect on our welfare conclusions of some important generalizations. Before moving beyond the baseline case, however, we now describe in more detail its implications for the response of the stock market and of consumption to a pandemic. Comparing these implications to the actual experience of 2020, we argue that a coherent interpretation is possible when viewed through the lens of the model. Hence, while there are inevitably descriptive limitations, these need not detract from the paper's objectives.

Consider first the **stock market**. From December 31, 2019 to March 23, 2020 the CRSP value-weighted experienced a return of approximately -36%, continuously compounded. The market then rebounded fully by early autumn. The cumulative return for the year was approximately +5% at end of October (where our clinical trial sample stops).

The calibration in the previous section implies a somewhat smaller drop, of -23.6% for the output claim (our depiction of the stock market) at the onset of a pandemic, based on our initial VPI forecast of an expected duration of four years. Thus, relative to this data point, our estimation of the potential damage of the pandemic is conservative compared to the market's assessment.

Subsequently, the model implies a partial market recovery due to the observed success of vaccine trials. From March 23 through October 30, our forecast of the pandemic's duration dropped by 2.5 years, of which 0.6 years was expected. The implied market response to this progress – calibrated to match the response estimated in Section 3.2 – is approximately 16.3%.

Thus, without conditioning on any other shocks, the basic dynamics of our model can account for approximately two-thirds of the observed market decline and about one-third of the recovery through our sample period. To shed light on factors the model may be missing, it is useful to decompose the initial market decline into components due to cash flow news, real interest rate news, changes in the equity risk premium. Recently, Knox and Vissing-Jorgensen (2021) report empirical estimates of the same decomposition during 2020 using information in options markets, inflation swaps, and S&P 500 dividend

futures. We describe in the online appendix a way to identify the return components, $r^{CF}$, $r^{RF}$,and $r^{RP}$ within the model. With the baseline calibration the results are:

$$r^{CF} = -0.2834, \qquad r^{RF} = 0.2201, \qquad r^{RP} = -0.1727.$$

Consistent with Knox and Vissing-Jorgensen (2021), we find substantial and nearly offsetting positive and negative components of discount rate news, that is $r^{RF} + r^{RP}$ is small.[20] The risk premium component is due to the the pandemic health shocks. As is well-known from the long-run risk literature, investors with Epstein-Zin preferences and $\gamma > 1/\psi$ are averse to uncertainty and growth-rate risk. Also, in the model, real rates decline on entering the pandemic with the riskless rate turning mildly negative, consistent with the data. However, the model's rate is higher in the non-pandemic state than in the data, leading us to overstate $r^{RF}$ relative to the estimates of Knox and Vissing-Jorgensen (2021).

Our model differs from Knox and Vissing-Jorgensen (2021) in attributing large effects to cash flow news. In fact, expected cash flows did decline steeply in early 2020: December 2020 S&P 500 dividend futures declined *more* in percentage terms than did the overall stock market,[21] However, as Knox and Vissing-Jorgensen (2021) show, near-term dividends makes up a small component of market value. So declines in the discounted sum (e.g., for 10 years ahead) cannot account for a large component of the market drop. As a result, and combined with the small net discount rate effects, the authors are left attributing most of the market decline to residual unidentified "long-term effects."

In our model, there are both short-term cash-flow effects from lower output, as well long-term effects from the loss of part of the capital stock. Evidently the market was anticipating less short-run impact, but greater long-term impact, perhaps due to scarring type effects that are absent from the model. Recall that, while we assume permanent

[20] More accurately, Knox and Vissing-Jorgensen (2021) find that during two weeks in March there was a large temporary positive spike in real interest rates due to a severe sell-off in the Treasury bond market, combined with a temporary spike in the equity premium as estimated from options market implied volatility. During that episode, the two discount rate components moved strongly in the same direction, fully accounting for the market sell-off. Outside that window, however, the net contribution of discount rate news to explaining cumulative returns is minor.

[21] The December contract, quoted in units of the S&P 500 index, dropped from 62.5 at the end of 2019 to 39 on 3/23/20, a decline of 47%. Using this contract as a denominator, the price-dividend ratio on the market actually went up over this period.

effects of the pandemic on the level, $q$, we assume purely transitory effects on the growth rate of $dq$ once the pandemic ends. The market may have not been so sure.

Turning to the implication for our conclusions, it is clear that adding negative long run effects in order to match the observed market decline (while holding other return components fixed) will imply larger welfare gains to mitigating the pandemic. It is important to recognize that, while the model's return decomposition can be altered (e.g., with different preference parameters), this will not necessarily lead to large welfare effects if we still impose that the calibration matches the magnitude of the market response to vaccine progress. As described in Section 4, the latter condition effectively pins down the severity of the pandemic.

Next consider the path of **consumption**. An extremely prominent feature of the 2020 experience was the rapid plunge in consumption in March and April followed by a complete rebound by early 2021. In the context of the model, consumption is driven primarily by the wealth process, $dq$. (The effect of changes in the marginal propensity to consume is second order.) A large decline in observed consumption is consistent with the occurrence of one or more health shocks to $q$ in the early part of the year. These Poisson events are the way in which the pandemic is realized within the model. In fact, the early occurrence of such a shock – which was not considered above – can also bring the model's implied stock market decline directly into line with the observed fall.

However, as just discussed, the model has no mechanism for the reversal of these shocks after the pandemic ends, still less while the pandemic remains in progress. How, then, can the model explain the consumption rebound?

In our view, the most coherent interpretation of the consumption experience is that a large component of the recovery must be regarded as having been unexpected. Indeed, from the analysis above, it would be seemingly impossible to build a model in which a strong rebound in consumption is expected *ex ante* within a pandemic and in which the stock market drops nearly 40% due to the arrival of the pandemic. Moreover, the strong rebound in stock prices after March is also consistent with the interpretation of substantial unexpected good news about fundamentals, further helping to reconcile the model's implications of a rally only partially explained by vaccine progress. Moreover, evidence in Hong et al. (2020a) and Gormsen and Koijen (2020), respectively, supports strong positive revision in corporate cash flows during the pandemic, by examining expectations of

stocks' earnings and implied dividend yields.

In the context of the model, unexpected consumption changes are described by the Gaussian component of wealth shocks, which can be viewed as encompassing mechanisms like (unanticipated) policy interventions that are outside the model. Invoking large positive shocks is more plausible if the scale of these shocks, governed by $\sigma(s), s > 1$, is large. For parsimony, we chose to fix the parameter $\sigma(s) = \sigma(0) = 0.05$ for all $s$. This value makes, for example, the 8% increase in consumption in the third quarter extremely unlikely. If, alternatively, we set $\sigma(s) = 0.10, s > 1$, such a realization, while still large, becomes a 1.6-$\sigma$ event, i.e., not unrealistically unlikely.

Returning to implications for the welfare calculation, increasing the Gaussian uncertainty within the pandemic requires lowering the expected magnitude of the health shocks in order to maintain consistency with our estimate of the market impact of vaccine progress. Such a substitution of less (asymmetric) disaster risk for more (symmetric) Gaussian risk makes the pandemic somewhat less bad in welfare terms, but does not qualitatively alter our conclusions. In particular, recalibrating with $\sigma(s) = 0.10, s > 1$ reduces the welfare benefit of a one-year duration reduction of the pandemic from 4.6% to 3.9% of wealth.

To summarize, fully accounting for the behavior of the financial markets and the real economy during 2020 is beyond the scope of our baseline stylized model. Nor is it the main objective of the paper. Nevertheless, the primary contours of the data can be reasonably described as an outcome within the model, given certain realizations of the stochastic shocks, as described above. We have noted the sensitivity of our central findings to some model variations that might better match the experience of that year. The next section considers in detail three distinct generalizations of the model.

# 6 Extensions

We next examine some extensions of the model to highlight features absent in our reduced form that may make ending the pandemic more or less valuable than our benchmark estimate.

## 6.1 Endogenous Vaccine Development

First, a potential criticism of the model is that it includes no actual vaccine development technology. The reason for this is simply that parameterizing and calibrating a bio-pharmaceutical R&D production function is beyond the scope of our study. However, there could be a concern that we overstate the value of ending the pandemic by not giving the economy a real option to address it. We now show a tractable way to do this, and we explain why our results are consistent with this extension. In a nutshell, optimal research effort will impose a constraint on the parameters that does not affect our empirical identification of the pandemic duration and severity.

Suppose that, when a pandemic arrives, the representative agent has the ability to choose an expenditure rate $\iota$ that increases the arrival rate of vaccine progress. The most parsimonious specification would just be linear:

$$\lambda(\iota) = L_0 + L_1\,\iota.$$

(The discussion will treat the 2-state model. Generalization to $S$-states is straightforward.) Given the rate, the dynamics of wealth, $dq/q$, picks up a new term $-\iota\,dt$ for the duration of the pandemic. Without loss of generality, we can assert that whatever $\iota$ level the agent chooses in the first pandemic is also optimal for all subsequent pandemics. For notational simplicity below, define the adjusted drift during the pandemic as

$$\mu_S(\iota) = \mu(1) - \iota$$

where $\mu(1)$ is the benchmark growth rate without research effort. While this formulation is too sparse to address issues of public versus private returns to research expenditure, it does allow us to formulate and solve a model in which vaccine progress (and exiting from pandemic) is an endogenous outcome.

Notice that, given a choice of $\iota$, the economy behaves exactly as in our reduced-form case. Hence the solution for optimal consumption and the value function are unchanged. In particular, we can write the value function within the pandemic as $H(1;\lambda(\iota),\mu_S(\iota))$. To choose the optimal policy, $\iota^*$, the agent simply maximizes this function. This verifies that the optimal rate is constant within a state and does not vary across pandemics. Of course,

a necessary condition for an interior optimum is

$$\frac{\partial H}{\partial \mu_S} = L_1 \frac{\partial H}{\partial \lambda}.$$

Optimality of the research effort does constrain admissible pairs of $\lambda$ and $\mu_S$ via this relation.

Clearly in an economy with powerful research technology (where $L_1$ is a large number), agents can make the pandemic very brief (in expectation) at low cost. Hence, the endogenous value of $\lambda$ would be high, and agents would pay less to return to the non-pandemic state than in an economy with inferior vaccine technology. However, recall that our benchmark calibration above already conditioned on different values of $\lambda$. We showed that the welfare gain depended strongly on the remaining expected duration of the pandemic, which could be inferred in the data from our estimation of the expected time to deployment of a vaccine during 2020.

Now, taking $\lambda$ as fixed at an observed value $\hat{\lambda}$ say, consider the ratio

$$f(\hat{\mu}_S) = \left.\frac{\partial H}{\partial \mu_S}\right|_{\hat{\lambda},\hat{\mu}_S} \Big/ \left.\frac{\partial H}{\partial \lambda}\right|_{\hat{\lambda},\hat{\mu}_S}.$$

Given any value of the technology parameter $L_1$, the first order condition above requires us to use the value of $\hat{\mu}_S$ satisfying $f(\hat{\mu}_S) = L_1$. Assuming a solution exists, this is the full economic content of endogenizing vaccine investment in this setting.

Will imposing this restriction on $\mu_S$ affect our estimated welfare gain? To see why it will not, recall that the stock market response to vaccine progress pinned down the quantity that we called $\Delta m_Q$, the difference between the (risk neutral) expected growth rate of $q$ in the pandemic and during normal times. As shown in Figure 6, this difference effectively determines $V$ (via the intermediate quantity $g_1$) regardless of the values of the other pandemic parameters. Determining $\mu_S$ from the above first order condition does not change our empirical inference about $\Delta m_Q$.[22]

To be clear, the conclusion is not that endogenizing vaccine development is unimportant in determining the value of ending the pandemic. Rather, we are pointing out that

[22] In terms of the model parameters, $\Delta m_Q$ depends upon several things besides $\mu_S$, including the expected health shocks per unit time and the degree of risk aversion.

our empirical work has already determined (approximately) the key inputs to that value. Taking those quantities at face value, adding assumptions about the development technology and imposing the restriction of optimal investment do not perturb the calculation.

## 6.2 Endogenous Pandemic Severity and Labor Externalities

In this subsection, we propose a version of the model in which the pandemic parameters for the wealth process are endogenized through the choice of labor supply. Doing so will allow us to examine how much the value of curtailing the pandemic is influenced by the extent to which individual choices deviate from the socially optimal policies.

In this version of the model, wealth accumulates according the stochastic process

$$dq = \ell^{\alpha} q\mu dt - Cdt + \sigma \ell^{\alpha/2} q dB_t \tag{21}$$

in the non-pandemic state, and

$$dq = \ell^{\alpha} q\mu dt - Cdt + \sigma \ell^{\alpha/2} q dB_t - [\ell\varepsilon + k + KL] q dJ_t. \tag{22}$$

in the pandemic state. As before, $C$ is the endogenous consumption rate, and now $\ell$ is the household's labor supply, and $\alpha \in (0,1)$ is the elasticity of expected output with respect to labor. The results below all go through with constant returns to scale in the drift term. Crucially, both individual and aggregate labor are assumed to affect the agent's exposure to the health shock via the jump size. Let

$$\chi(\ell, L) \equiv [\ell\varepsilon + k + KL], \tag{23}$$

where $\varepsilon$ is exposure to the pandemic via private labor, $k$ is exposure to the pandemic unrelated to labor, $L$ is aggregate labor supply, and $K$ is exposure via aggregate labor. These parameters can capture losses of wealth due to health-induced disruptions to work, the need to work from home with attendant productivity impact and loss of human capital, deadweight losses from bankruptcy, and frictions from labor reallocation. We will assume parametric restrictions on $\varepsilon$, $k$ and $K$ to be small enough that $(1-\chi) \in (0,1)$. The agent takes the aggregate supply of labor $L$ as given in her optimization problem.

Agents' preferences are as in Section 4.2. We assume no disutility to labor supply and

no frictions in adjusting $\ell$. We assume $\ell \in [0, \overline{\ell}]$, where the upper bound $\overline{\ell}$ is the agents' total available work capacity. (In the numerical work we normalize $\overline{\ell} = 1$.)

The agent's problem is now to choose in each state $s$ optimal consumption $C(s, L^*(s))$ and labor $\ell(s, L^*(s))$ that maximizes the objective function. We impose that agents have rational expectations about $L^*(s)$, the aggregate labor in equilibrium. In other words, individual agents' decisions in the aggregate should lead to a wealth (consumption) dynamic that is confirmed in equilibrium. This implies the following for wealth dynamics in the pandemic regime:

$$dq(s) = [\ell(s, L^*(s))]^{\alpha} q\mu dt - C(s, L^*(s))dt + \sigma[\ell(s, L^*(s))]^{\alpha/2} q dB - \chi(\ell(s, L^*(s)), L^*(s)) q dJ_t \tag{24}$$

Since $L^*(s)$ is a constant for each $s$, as the agent has rational expectations about $L^*(s)$, the above dynamics are identical to those assumed by the agent. Substituting for the equilibrium fixed point that $L^*(s) = \ell(s, L^*(s))$, we can then obtain the rational expectations equilibrium outcomes.

**Proposition 4.** *Equilibrium labor in the non-pandemic state is given by*

$$L(0) = L(S) = \overline{\ell} \tag{25}$$

*Equilibrium labor in pandemic states* $L^*(s)$ $\forall s \in \{1, \ldots, S-1\}$ *solves*[23]

$$\chi(L(s), L(s)) = k + (\varepsilon + K)L(s) = \left[1 - (L(s))^{\frac{1-\alpha}{\gamma}} \nu\right] \tag{27}$$

*where*

$$\nu \equiv \left[\frac{\alpha\left(\mu - \frac{1}{2}\gamma\sigma^2\right)}{\zeta\varepsilon}\right]^{-\frac{1}{\gamma}}. \tag{28}$$

[23] It can be shown that given $\alpha \in (0,1)$, the second order condition for a maximum is satisfied whenever

$$\mu - \frac{1}{2}\gamma\sigma^2 > 0 \tag{26}$$

which also implies $\nu > 0$.

In the non-pandemic state, the agent faces no cost to supplying labor and exerts effort fully. However, in the pandemic states, the agent increases exposure to health risk by supplying labor, which creates a tradeoff between augmenting the capital stock and reducing the loss of capital that arises from health shocks. A key property of the model is that the agent contracts labor relative to the non-pandemic state.

Note the externality in our set up via the $KL$ term in the size of the Poisson shock (where $L$ is aggregate labor) that is not internalized by each agent. A central planner would factor this in the socially efficient choice of labor. This is tantamount to replacing $\varepsilon$ by $(\varepsilon + K)$ in $\nu$ above to obtain $\nu^{CP}$:

$$\nu^{CP} \equiv \left[ \frac{\alpha \left( \mu - \frac{1}{2}\gamma\sigma^2 \right)}{\zeta(\varepsilon + K)} \right]^{-\frac{1}{\gamma}} \tag{29}$$

Socially efficient labor choice $L^{CP}(s)$ in the pandemic states is then given by

$$\chi\left(L(s), L(s)\right) = k + (\varepsilon + K)L(s) = \left[ 1 - \left(L(s)\right)^{\frac{1-\alpha}{\gamma}} \nu^{CP} \right] \tag{30}$$

It is then straightforward to show that $\nu^{CP} > \nu$ for $K > 0$ and $\gamma > 0$, and hence $L^{CP}(s) < L(s)$, i.e., the socially efficient choice of labor in pandemic states is smaller than the privately optimal one.

Given the optimal labor and consumption policies, the model solutions in Proposition 1 can be directly applied. As before, the pandemic parameters only enter the system of equations via the constants $g_0$ and $g_1$, which we can write compactly as

$$g(x, y) \equiv \frac{(1-\gamma)\rho}{(1-\psi^{-1})} - x^{\alpha}(1-\gamma)\left( \mu - \frac{1}{2}\gamma\sigma^2 \right) - y\left( \left[ 1 - \chi(x, x) \right]^{1-\gamma} - 1 \right) \tag{31}$$

with $g_0 = g(\bar{\ell}, 0)$ and $g_1 = g(\ell(s), \zeta)$.

To quantitatively evaluate the model's implications, we require that the parameters are such that the endogenous severity of the pandemic is in line with our empirical estimates. To this end we report the implied $\Delta m_Q$ for a range of values of $K$ and $\varepsilon$ in Table 6.[24] Recall, our empirical estimates suggested a value for this quantity in the range of

[24]The exercise fixes $\alpha$ and $k$. These parameters have less direct impact on the degree of labor externality.

0.05-0.06. We also report the optimal labor supply in the pandemic state, $\ell^\star$. Some empirical evidence suggests labor contraction ≈20% in April 2020 (see, e.g., Cajner et al. (2020)) corresponding to $\ell^\star \approx 0.80$. The table identifies parameter regions (e.g., the upper left of the tables) that can match both restrictions.

Table 7 shows the effect on $V$ of the labor market externality for the same range of parameter values. The left panel provides a direct measure of the scale of the externality via the ratio of the central planner's solution for optimal labor in the pandemic to that actually chosen by agents. With parameters in the region identified above, the socially optimal lockdown is quite severe with labor restricted to 30%-40% of the privately optimal amount.[25] The right panel shows that, in this region, the welfare gain is 12%-19% lower under the central planner's solution.

In addition to the finding that ending the pandemic is less valuable under a central planner, comparing variation across the two panels reveals the pattern that a stronger externality (as measured by lower values of $\ell^\star_{cp}/\ell^\star$) are associated with decreasing relative welfare gains under the central planner. The extra degree of lockdown that the planner would impose decreases the expected welfare cost. We acknowledge that if the arrival of the pandemic were to result in social costs that are outside the capital stock dynamics for the agent, then the planner might value the ending the pandemic more than the representative agent.

## 6.3 Learning and Uncertainty

We have used the $S$-state version of our model to study the reaction of markets to vaccine news within a pandemic. Relating its predictions to the empirical evidence in Section 3 has helped identify plausible parameters affecting the value of a vaccine. Now we return to the two-state version of our model in order to examine the role of vaccine news from a different angle. Specifically, we are interested in the accumulation of information over longer horizons about the frequency and duration of pandemics. We study the effect upon the value of a vaccine of uncertainty about these quantities and of differing attitudes towards uncertainty.

[25] While our model does not feature SIR dynamics, models with SIR dynamics and labor externalities generally see more severe lockdown policies under a central planner (see Abel and Panageas (2021)).

### 6.3.1 Information Structure

Recall that in the two-state model $\eta$ is the intensity of switching from state 0 ("off") to state 1 ("on") and $\lambda$ is the intensity of switching from 1 to 0. In this section, we assume that agents have imperfect information about these intensities.

Let us stipulate that at time zero the agent has beliefs about the two parameters that are described by gamma distributions, which are independent of each other. Each gamma distribution has a pair of non-negative hyperparameters, $a^\eta, b^\eta$ and $a^\lambda, b^\lambda$, that are related to the first and second moments via

$$\mathbb{E}[\eta] = \frac{a^\eta}{b^\eta}, \qquad \text{Std}[\eta] = \frac{\sqrt{a^\eta}}{b^\eta}, \tag{32}$$

and likewise for $\lambda$.

By Bayes' rule, under this specification, as the agent observes the switches from one regime to the next, her beliefs remain in the gamma class with the hyperparameters updating as follows

$$\begin{aligned} a_t^\eta &= a_0^\eta + N_t^\eta \\ b_t^\eta &= b_0^\eta + t^\eta \end{aligned}$$

where $t^\eta$ represents the cumulative time spent in state 0 and $N_t^\eta$ represents the total number of observed switches from 0 to 1. Analogous expressions apply for $\lambda$. Thus, during the "off" regime, the only information that arrives (on a given day, say) is whether or not we have switched to "on" on that day. If that has occurred, the counter $N^\eta$ increments by one and the clock $t^\eta$ turns off (and $t^\lambda$ turns on). In this version of the model, that is the entirety of the information revelation. In contrast to the previous section, no good or bad news arrives about progress during a regime. Although this setting lessens the model's ability to speak to high-frequency dynamics, it allows us to study the role of uncertainty in the economy's longer term evolution.

Under the above information structure, the economy is characterized by a six-dimensional state vector consisting of the stock of wealth, $q$, $a^\eta, b^\eta, a^\lambda, b^\lambda$ and the regime indicator $S$. However this six-dimensional space can actually be reduced to three.

Since the switches between states alternate, let us define an integer index $M_t$ to be the

total number of switches $N_t^\eta + N_t^\lambda$ and then (assuming we are in state 0 at time 0) $N_t^\eta = M_t/2$ when $M$ is even, and $N_t^\lambda = (M_t + 1)/2$ when $M$ is odd. Knowing $M$ (along with the priors $a_0^\eta$ and $a_0^\lambda$) is equivalent to knowing $a_t^\eta$ and $a_t^\lambda$. Given these values, specifying the current estimates

$$\hat{\eta}_t \equiv \mathbb{E}_t[\eta] \quad \text{and} \quad \hat{\lambda}_t \equiv \mathbb{E}_t[\lambda] \tag{33}$$

is equivalent to specifying the remaining hyperparameters $b_t^\eta$ and $b_t^\lambda$. Thus, solutions to the model can be described as a sequence of functions $H_M(\hat{\eta}, \hat{\lambda})$ for the agent's value function at step $M$.

Compared to the full-information model in Section 4, within each regime the only new changes to the state come through variation in the estimates $\hat{\eta}_t$ and $\hat{\lambda}_t$ which change deterministically with the respective clocks $t^\eta$ and $t^\lambda$. Holding $M$ fixed, the dynamics of $\hat{\eta}_t$ are given by

$$d\hat{\eta}_t = d\frac{a_t^\eta}{b_t^\eta} = a_t^\eta d\frac{1}{b_t^\eta} \tag{34}$$

$$= -\frac{a_t^\eta}{(b_t^\eta)^2}\, dt \tag{35}$$

$$= -\frac{(\hat{\eta}_t)^2}{a_t^\eta}\, dt. \tag{36}$$

Under partial information, we proceed as in Section 4 to write-out the HJB equation with the state variables following the dynamics determined by the representative agent's information set. As before, we can conjecture a form of the value function

$$\mathbb{J} = \frac{q^{1-\gamma}}{1-\gamma}\, H(\hat{\eta}, \hat{\lambda}, M; C, \ell). \tag{37}$$

And, as before the first order condition for consumption yields $C = q\ (\rho^\psi)\ H_1^e$ (where $e_1$ is defined in Section 4.1). This follows because consumption does not enter into any of the new terms involving the information variables. Also fortunately, none of the information variables appears in terms affected by labor supply, $\ell$, and the function $H$ drops out of the first-order condition for $\ell$. (Intuitively, nothing about the likelihood of changing regimes

affects the optimal choice of labor within a regime.) This means that the solutions for $\ell^\star$ can be computed independent of the rest of the system.

Using these the results, the HJB system can be written as the infinite-dimensional linked PDEs, where $M$ runs over the even integers, with the constants $g_0$ and $g_1$ are as defined in Section 4 (see the Online Appendix for a derivation of (38)-(39):

$$g_0 = \rho^\psi \left(\frac{\theta}{\psi}\right) H_M^{-\psi/\theta} + \hat{\eta}\left(\frac{H_{M+1}}{H_M} - 1\right) - \frac{(\hat{\eta})^2}{a^\eta H_M}\frac{\partial H_M}{\partial \hat{\eta}} \tag{38}$$

$$g_1 = \rho^\psi \left(\frac{\theta}{\psi}\right) H_{M+1}^{-\psi/\theta} + \hat{\lambda}\left(\frac{H_{M+2}}{H_{M+1}} - 1\right) - \frac{(\hat{\lambda})^2}{a^\lambda H_{M+1}}\frac{\partial H_{M+1}}{\partial \hat{\lambda}}. \tag{39}$$

For large $M$, the estimation errors for both $\eta$ and $\lambda$, expressed as a fraction of the posterior estimates, go to zero:

$$\frac{\text{Std}[\eta]}{\mathbb{E}[\eta]} = \frac{1}{\sqrt{a^\eta}} = \frac{1}{\sqrt{a_0^\eta + M_t}}. \tag{40}$$

The system always converges to the full-information solution, providing a boundary condition, which, together with the single-regime solutions on the edges of the $(\hat{\eta}, \hat{\lambda})$ plane, enables computation of all individual $H$ functions.[26] It can be shown that, as in the full-information case, a necessary and sufficient condition for existence of a solution is $g_0 > g_1$.

As in the previous section, once the value function is obtained, we can characterize the certainty equivalent value of a vaccine that produces an immediate transition from the pandemic state to the non-pandemic state. The next section performs this calculation and analyzes the drivers of variation in that value.

### 6.3.2 Results

Table 8 shows numerical solutions for the value of a vaccine using the benchmark parameters from Section 4 but varying the elasticity of intertemporal substitution (EIS). The upper two panels show the full-information solution, with the upper right case corresponding to the benchmark $\psi = 1.5$, whereas the left panel lower the EIS to $\psi = 0.15$. There is almost no difference between the two solutions (which verifies the robustness of

[26] Knowing the solution for higher $M$ enables direct evaluation of the jump-terms in (38)-(39). Knowing the solution on the inner edges enables explicit approximation of the first partial derivatives.

the conclusions in Section 4 on this dimension). The bottom two panels show the results under partial information. Specifically, results are computed under the assumption that agents' standard deviation of beliefs about the two parameters are equal to their mean beliefs. Comparing the right-hand panels, we see that this degree of parameters uncertainty has the effect of raising the level of wealth agents in the economy would be willing to surrender to curtail the pandemic in the baseline case of a high EIS by between 7 and 15 percentage points, or up to a factor of three times the full information value. The left hand panels show the same effect, but amplified to an extreme level. With a low intertemporal elasticity, the representative agent would be willing to sacrifice on the order of 50 to 60 percent of accumulated wealth.

An additional computation that our framework can address is the value of a permanent end to pandemics. Table 9 shows the fraction of wealth agents in the economy would exchange to live in a world with no pandemics. (Formally, this is equivalent to letting $\lambda$ go to infinity.) As expected, the values now show the same pattern as in Table 8, but exaggerated still further. In this case, eliminating the threat *and* resolving the parameter uncertainty can lead to valuation of 25 to 50% for high EIS agents and 60 to 80 percent for low EIS agents.

The latter finding may be counterintuitive based on the common understanding of Epstein-Zin preferences under which agents with $\psi < 1/\gamma$ can be viewed as having a preference for "later resolution of uncertainty." In the current model, agents facing a pandemic are much worse off with parameter uncertainty. This is verified in Table 10 where we compute the value that agents would pay to resolve parameter uncertainty *without* ending the on-going pandemic.

For both values of EIS the numbers are again extremely high, and for the low EIS case they are even higher than in the previous table. Apparently, in this economy, low-EIS agents would pay dearly for early resolution of uncertainty. The source of the extreme welfare loss in this case is the endogenous consumption response. Recall that low-EIS agents cut their consumption during a pandemic. With parameter uncertainty this response becomes extreme because agents cannot rule out the worst case scenario that $\lambda \sim 0$, i.e., that there will be no vaccine and the pandemic effectively lasts forever. This possibility leads to extreme savings and, consequently, little utility flow from consumption.

Even with high EIS however, the effect of parameter uncertainty is economically large,

and is again due to agents being unable to rule out worst-case scenarios. From a policy perspective, the implication of this finding is that, while working to end the current pandemic is enormously valuable, equally and perhaps even more valuable is anything that resolves uncertainty about the frequency and, especially, the duration of current and future pandemics. In addition to developing potential cures and vaccines, understanding the fundamental science behind the fight against viral pathogens and investing in the infrastructure for future responses can provide crucial gains to welfare.

# 7 Conclusion

This paper provides an estimate of the value of reducing the expected duration of a pandemic using the joint behavior of stock prices and a novel vaccine progress indicator based on the chronology of stage-by-stage advance of individual vaccine candidates and related news during 2020. In the context of a general equilibrium regime-switching model of repeated pandemics, the sensitivity of the stock market to vaccine progress indicator is essentially determined by the expected rate of loss (or lower growth rate) of wealth during a pandemic. Our empirical estimate can thus be translated into an implied welfare gain attributable to reverting to the non-pandemic state. With standard preferences parameters, this gain is approximately 5-15% of wealth, depending on the expected remaining duration of the pandemic. This number can also be interpreted as a measure of the expected cost of the pandemic.

We extend the model to endogenize vaccine research and show that our results are robust to this generalization. We also endogenize the degree of pandemic severity by including labor choice, which affects agents' exposure to the virus. When agents do not internalize the effect of their exposure choice on the economy's overall exposure, the cost of the pandemic rises relative to central planning. The socially optimal lockdown policy lessens the welfare improvement due to exiting the pandemic.

We also show that the cost rises sharply when there is uncertainty about the stochastic parameters governing the frequency and duration of pandemics. Indeed, we find that the representative agent would be willing to pay as much for resolution of this parameter uncertainty as for resolving the pandemic itself. An important policy implication is that understanding the fundamental biological and social determinants of future pandemics, for instance, whether pandemics are related to zoonotic diseases triggered more

frequently by climate change, may be as important to mitigating their economic impact as resolving an immediate pandemic-induced crisis.

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## Table 1: Forecast Comparison

| | *Deutsche Bank* | | |
|---|---|---|---|
| Date | Survey median | VPI | % respondents below |
| May | 1.158 | 0.958 | 35.0 |
| June | 1.162 | 0.893 | 31.2 |
| July | 0.920 | 0.595 | 20.8 |
| Sep | 0.625 | 0.561 | 44.3 |
| | *Superforecasters* | | |
| Date | Survey median | VPI | % respondents below |
| April | 1.902 | 1.291 | 16.1 |
| May | 1.603 | 0.958 | 14.6 |
| June | 1.189 | 0.893 | 31.0 |
| July | 0.808 | 0.595 | 32.7 |
| August | 0.519 | 0.606 | 58.4 |
| September | 0.445 | 0.518 | 57.2 |

**Note:** Table compares forecasts for the earliest date of vaccine availability in years. The top panel compares the median from a survey conducted by Deutsche Bank, while the bottom panel compares the median from a survey conducted by Good Judgement Inc. The column VPI denotes the forecast from our estimated vaccine progress indicator, and the last column reports the percent of respondents from each survey with forecasts below ours. Survey respondents are reported in calendar intervals. The comparison assumes a uniform distribution of forecasts in time within the median bin. The survey dates are as of the end of the month in the first column, except the Deutsche Bank September survey which is for the week ending September 11, 2020.

## Table 2: Stock Market Sensitivity to Vaccine Progress

| | (1) OLS | (2) KPSS (Prior 1) | (3) KPSS (Prior 2) |
|---|---|---|---|
| $\gamma_1$ | -0.070 | -0.088 | -0.096 |
| | (0.067) | (0.035) | (0.035) |
| $\gamma_2$ | 0.131 | 0.163 | 0.168 |
| | (0.092) | (0.035) | (0.035) |
| $\beta_{t-2}$ | 1.316 | -0.536 | -0.382 |
| | (1.526) | (0.423) | (0.290) |
| $\beta_{t-1}$ | -4.124 | -1.924 | -1.269 |
| | (3.121) | (0.746) | (0.586) |
| $\beta_t$ | -1.100 | -0.942 | -0.991 |
| | (0.739) | (0.592) | (0.606) |
| $\beta_{t+1}$ | 0.719 | -0.517 | -0.432 |
| | (2.054) | (0.412) | (0.342) |
| $\beta_{t+2}$ | -5.404 | -2.446 | -1.011 |
| | (1.729) | (0.760) | (0.458) |
| $\alpha$ | 0.204 | 0.240 | 0.279 |
| | (0.097) | (0.079) | (0.078) |
| $\sum_{h=-2}^{2} \beta_{t+h}$ | -8.593 | -6.365 | -4.086 |
| | (0.653) | (1.345) | (1.056) |
| N | 206 | 206 | 206 |

**Note:** Table shows the results from regression (1). The dependent variable is daily excess returns on the market portfolio in percent. Independent variables include two lags of excess returns on the market portfolio, a five-day window of changes in vaccine progress indicator in years, and dummy variables for each jump date from Baker et al. (2020) unrelated to news about vaccine progress. The return on the value-weighted CRSP index is used from January 1, 2020 to October 31, 2020. All columns are employ the baseline specification with news applying to all states, deterministic depreciation, base copula correlation of 0.2, probability of success in the application state equal to 0.95 and excludes candidates from China and Russia. Column 1 estimates the regression using OLS. Columns 2 and 3 employ the methodology of Kogan et al. (2017) and assume the pre-truncated normal distribution for $\beta_t$ has standard deviation equal to 1. Column 2 further uses the same prior for all response coefficients, while column 3 uses a pre-truncated standard deviation of 0.7 for the first lead and lag and 0.5 for the second lead and lag. OLS results display Newey-West standard errors with four lags in parentheses and standard deviation of the $F$-statistic on $\sum_{h=-2}^{2} \beta_{t+h}$. KPSS results show posterior standard deviations in parentheses.

## Table 3: Stock Market Sensitivity to Vaccine Progress – Robustness

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| News | All states | None | Current state | All states | All states | All states |
| Depreciation | Y | N | Y | Y | Y | Y |
| Cor$(n,n')$ | 0.2 | 0.2 | 0.2 | 0.4 | 0.2 | 0.2 |
| $\pi^{\text{base}}_{\text{approval}}$ | 0.95 | 0.95 | 0.95 | 0.95 | 0.85 | 0.95 |
| Ex-China and Russia | Y | Y | Y | Y | Y | N |
| $\gamma_1$ | -0.070 | -0.067 | -0.068 | -0.075 | -0.073 | -0.080 |
| | (-1.04) | (-1.01) | (-1.02) | (-1.10) | (-1.08) | (-1.50) |
| $\gamma_2$ | 0.131 | 0.116 | 0.127 | 0.131 | 0.134 | 0.111 |
| | (1.43) | (1.32) | (1.42) | (1.42) | (1.46) | (1.37) |
| $\beta_{t-2}$ | 1.316 | 2.389 | 1.543 | 1.275 | 0.959 | 1.980 |
| | (0.86) | (1.07) | (0.90) | (0.73) | (0.63) | (1.19) |
| $\beta_{t-1}$ | -4.124 | -5.400 | -3.168 | -3.566 | -3.927 | -5.331* |
| | (-1.32) | (-1.36) | (-1.21) | (-1.16) | (-1.31) | (-1.80) |
| $\beta_t$ | -1.100 | -0.570 | -1.046 | -1.185 | -1.157 | 1.084 |
| | (-1.49) | (-0.50) | (-1.41) | (-1.57) | (-1.56) | (0.78) |
| $\beta_{t+1}$ | 0.719 | 2.085 | 1.112 | 0.807 | 0.600 | -0.696 |
| | (0.35) | (0.79) | (0.59) | (0.43) | (0.30) | (-0.44) |
| $\beta_{t+2}$ | -5.404*** | -7.310*** | -5.189*** | -4.872*** | -5.057*** | -4.171 |
| | (-3.13) | (-4.30) | (-3.65) | (-2.84) | (-2.72) | (-1.61) |
| $\alpha$ | 0.204** | 0.195* | 0.226** | 0.220** | 0.203** | 0.210** |
| | (2.11) | (1.94) | (2.28) | (2.27) | (2.11) | (2.14) |
| $\sum_{h=-2}^{2}\beta_{t+h}$ | -8.593 | -8.806 | -6.746 | -7.541 | -8.582 | -7.134 |
| $F$-stat (P-value) | 8.21 (0.00) | 5.50 (0.02) | 5.37 (0.02) | 5.52 (0.02) | 8.62 (0.00) | 3.69 (0.06) |
| N | 206 | 206 | 206 | 206 | 206 | 206 |

**Note:** Table shows the results from (1). The dependent variable is daily percent excess returns on the market portfolio. Independent variables include two lags of excess returns on the market portfolio, a five-day window of changes in vaccine progress indicator in years, and dummy variables for each jump date from Baker et al. (2020) unrelated to news about vaccine progress. The first column is the baseline specification with news applying to all states, deterministic depreciation, base copula correlation of 0.2, probability of success in the application state equal to 0.95 and excludes candidates from China and Russia. Column 2 removes news and depreciation; 3 restricts news to the current state and increases the $\Delta\pi$ from news on positive data releases, positive enrollment and dose starts to 15%, 5% and 5%, respectively; 4 doubles the base copula correlation to 0.4; 5 decreases the probability of success to 0.85 in the application state; and 6 includes candidates from China and Russia. The return on the value-weighted CRSP index is used from January 1, 2020 to October 31, 2020. The table uses Newey-West standard errors with 4 lags; $t$-statistics are shown in parentheses. Significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## Table 4: Parameter Values

| Parameter | Symbol | Value |
|---|---|---|
| Coefficient of relative risk aversion | $\gamma$ | 4.0 |
| Elasticity of intertemporal substitution | $\psi$ | 1.5 |
| Rate of time preference | $\rho$ | 0.04 |
| Non-pandemic expected output growth | $\mu(0)$ | 0.055 |
| Non-pandemic output volatility | $\sigma(0)$ | 0.05 |

**Note**: Table shows the preference and non-pandemic parameter values used in inferring the welfare benefit $V$ from the stock market reaction to vaccine progress.

## Table 5: Welfare Gain as a Function of Reduction in Expected Duration

| | $T2$: EXPECTED DURATION AFTER INTERVENTION (YEARS) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 3.50 | 3.00 | 2.50 | 2.00 | 1.50 | 1.00 | 0.50 | 0 |
| $T1$: INITIAL EXPECTED DURATION | | | | | | | | |
| 4.00 | 1.98 | 3.95 | 5.93 | 7.92 | 9.90 | 11.88 | 13.85 | 15.82 |
| 3.50 | - - | 2.02 | 4.04 | 6.06 | 8.08 | 10.10 | 12.12 | 14.13 |
| 3.00 | - - | - - | 2.06 | 4.13 | 6.19 | 8.25 | 10.31 | 12.36 |
| 2.50 | - - | - - | - - | 2.11 | 4.21 | 6.32 | 8.42 | 10.51 |
| 2.00 | - - | - - | - - | - - | 2.15 | 4.30 | 6.45 | 8.59 |
| 1.50 | - - | - - | - - | - - | - - | 2.20 | 4.39 | 6.58 |
| 1.00 | - - | - - | - - | - - | - - | - - | 2.24 | 4.48 |
| 0.50 | - - | - - | - - | - - | - - | - - | - - | 2.29 |

**Note**: The table shows the percentage of wealth that the representative would be willing to trade for an intervention that shortens the pandemic from an initial expected duration of $T1$ years to another state with $T2 < T1$ years remaining in expectation. The pandemic parameters are $S = 9, \eta = 0.03, \lambda = 0.25, \chi = 0.0475$, and $\zeta = 1$.

## Table 6: Endogenous Pandemic Parameters via Labor

| | $\ell^\star$ | | | | $\Delta m_Q$ | | |
|---|---|---|---|---|---|---|---|
| | $K \rightarrow$ | | | | $K \rightarrow$ | | |
| $\varepsilon \downarrow$ | 0.8471 | 0.8204 | 0.7959 | $\varepsilon \downarrow$ | 0.0517 | 0.0577 | 0.0636 |
| | 0.7885 | 0.7651 | 0.7435 | | 0.0509 | 0.0565 | 0.0619 |
| | 0.7357 | 0.7151 | 0.6960 | | 0.0503 | 0.0555 | 0.0605 |
| | 0.6880 | 0.6698 | 0.6529 | | 0.0497 | 0.0546 | 0.0593 |

**Note:** Table shows the implied values of equilibrium labor, $\ell^\star$, and decline in expected growth rate of $q$ in pandemic states, $\Delta m_Q$, by fixing the elasticity of expected output with respect to labor $\alpha = 0.5$, exposure to the pandemic unrelated to labor $k = 0.006$, intensity of switching to the pandemic state $\eta = 0.04$, and intensity of switching to the non-pandemic state $\lambda = 0.5$. Each panel varies the exposure to the pandemic via private labor, $\varepsilon$, and via aggregate labor, $K$. $\varepsilon$ increases down the rows and takes the values 0.023, 0.024, 0.025 and 0.026, while $K$ increases left-to-right across columns and takes the values 0.018, 0.024 and 0.030.

## Table 7: Externality and Welfare Gain

| | $\ell^\star_{cp}/\ell^\star$ | | | | $V_{cp}/V$ | | |
|---|---|---|---|---|---|---|---|
| | $K \rightarrow$ | | | | $K \rightarrow$ | | |
| $\varepsilon \downarrow$ | 0.3762 | 0.2994 | 0.2450 | $\varepsilon \downarrow$ | 0.8661 | 0.8167 | 0.7725 |
| | 0.3860 | 0.3083 | 0.2530 | | 0.8777 | 0.8309 | 0.7884 |
| | 0.3957 | 0.3170 | 0.2609 | | 0.8882 | 0.8438 | 0.8031 |
| | 0.4049 | 0.3256 | 0.2686 | | 0.8975 | 0.8555 | 0.8165 |

**Note:** The left panel provides a direct measure of the scale of the externality via the ratio of the central planner's solution for optimal labor in the pandemic to that actually chosen by agents. The right panel shows the ratio of $V$ as determined by the central planner to that chosen by agents. Both fix the elasticity of expected output with respect to labor $\alpha = 0.5$, exposure to the pandemic unrelated to labor $k = 0.006$, intensity of switching to the pandemic (non-pandemic) state $\eta = 0.4$ ($\lambda = 0.5$). Exposure to the pandemic via private labor, $\varepsilon$, increases down to rows and takes values $\{0.023, 0.024, 0.025, 0.026\}$. Exposure via aggregate labor, $K$, increases left-to-right and takes values $\{0.018, 0.024, 0.030\}$.

## Table 8: Welfare Gain under Parameter Uncertainty

| | Low Uncertainty / Low EIS | | | |
|---|---|---|---|---|
| | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.242 | 0.114 | 0.058 |
| | 0.05 | 0.192 | 0.102 | 0.055 |

| | Low Uncertainty / High EIS | | | |
|---|---|---|---|---|
| | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.242 | 0.116 | 0.058 |
| | 0.05 | 0.185 | 0.102 | 0.055 |

| | High Uncertainty / Low EIS | | | |
|---|---|---|---|---|
| | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.633 | 0.613 | 0.558 |
| | 0.05 | 0.456 | 0.479 | 0.477 |

| | High Uncertainty / High EIS | | | |
|---|---|---|---|---|
| | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.379 | 0.302 | 0.222 |
| | 0.05 | 0.256 | 0.222 | 0.186 |

**Note:** Table shows the fraction of wealth the agent would be willing to surrender for a one-time transition out of the pandemic state. High (low) EIS sets $\psi = 1.5$ ($\psi = 0.15$). Agents know the parameters $\lambda$ and $\eta$ in low uncertainty, and in high uncertainty have posterior standard deviation equal to their point estimates of them. All use coefficient of relative risk aversion $\gamma = 4$, rate of time preference $\rho = 0.04$, elasticity of expected output with respect to labor $\alpha = 0.5$, output volatility $\sigma = 0.05$, expected output growth $\mu = 0.05$, and exposure to the pandemic via private labor $\varepsilon = 0.4$, unrelated to labor $k = 0.1$, and via aggregate labor $K = 0.4$, and $P_t$ intensity $\zeta = 1$.

## Table 9: Value of Eliminating Pandemics

| | Low Uncertainty / Low EIS | | | | Low Uncertainty / High EIS | | | |
|---|---|---|---|---|---|---|---|---|
| | | $\hat{\lambda}$ | | | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.308 | 0.136 | 0.068 | 0.01 | 0.327 | 0.148 | 0.074 |
| | 0.05 | 0.430 | 0.214 | 0.111 | 0.05 | 0.429 | 0.239 | 0.130 |
| | High Uncertainty / Low EIS | | | | High Uncertainty / High EIS | | | |
| | | $\hat{\lambda}$ | | | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.813 | 0.720 | 0.613 | 0.01 | 0.503 | 0.378 | 0.265 |
| | 0.05 | 0.831 | 0.751 | 0.658 | 0.05 | 0.538 | 0.435 | 0.335 |

**Note:** Table shows the fraction of wealth the agent would exchange to live in a world with no pandemics. High (low) EIS sets $\psi = 1.5$ ($\psi = 0.15$). Agents know the parameters $\lambda$ and $\eta$ in low uncertainty, and in high uncertainty have posterior standard deviation equal to their point estimates of them. All use coefficient of relative risk aversion $\gamma = 4$, rate of time preference $\rho = 0.04$, elasticity of expected output with respect to labor $\alpha = 0.5$, output volatility $\sigma = 0.05$, expected output growth $\mu = 0.05$, and exposure to the pandemic via private labor $\varepsilon = 0.4$, unrelated to labor $k = 0.1$, and via aggregate labor $K = 0.4$, and $P_t$ intensity $\zeta = 1$.

## Table 10: Value of Information

| | Low EIS | | | | High EIS | | | |
|---|---|---|---|---|---|---|---|---|
| | | $\hat{\lambda}$ | | | | $\hat{\lambda}$ | | |
| | | 0.2 | 0.5 | 1.0 | | 0.2 | 0.5 | 1.0 |
| $\hat{\eta}$ | 0.01 | 0.733 | 0.675 | 0.587 | 0.01 | 0.270 | 0.273 | 0.209 |
| | 0.05 | 0.708 | 0.682 | 0.617 | 0.05 | 0.200 | 0.255 | 0.236 |

**Note:** Table shows the fraction of wealth the agent would be willing to surrender for a one-time transition from high to low parameter uncertainty. High (low) EIS sets $\psi = 1.5$ ($\psi = 0.15$). Agents know the parameters $\lambda$ and $\eta$ in low uncertainty, and in high uncertainty have posterior standard deviation equal to their point estimates of them. All use coefficient of relative risk aversion $\gamma = 4$, rate of time preference $\rho = 0.04$, elasticity of expected output with respect to labor $\alpha = 0.5$, output volatility $\sigma = 0.05$, expected output growth $\mu = 0.05$, and exposure to the pandemic via private labor $\varepsilon = 0.4$, unrelated to labor $k = 0.1$, and via aggregate labor $K = 0.4$, and $P_t$ intensity $\zeta = 1$.