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ABSTRACT

COVID-19's economic damage depends nonlinearly on a vaccine arrival rate and other forms of costly mitigation in the interim. We derive and estimate a parsimonious damage function using timely measures of expected damage given by revisions of industry-level earnings forecasts. We propose identifying restrictions related to forecast rationality that allow for estimation using nonlinear least squares. Forecast revisions in mid-May 2020 imply an earnings crash in excess of -50% and no earnings growth until a vaccine arrives, which is expected in 0.74 years. Similar estimates are obtained using a subsample of levered or face-to-face industries. We extend our framework to account for time-varying vaccine arrival rates and damages.

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1 Introduction

Damage to the economy from a pandemic depends on the arrival of a vaccine and other forms of costly mitigation in the interim. In the vast epidemiology literature, optimal mitigation typically entails quickly implementing vaccination programs (Anderson and May (1992), Bailey et al. (1975)). To the extent that vaccination takes time or is uncertain, other types of costly mitigation such as quarantines or social distancing are used (Wickwire (1977), Behncke (2000)). This perspective is also adopted in recent models of economic damage from COVID-19 (Kruse and Strack (2020), Alvarez, Argente, and Lippi (2020), Acemoglu, Chernozhukov, Werning, and Whinston (2020)).

While this recent work captures more richness in terms of externalities and markets, their economic damage functions are similar to earlier epidemic models. For instance, a social planner (Eichenbaum, Rebelo, and Trabandt (2020)) or firms (Hong, Wang, and Yang (2020)) take into account when a vaccine will arrive in deciding optimal mitigation that comes at the expense of earnings in the interim.[1] When the vaccine arrives, these costs no longer need to be paid and there is an upward jump in earnings.

However, estimating this damage function is challenging for a few reasons. First, it can involve many parameters. Second, it is inherently nonlinear in key parameters such as the expected vaccine arrival. Third, estimating nonlinear models requires more and timelier data of expectations regarding economic damages. That is, estimating nonlinear damage functions using ex-post outcomes on GDP observed annually will be challenging from a power perspective.

To this end, we develop a parsimonious tractable continuous-time regime-switching model of firm earnings with just a few parameters: vaccine arrival rate, jump in earnings (both on pandemic impact and reflation upon vaccine arrival), and the ratio of growth rates across normal (or non-pandemic) versus pandemic regimes. Firm earnings are assumed to follow a log-normal process in the absence of jumps (Black and Scholes (1973), Merton (1974),

[1] Andersen, Hansen, Johannesen, and Sheridan (2020) and Farboodi, Jarosch, and Shimer (2020) also point to the importance of voluntary mitigation by households who stop consuming even in advance of government-imposed lockdowns.

Leland (1994)), and the arrival of vaccines is assumed to follow a time-homogeneous Poisson process (Arnold, Galloway, McNicholas, and O'Hallahan (2011), Lee, Norman, Assi, Chen, Bailey, Rajgopal, Brown, Wiringa, and Burke (2010), Ball and Sirl (2018)).

We derive a tractable expectations formula that relates earnings forecast revisions from just before the pandemic arrival to just after its arrival to these underlying parameters and several independent variables (i.e., a closed-form damage function). We fit our nonlinear model to timely measures of expected damage to firm earnings using revisions of industry-level consensus earnings forecasts made by security analysts. Security analyst forecasts should integrate not only scientific evidence on the development of effective vaccines but also logistical issues surrounding their distribution as well as macroeconomic consequences to consumers and firms. Plentiful timely data on these forecasts allow for precise estimates of these parameters.

Broadly, the vaccine arrival rate moderates the persistence of the COVID-19 shock to earnings. To the extent an effective vaccine is expected to arrive quickly, the shock should be mostly felt in short-term as opposed to medium-term or long-term earnings forecasts. Hence, we can infer from the revision of forecasts of different horizons the parameters of the earnings process taking into account the effects of COVID-19.

The structure of our model points to a natural set of identifying restrictions related to forecast rationality that allow for estimation using nonlinear least squares (NLS). If forecasts are rational, i.e., they take into consideration the key variables of our analysis in their information set (Nordhaus (1987), Keane and Runkle (1998)), then NLS can retrieve consistent parameter estimates.

But forecasts can be boundedly rational or systematically biased for different reasons (Coibion and Gorodnichenko (2012), Laster, Bennett, and Geoum (1999), Hong and Kubik (2003)). We show that as long as the ratio of these biases across forecast horizons is uncorrelated with our independent variables, then consistent parameter estimates can still be retrieved using NLS. We argue below that this exclusion restriction is plausible. Indeed, industry-level forecast revisions following COVID-19 in mid-May 2020 seem well-calibrated as they are highly correlated with cross-sectional industry stock price reactions to COVID-19

(Landier and Thesmar (2020)).

We associate a medical intervention that returns the economy to normal as being a vaccine since the bulk of the government funding in the US and Europe have been for its development.[2] Nonetheless, our regime-switching model can be applied to other countries where it might be the arrival of therapeutics or testing that returns these countries to normal. For instance, rigorous testing has played a bigger role in Asian countries.[3]

In our empirical work, our main dependent variable is the revision of earnings forecasts after the arrival date of COVID-19 in the US, which we take to be February 20, 2020. To reduce measurement error, we work with industry portfolios by value-weighing median forecasts for stocks at the GICS 8-digit industry classification. To be conservative and to allow forecasts to be fully revised, we use May 2020 as our forecast date.[4]

The main independent variables from our theory are the horizon of the earnings forecasts and the earnings growth rates in the non-pandemic and pandemic regimes. The horizon of earnings forecasts is straightforward to measure. For our baseline specifications, we pool together both industry FY1 (nearest next fiscal year-end), FY2, FY3, FY4 and FY5 (farthest fiscal year-end) forecasts made in May of 2020. We measure the growth rate in the non-pandemic regime using analysts' growth rate forecasts on January of 2020 and also aggregate these to the industry level. That is, our specification assumes that growth rates return to non-pandemic levels after the arrival of a vaccine.

Our model allows us to simultaneously infer not just the vaccine arrival rate but also disentangle jumps in earnings due to mitigation from the growth rate effects in a pandemic regime. We have the following estimates using forecast revisions in May 2020. The vaccine arrival rate λ is 1.354 with a 95% bootstrap confidence interval of [0.78, 1.71]. This implies that a vaccine is expected in $1/\lambda = 0.74$ years as of mid-May 2020. This estimate is robust

[2] According to Bloomberg News article "Trump administration dips into protective gear, CDC funds to fund vaccine push" (September 23, 2020), the Warp Speed budget is as large as $18 billion and almost all of it allocated to vaccine developments (Moderna, Sanofi, GSK, Pfizer, Novavax, J&J and AstraZeneca) and only a small amount toward therapeutics (Regeneron's antibody cocktail).

[3] Another medical scenario that returns the economy to normal is herd immunity. But this possibility does not seem likely given limited evidence on the length of individual immunity.

[4] There is naturally a lag in analyst revisions and we only begin to see some revisions starting in April and then most of the forecasts have been revised by May of 2020.

to different cuts of the data such as how much to weigh FY4 and FY5 in our sample since these further out forecasts are less populated compared to FY1-FY3. The initial jump in earnings corresponds to costly mitigation measures (e.g. social distancing) meant to keep the virus at bay. The jump in earnings following the arrival of COVID-19 is given by e^{-n}. The coefficient n is 2.022 with a 95% bootstrap confidence interval of $[0.99, 4.1]$. This statistically significant estimate of n implies around a negative 80% jump in earnings level. Our growth rate estimate is sensitive to how we weigh further out forecasts, but typically the ratio of the growth rate in the pandemic regime to the non-pandemic regime is low to negative.

Using likelihood ratio tests, we reject the constrained model where $\lambda = 0$ (i.e., there is no vaccine or a vaccine is expected to arrive in an infinite number of years) in favor of the unconstrained model. We also reject the constrained model where $g = 1$ (i.e., there is no damage to growth rates) in favor of our unconstrained model. That is, short-run growth rates in the pandemic regime absent a vaccine are severely impacted. These findings complement the literature on damage to short-run earnings growth (Gormsen and Koijen (2020), Giglio, Maggiori, Stroebel, and Utkus (2020)) but not necessarily the literature on long-run damage due to government intervention (Elenev, Landvoigt, and Van Nieuwerburgh (2020)).

To gain an intuition for our unconstrained model, consider the plot in Figure 4 of consensus earnings forecasts issued in the middle of May 2020 deflated by the consensus earnings forecasts before COVID-19 in the middle of January 2020. We can see that the FY1 forecast within twelve months before forecast end are significantly revised down: 54% on average across the 130 8-digit GICS industries in our sample. This is consistent with a significant negative jump on average in our model. But we can also see that the FY2 forecasts farther out are not nearly as impacted. If an effective vaccine is expected to arrive far out in the future, then analyst revisions will be large for both near term (FY1) and longer term forecasts (FY2, FY3, FY4 and FY5). That is, there is effectively a permanent downward jump in earnings followed by a different pandemic regime growth rate than the one in the non-pandemic regime. In contrast, if analysts expect a vaccine in a year, then the FY2 forecasts will be revised down much less in comparison to FY1. The only other way potentially to reconcile the data is to have the pandemic growth rates be counterfactually much higher than the non-pandemic growth rates. But in fact our estimate is for a lower pandemic growth rate. In other words, the anticipated reflation of earnings conditioned on a vaccine arrival will make it appear that growth rates in the pandemic regime, when comparing FY1 versus longer-term forecasts (e.g. FY2 or FY3), are unrealistically high.

We consider several robustness exercises. Earlier work suggests that levered or face-to-face (Montenovo, Jiang, Rojas, Schmutte, Simon, Weinberg, and Wing (2020)) industries are particularly hit by COVID-19. Hence, these industries ought to be the most informative for the COVID-19 earnings damage function. To this end, we re-estimate our model using a subsample of levered or face-to-face industries. We retrieve a similar damage function as that of based on the overall sample. Since the vaccine arrival rate is the same for these hardest hit industries as for the overall sample, this means that the rollout of the vaccine will not be preferentially based on business interest groups despite speculation in the media.[5]

Another way to demonstrate the sensibility of our model and estimates is to present a placebo exercise whereby we conduct exactly the same empirical analysis but using data from 2019. As we expect, we estimate that the arrival rate of a vaccine is zero, growth rates are unimpaired and there is no jump in the earnings level using this placebo sample.

Finally, we then extend our model to account for a time-varying damage function due to vaccine news. This extension then allows us to draw inferences using the June, July, and August 2020 forecasts (the latest data we have available on IBES). The only caveat to this analysis is that as we move increasingly further away from when COVID-19 hit, estimates of the damage function become increasingly less precise.

To this end, we develop a vaccine model in which the vaccine arrives after two jumps. We can interpret the two jumps as stages in the vaccine development process. The first stage is the news arrival stage. For instance, the first stage corresponds to basic analysis on whether COVID-19 is a difficult virus to find a vaccine such as HIV or an easy one. The second stage is the actual development of the particular treatment. After the end of the first stage, news arrives, which can be either good or bad. In either case, investors become better informed

[5]J. David Goodman and Luis Ferre-Sadurni, "Big fight breaks out over which interest groups get vaccine first," *NYTIMES*, December 20, 2020.

about the rate at which effective vaccines arrive.

Then using our May 2020 estimates for the jump in earnings and latent growth rates, we re-estimate the vaccine arrival rate using subsequent forecasts. Differences in arrival rates from our baseline May 2020 estimates represent news. The arrival rates estimated in June and July are identical to those estimated in May. However, the August 2020 forecasts imply a higher vaccine arrival rate: a vaccine is expected in 4 months, or early 2021. In other words, our model's estimates indicate that there was good news on vaccines in the late summer and a lowering of expected damage, consistent with qualitative narratives in the stock market.[6]

Our estimates do not look overly optimistic given news on Pfizer, Moderna and AstraZeneca vaccine effectiveness in November 2020. This consistency alleviates concerns we might have regarding the exclusion restriction needed to estimate with NLS. But it remains to be seen if the vaccines are indeed effectively distributed by early 2021 and if the economy will return to normal then.

Our paper proceeds as follows. We present our model of earnings damage function and estimation strategy in Section 2. Section 3 describes the dataset and main variables. Estimates of our model are presented in Section 4. We extend the model to account for vaccine news in Section 5. We conclude in Section 6.

2 Model

We assume that the economy can be in one of the two regimes: the normal (or non-pandemic) and pandemic regimes. The economy starts in the normal regime. At stochastic time t_0, it unexpectedly enters into the pandemic regime. Afterwards, the pandemic becomes extinct and the economy returns back to the normal regime when a successful vaccine is developed at time τ, which occurs with probability λ per unit of time.

[6]See for instance *MarketWatch* article on August 24, 2020 entitled "COVID-19 vaccine hopes are driving the stock-market rally — here's how much".

2.1 Normal Regime

We let $\widehat{Y}_t$ denote the earnings (EBITDA) process of the asset in the normal regime. We assume that $\widehat{Y}_t$ follows a commonly used geometric Brownian motion (GBM) process:[7]

$$\frac{d\widehat{Y}_t}{\widehat{Y}_{t-}} = \widehat{g}dt + \rho\phi\, d\mathcal{B}_t + \sqrt{1-\rho^2}\,\phi\, d\mathcal{W}_t\,, \tag{1}$$

where $\mathcal{B}_t$ is the standard Brownian motion driving the "business-as-usual" aggregate risk and $\mathcal{W}_t$ is the standard Brownian motion driving the idiosyncratic earnings risk. By construction, $\mathcal{B}_t$ and $\mathcal{W}_t$ are orthogonal. In equation (1), $\widehat{g}$ is the expected earnings growth (drift) and ϕ is the volatility of earnings growth, which includes the aggregate component $\rho\phi$ and the idiosyncratic component $\sqrt{1-\rho^2}\,\phi$. That is, ρ is the correlation coefficient between the aggregate shock $\mathcal{B}_t$ and the asset's earnings. For simplicity, we let $\widehat{g}$, ϕ, and ρ all be constant.

2.2 Pandemic Regime

Next, we specify the impact of the *unexpected* pandemic arrival and the *anticipated* stochastic vaccine arrival. Let Y_t denote the asset's earnings process during the pandemic regime. Once in the pandemic regime ($t_0 < t < \tau$), the asset's earnings process Y_t follows:

$$\frac{dY_t}{Y_{t-}} = gdt + v\, d\mathcal{Z}_t + \rho\phi\, d\mathcal{B}_t + \sqrt{1-\rho^2}\,\phi\, d\mathcal{W}_t + (e^n - 1)\, d\mathcal{J}_t\,, \tag{2}$$

where $\mathcal{J}_t$ is a pure jump process and $d\mathcal{J}_t = 1$ if and only if the vaccine arrives.

There are four terms in equation (2). First, earnings will jump discretely by a fraction $(e^n - 1)$ at the moment of the vaccine arrival, i.e., when $d\mathcal{J}_t = 1$. This is to capture earnings reflation once the vaccine returns the economy to normal. (Absent vaccine arrival, $d\mathcal{J}_t = 0$). Second, the pandemic arrival changes the expected earnings growth rate from $\widehat{g}$ to g (leaving aside the effect of vaccine arrival.) Third, the pandemic shock $d\mathcal{Z}_t$ directly causes additional earnings growth volatility, v. Finally, as in the normal regime, earnings is subject to the

[7]The GBM process is widely used in asset pricing and corporate finance to model corporate earnings, e.g., Gordon growth model, capital structure models in the tradition of Black and Scholes (1973) and Merton (1974) and Leland (1994) models. While earnings is always positive in this formulation, we can generalize this model to allow for negative earnings. By assuming that a firm's earnings at the enterprise level (after we unlever the firm) follows a GBM earnings process, earnings for equity holders can be negative even when earnings for the enterprise is positive.

business-as-usual aggregate shock $d\mathcal{B}_t$ and idiosyncratic shock $d\mathcal{W}_t$ with volatility $\rho\phi$ and $\sqrt{1-\rho^2}\,\phi$, respectively. All shocks are orthogonal to each other.[8] For simplicity, we let n be constant and keep $\widehat{g}$, ϕ, and ρ the same as in the normal regime.

More generally, the growth rate g and earnings volatility v in the pandemic regime depend on the optimally mitigated infections in the economy. For simplicity, we model these parameters as constants with particular emphasis that g is expected to be less than $\widehat{g}$ due to the adverse direct effect of the pandemic.

2.3 Transition from Normal to Pandemic Regime

The arrival of COVID-19 triggers optimal mitigation in the form of foregone earnings. There is both a fixed and variable cost to mitigation that have to be paid out of earnings each period there is a pandemic. This unexpected but optimal corporate mitigation spending decreases its earnings. That is, as the COVID-19 shock unexpectedly hits at t_0, the earnings drops by a fixed fraction δ:

$$Y_{t_0} = Y_{t_0-}e^{-\delta}. \tag{3}$$

And at the moment of vaccine arrival, the earnings instantaneously increases by a fraction n from the pre-arrival time since mitigation costs no longer need to be paid as shown in equation (2):

$$Y_\tau = e^n Y_{\tau-}\,. \tag{4}$$

We further set $\delta = n$. That is, the percentage of earnings increase at the moment of vaccine arrival τ is equal to the percentage of earnings decrease at the moment of pandemic arrival time t_0. Consider the counter-factual case that helps us understand the mechanism: If $\lambda \to \infty$, we have $\tau- = t_0$. For this case, earnings is not impacted at all by the jumps as $Y_\tau = e^n Y_{\tau-} = e^n Y_{t_0} = e^n e^{-n} Y_{t_0-} = Y_{t_0-}$.

[8] The vaccine arrival process $\mathcal{J}_t$ is independent of $[\mathcal{W}_t, \mathcal{B}_t, \mathcal{Z}_t]^\top$, which is a 3×1 standard Brownian motion.

2.4 Linking Earnings Forecasts to Pandemics Damage Model

We can now relate earnings forecasts to our model. Recall that τ denotes the stochastic vaccine arrival time. Assuming that the consensus analyst forecast is being generated by our model, we have for t in the pandemic regime:

$$
\begin{aligned}
\frac{1}{Y_t}\mathbb{E}_t[Y_s] &= \int_t^s \lambda e^{-\lambda(\tau-t)} e^{g(\tau-t)} e^n e^{\widehat{g}(s-\tau)} d\tau + e^{-\lambda(s-t)} e^{g(s-t)} && (5)\\
&= \frac{\lambda}{\lambda - g + \widehat{g}} \left[e^{\widehat{g}(s-t)} - e^{(g-\lambda)(s-t)}\right] e^n + e^{(g-\lambda)(s-t)}\,. && (6)
\end{aligned}
$$

Recall that $\widehat{g}$ is the pre-COVID long-term growth (LTG) rate and g is the constant growth conditional on being in the COVID-19 regime. As we assume that there are only two regimes, normal and pandemic, the non-pandemic regime growth rate is the same as the post-pandemic regime growth rate. In a later section, we extend this formula to allow for these two rates to differ.

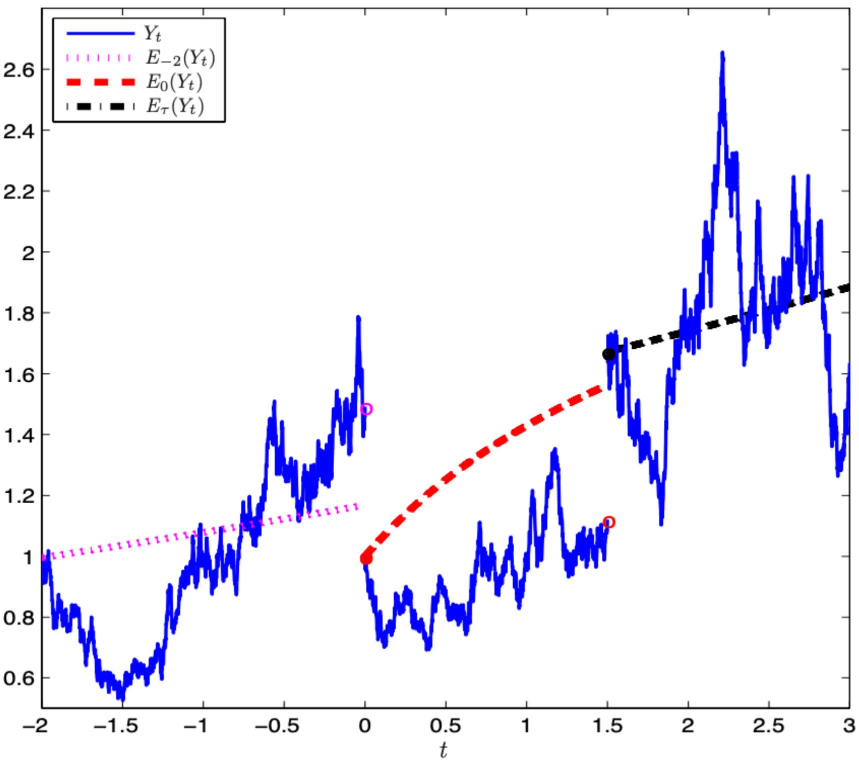
The first term of equation (5) is conditioned on a vaccine arriving in the interval between t and s. Inside the first term, the density of the stochastic vaccine arrival time τ is $\lambda e^{-\lambda(\tau-t)}$. Before the vaccine arrives (from t to τ) the cumulative (gross) growth is $e^{g(\tau-t)}$. After the vaccine arrives at τ in this interval (t, s), there is reflation of earnings by a multiple of e^n, i.e., $Y_\tau = e^n Y_{\tau-}$, and during the subsequent sub-period (τ, s), earnings growth reverts to the pre-COVID LTG rate $\widehat{g}$, which gives the cumulative (gross) growth is $e^{\widehat{g}(s-\tau)}$ from τ to s.

As a result, for a given $\tau \in (t, s)$, $\mathbb{E}_t[Y_s] = Y_t e^{g(\tau-t)} e^n e^{\widehat{g}(s-\tau)}$, which explains why the first term is the contribution to $\mathbb{E}_t[Y_s]/Y_t$ conditional on $\tau \in (t, s)$. The probability that a vaccine does not arrive in (t, s) is $e^{-\lambda(s-t)}$. If this is the case, the growth rate in (t, s) is g. Therefore, the second term gives the contribution to $\mathbb{E}_t[Y_s]/Y_t$ conditional on $\tau > s$. Adding the two terms together gives $\mathbb{E}_t[Y_s]/Y_t$ for any t in the pandemic regime.

Below in Figure 1, we provide a simulated path of earnings going through the non-pandemic, during-pandemic, and non-pandemic regimes. The plot starts with earnings at 0.98 at $t = -2$. The (continuously compounded) growth rate in the non-pandemic regime is set at $\widehat{g} = 8\%$ per annum. The pandemic unexpectedly arrives at time $t = t_0 = 0$, at which point earnings jumps downward from the magenta dot $Y_{t_0-} = 1.492$ to the red solid

Figure 1: Earnings Path and Expectation Calculations

The parameter values are: $n = \delta = 0.4$, $\widehat{g} = 0.08$, $g = .85 \times \widehat{g} = 0.068$, and $\lambda = 1.1$. Parameter values are annualized whenever applicable. $Y_{-2} = 0.98$. At time $t = 0$, earnings jumps from $Y_{t-} = 1.492$ to $Y_t = 1$. And at time $t = 1.5$, earnings jumps from $Y_{t-} = 1.120$ to $Y_t = 1.672$.



dot $Y_{t_0} = 1$ — which we have parameterized as a $\delta = 40\%$ drop. At $t = \tau = 1.5$, the vaccine arrives, earnings Y_t jumps upward by $n = \delta = 40\%$ from $Y_{\tau-} = 1.120$ (the red open dot) to $Y_\tau = 1.672$ (the black solid dot).

We set the vaccine arrival rate at $\lambda = 1.1$ per year (with an implied expected arrival time of around $1/\lambda = 0.9$ years, i.e., $\mathbb{E}_{t_0}(\tau - t_0) = 0.9$) after the unexpected arrival of the pandemic at t_0. The (conditional) growth rate in the pandemic regime, g, is set to be 0.85 times that of the pandemic regime, $\widehat{g}$, which means $g = \widehat{g} \times 0.85 = 8\% \times 8.5\% = 6.8\%$.

In addition to plotting a sample path, we also plot the expected earnings immediately after the pandemic arrival, $\mathbb{E}_0(Y_t)$ given the value of $Y_0 = 1$ at $t = 0$ (see the red dashed line). In contrast, if investors were naive ignoring vaccine arrival and using a constant expected earnings rate g forever, the expected earnings at $t = 0$ is then equal to $Y_0 e^{gt}$. The naive forecasts of Y_t is lower than $\mathbb{E}_0(Y_t)$ due to the assumption that $g \le \widehat{g}$ and earnings will jump by a fraction $(e^n - 1) > 0$ upon the vaccine arrival.

The magenta dotted line plots the expected earnings at $t = -2$ before the pandemic arrival. As the pandemic is unexpected, we have $\mathbb{E}_{-2}(Y_t) = Y_{-2}e^{\widehat{g}(t+2)} = Y_{-2}e^{0.08\times(t+2)}$. Similarly, the black dash dotted line plots expected earnings Y_t immediately after the arrival of the vaccine at time τ, which is given by $\mathbb{E}_\tau(Y_t) = Y_\tau e^{\widehat{g}(t-\tau)}$. That is, the earnings processes in the normal regimes (both before the pandemic arrival and after the vaccine arrival) are the same. Notice that the growth rate in the non-pandemic regime (the dotted black line) is equal to $\widehat{g}$, which is larger than the growth rate for the dashed red line (the pandemic regime.) Notice that the growth rate (anticipating stochastic vaccine arrival) in the pandemic regime is time-varying and smaller than that in the non-pandemic regime.

Now we calculate the expected earnings from t_0-, i.e., the moment that is just prior to the unexpected COVID-19 arrival time t_0. Substituting equation (3), $Y_{t_0}/Y_{t_0-} = e^{-\delta}$, into (6) and with $\delta = n$, we obtain[9]

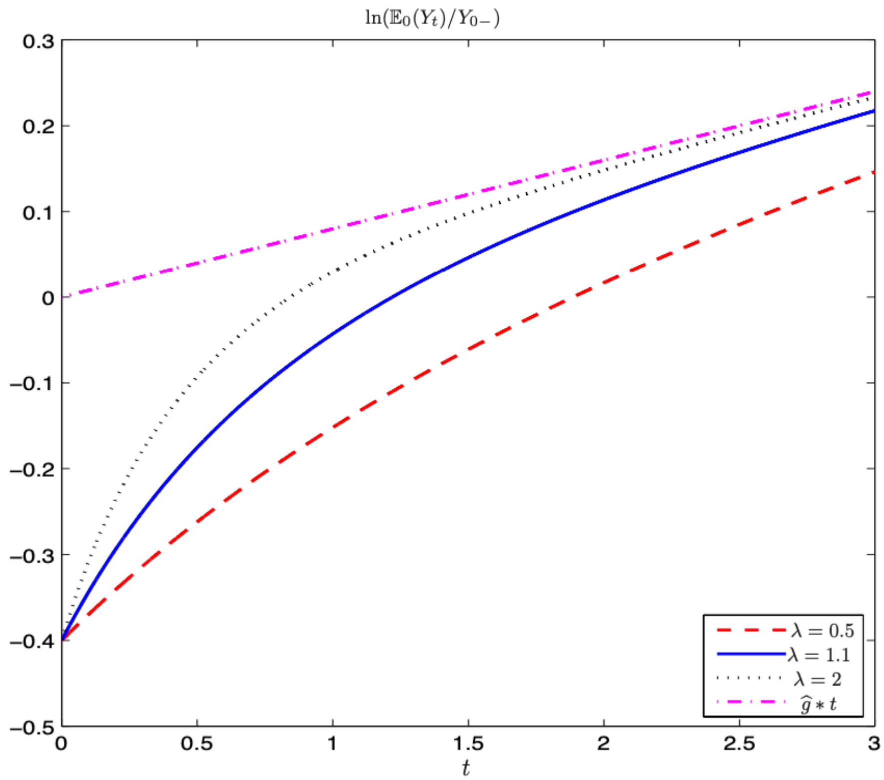
$$\frac{1}{Y_{t_0-}}\mathbb{E}_{t_0}[Y_s] = \frac{Y_{t_0}}{Y_{t_0-}}\frac{1}{Y_{t_0}}\mathbb{E}_{t_0}[Y_s] = \frac{\lambda}{\lambda - g + \widehat{g}}\left[e^{\widehat{g}(s-t_0)} - e^{(g-\lambda)(s-t_0)}\right] + e^{-n}e^{(g-\lambda)(s-t_0)}\,. \quad (7)$$

Figure 2 provides another way to understand the evolution of expectations across the normal and pandemic regimes. In this figure, we examine the effect of the vaccine arrival rate λ on $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$, the log of forecast revisions between $t = 0-$, the moment just before the pandemic arrives, and any time t subsequently. Compared with the counterfactual that the pandemic did not arrive and the business is then as usual (which means earnings grow at an expected rate of $\widehat{g}$ indefinitely, the earnings responses are naturally negative, meaning that $\mathbb{E}_0(Y_t) < Y_{0-}\,e^{\widehat{g}\,t}$. But because of the anticipated vaccine arrival and the economy eventually reverts to normal, earnings increase over time and approaches the long-run cumulative growth for logarithmic earnings, $\widehat{g}\,t = 0.08t$ (the magenta dash-dotted straight line). For all levels of λ, the forecast $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$ starts at the initial drop $\delta = -0.4$ at $t = 0$ and then increases over time due to anticipated vaccine arrival and eventually approaches the straight line, $\widehat{g}\,t = 0.08t$.

[9] As COVID-19 is unexpected, we calculate $\mathbb{E}_{t_0}[Y_s]$ from t_0, but divide the forecast by Y_{t_0-} for empirical measurement purposes.

Figure 2: The Effect of the Vaccine Arrival Rate λ on $\ln[\mathbb{E}_0(Y_t)/Y_{0-}]$

The forecast $\ln[\mathbb{E}_0(Y_t)/Y_{0-}]$ starts at $-\delta = -0.4$ at $t = 0$ and eventually converges to the business-as-usual scenario, depicted by the straight line $\widehat{g}\,t$ as $t \to \infty$. The higher the value of λ, the faster the convergence. The parameter values are: $n = \delta = 0.4$, $\widehat{g} = 0.08$, and $g = .85 \times \widehat{g} = 0.068$.



Intuitively, if an effective vaccine is expected to arrive far out in the future (lower λ), then forecast revisions will be large for both near term and longer term forecasts (the red dashed line) — that is there is effectively a permanent downward jump in earnings followed by a different pandemic regime growth rate than the one in the non-pandemic regime. In contrast, if we expect a vaccine in a year, then the longer-term forecasts will be revised down much less in comparison to the near-term forecasts.

Figure 3 examines the effect of the size of the jump n and pandemic growth rate g on the term structure of the forecast revision $\ln[\mathbb{E}_0(Y_t)/Y_{0-}]$. Take the blue line as the benchmark case, we implement two experiments to investigate how the shape of the term structure change with respect to different n and g.

First, the size of the initial jump is determined by n. As we change n from 0.4 to 0.8 (from the blue line to the red dashed line), we see a larger drop in $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$ in lower horizon compared to longer horizon. From an identification point of view, this observation implies that data in the shorter horizon are driving the identifiability of n since they are very informative about the initial jump in earnings.

Second, if we further change g to -1.2, we see that there are sizable drops in the level of the $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$ (black dotted line compared to the red dashed line) in all horizons. Moreover, the drop is smaller in the short horizon compared to the median and longer horizon. Therefore, the data with longer horizons can help us better identify g given the larger difference generated by the g parameter in the median and longer horizon.

2.5 Estimation

Using this insight from Figure 2, we take our model to data on analyst forecasts in the following manner. In reality, we do not observe analyst forecasts at t_0, which is the immediate moment after the pandemic arrival time. Instead, we observe forecasts at a later time, t. As such, we will employ the approximation $Y_t/Y_{t_{0-}} \approx Y_{t_0}/Y_{t_{0-}} = e^{-\delta}$ and assume $\delta = n$ to obtain the following relation:

$$\begin{aligned}\frac{1}{Y_{t_0-}}\mathbb{E}_t[Y_s] = \frac{Y_t}{Y_{t_0-}}\frac{1}{Y_t}\mathbb{E}_t[Y_s] \;&\approx\; e^{-\delta}\left[\frac{\lambda}{\lambda-g+\widehat{g}}\left[e^{\widehat{g}(s-t)}-e^{(g-\lambda)(s-t)}\right]e^{n}+e^{(g-\lambda)(s-t)}\right] \\ &=\; \frac{\lambda}{\lambda-g+\widehat{g}}\left[e^{\widehat{g}(s-t)}-e^{(g-\lambda)(s-t)}\right]+e^{-n}e^{(g-\lambda)(s-t)}. \end{aligned} \tag{8}$$

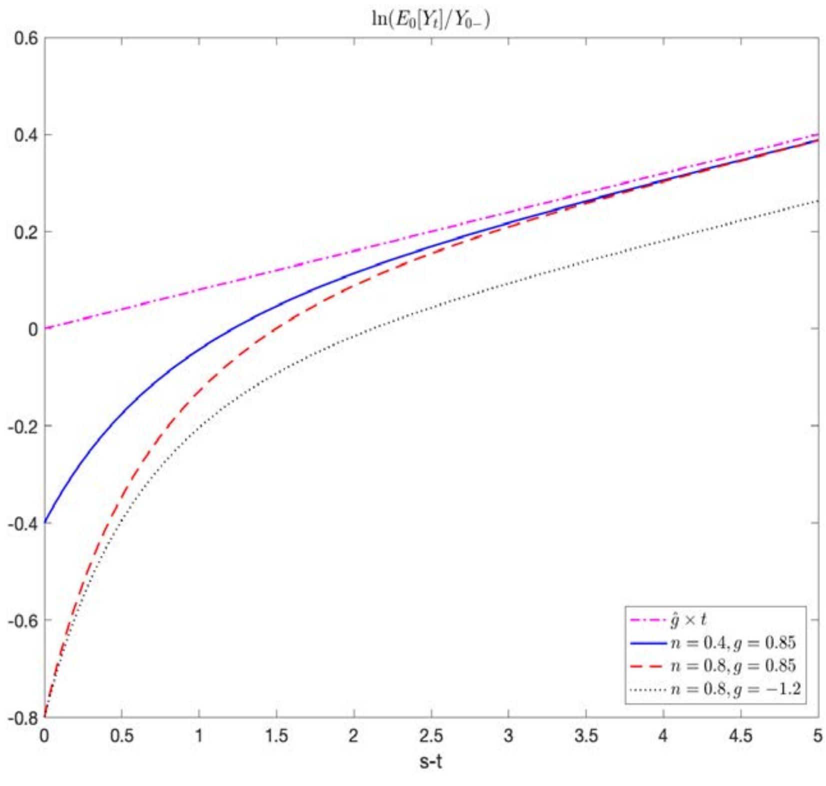
That is, we assume that the jump which in our model occurs over an instant takes place over the period from the end of February 20 to May 14 of 2020.

Moreover, we aggregate corporate earnings forecasts at the firm level up to the industry level, which we denote by j. The main dependent variable of interest given by the right side of equation (8) is constructed in the following manner. As Y_{j,t_0-} is not empirically observable, we measure Y_{j,t_0-} by using the earnings forecast expression before the arrival of COVID-19: $\mathbb{E}_{t_{0-}}[Y_{j,s}] = Y_{j,t_0-}e^{\widehat{g}^{(j)}(s-t_0)}$, where $\widehat{g}^{(j)}$ is the long-run growth rate in the non-pandemic regime, which as we discuss below is observable. Equivalently, we have

$$Y_{j,t_0-} = \exp\left[-\widehat{g}^{(j)}\cdot(s-t_{0-})\right]\cdot\mathbb{E}_{t_{0-}}[Y_{j,s}]\;. \tag{9}$$

Figure 3: The Effect of n and g on $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$

In this figure we present the forecast $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$ based on four sets of parameter values to show the sensitivity of the path to the jump parameter n and the pandemic growth rate parameter g. The other parameter values are: $\lambda = 1.1$, $\widehat{g} = 0.08$. The magenta line is the business-as-usual scenario. The blue solid line shows the path when $n = 0.4$ and $g = .85 \times \widehat{g} = 0.068$. The red dashed line shows the path when $n = 0.8$ and $g = .85 \times \widehat{g} = 0.068$. The black dotted line presents the path when $n = 0.8$ and $g = -1.2 \times \widehat{g} = -0.096$.



Using equations (8) and (9), and taking natural logs on both sides, we obtain the following relation that we take to data:

$$\ln\left[\frac{\mathbb{E}_t[Y_{j,s}]}{e^{-\widehat{g}^{(j)}(s-t_{0-})}\mathbb{E}_{t_0-}[Y_{j,s}]}\right] = \ln\left[\frac{\lambda}{\lambda - g^{(j)} + \widehat{g}^{(j)}}\left(e^{\widehat{g}^{(j)}(s-t)} - e^{(g^{(j)}-\lambda)(s-t)}\right) + e^{-n^{(j)}}e^{(g^{(j)}-\lambda)(s-t)}\right]. \tag{10}$$

We parameterize the earnings jump parameter $n^{(j)}$ for firms in industry j by

$$n^{(j)} = n_0, \tag{11}$$

The growth rate g for firms in industry j in the pandemic regime, $g^{(j)}$, is parameterized as

$$g^{(j)} = g_0 \cdot \widehat{g}^{(j)}\,. \tag{12}$$

That is, the growth rate in the pandemic regime $g^{(j)}$ is a multiple of $\widehat{g}^{(j)}$, the growth rate in the non-pandemic regime for firms in industry j. The ratio between the two growth rates, $g^{(j)}/\widehat{g}^{(j)}$, captures the average difference in growth rates across the two regimes.

Finally to estimate our model, we need to specify analyst forecast errors. Denote IBES forecast of industry j at t of horizon s by $f^s_{t,j}$. Suppose

$$f^s_{t,j} = \mathbb{E}_t[Y_{j,s}] \cdot u^s_{t,j}\,, \tag{13}$$

where $u^s_{t,j}$ is a mean one random variable that is conditionally independent of $\mathbb{E}_t[Y_{j,s}]$. Then, taking logs on both sides of (13) and then using (10) for $\mathbb{E}_t[Y_{j,s}]$, we obtain

$$\ln\left[\frac{f^s_{t,j}}{e^{-\widehat{g}^{(j)}(s-t_{0-})}f^s_{0-,j}}\right] = \ln\left[\frac{\lambda}{\lambda - g^{(j)} + \widehat{g}^{(j)}}(e^{\widehat{g}^{(j)}(s-t)} - e^{(g^{(j)}-\lambda)(s-t)}) + e^{-n^{(j)}}e^{(g^{(j)}-\lambda)(s-t)}\right] + \ln\left(\frac{u^s_{t,j}}{u^s_{0-,j}}\right) \tag{14}$$

Therefore, an identifying restriction allowing for estimation of equation (14) using non-linear least squares (NLS) (Cameron and Trivedi (2005)) is given by:

$$\mathbb{E}\left[\ln\left(\frac{u^s_{t,j}}{u^s_{0-,j}}\right)\middle| s-t, \widehat{g}^{(j)}\right] = 0\,. \tag{15}$$

Obviously, if forecasts are rational, i.e., forecast errors are white noise, then the exclusion restriction is satisfied. More generally, as long as the log difference of these biases across forecast horizons is uncorrelated with our independent variables, then consistent parameter estimates can still be retrieved using NLS.

This exclusion restriction is plausible. Intuitively, imagine if analyst forecasts were overly optimistic at 5 years out and overly-pessimistic say at 2 years out, then this can bias estimates of the vaccine arrival rate. We know of no obvious research to suggest that our exclusion restriction is unlikely. At the same time, our setting is unique in that we can also compare our estimates implied with forecast to subsequent actual outcomes. Presumably, biased estimates will not be very predictive or subsequent outcomes. But we show below that the vaccine arrival estimate is predictive.

2.6 Comments

The upside of our baseline set-up is parsimony. In practice, rather than assuming that a successful vaccine is a silver bullet that instantly brings the economy back to normal upon its arrival as in our baseline model, we may consider a more realistic setting where a successful vaccine development brings the economy back to normal in several stages over time. These stages might correspond to an increasing fraction of the population being vaccinated over time. For example, consider the following setting with N sequentially ordered stages, denoted by $\{S_1, \cdots, S_N\}$, in addition to the pandemic regime, which we denote by S_0. We assume that as the stage transitions from stage S_m to stage S_{m+1} at stochastic time τ_m, where $m = 0, \cdots, N-1$, at a constant rate of λ_m per unit of time, earnings jumps upward by a constant fraction $\delta_m > 0$. That is, $Y_{\tau_m} = Y_{\tau_m -} e^{\delta_m}$. We can compute the earnings forecast and other key objects in this more general model in closed form, but the model would be less parsimonious.

3 Data and Variables

3.1 Earnings Forecasts

We obtain the forecasts on earnings per share (EPS) and growth rate forecasts from the monthly IBES summary history files from WRDS. Our data is from January 2020 to May 2020. We keep all stocks that are also in CRSP. We set the starting date of the pandemic regime, t_0, to be February 20, 2020. We take the median forecast for each firm in May as the consensus forecast during the pandemic period. We treat the forecasts in January as the most recent non-pandemic period forecast. That is, we link our model notations to our empirical measurement as follows: January 2020 is our t_0-, May 2020 is time t for our forecast, and s is the fiscal year end date of the forecasts.

Using February and March of 2020 forecasts is problematic from the point of view of identification since we want timely measures of analyst expectation revisions from just before COVID-19 arrived to after its arrival. February 2020 may capture a bit of information about the pandemic since some analysts might have started revising their forecasts based on infections in other countries such as China. On the other hand, March 2020 might not capture the full extent of the pandemic regime to the extent some analysts might have been slow in revising. As such, we view using January 2020 forecasts as cleanly capturing non-pandemic earnings expectations and either April or May 2020 forecasts as capturing revisions accounting for the pandemic and hence embedding information regarding vaccines. We prefer May 2020 to April 2020 since almost all the analysts have revised their forecasts by then.[10]

We label the EPS annual forecasts based on the time gap between their forecast period end date s (i.e. the fiscal end year end date of the company) and the forecast date t, i.e., the gap $(s - t)$. If the time gap is less than 365 days, we label the annual forecast as $FY1_t$. If the time gap is between 366 days and 730 days, we label the annual forecast as $FY2_t$. We also similarly collect FY3 and FY4 annual forecasts from IBES. In addition, we convert LTG forecasts, which are defined as long-run growth rates from the previous announced earnings out to 5 years, to FY5 forecasts.

We use this methodology to label annual forecasts instead of using the classification provided by IBES because their classification is based on when the actual earnings is reported not when the fiscal year ends. For example, IBES will label an April annual forecast of a firm with a fiscal year that ended the previous month as FY1 if the firm has not yet reported the actual earnings for that fiscal year. We want FY1 to reflect future earnings so we use

[10]Moreover, most of the government intervention programs have already been announced and hence ought to be reflected in analyst forecasts as well by then.

our methodology instead.

In our empirical analysis, FY1 forecasts need to be adjusted for the fact that a certain fraction of the fiscal year has already been realized before the pandemic arrived at t_0. Consider a firm in our sample that has a fiscal year ending in October 2020 (time s in our model). In this case, for $FY1_t$, the FY1 earnings forecast for the period from November 2019 to October 2020, made in May 2020 (our t), only the sub-period between February 20, 2020 (our t_0) to October 2020 is exposed to COVID-19.

Therefore, we need to make adjustments to $FY1_t$ forecasts (e.g. May as our t) considering the differential impact of the pandemic on earnings resulting from heterogeneous fiscal year end dates. What enters into our calculation of earnings forecast in equation (10) at t (May in our empirical analysis) is adjusted as follows:

$$FY1_t^{adj} = FY1_t \cdot \left(\frac{1}{s - t_0} \right) + FY1_{t_0-} \cdot \left(1 - \frac{1}{s - t_0} \right) , \tag{16}$$

where $(s - t_0)$ is the fraction of the fiscal year that is exposed to COVID-19.

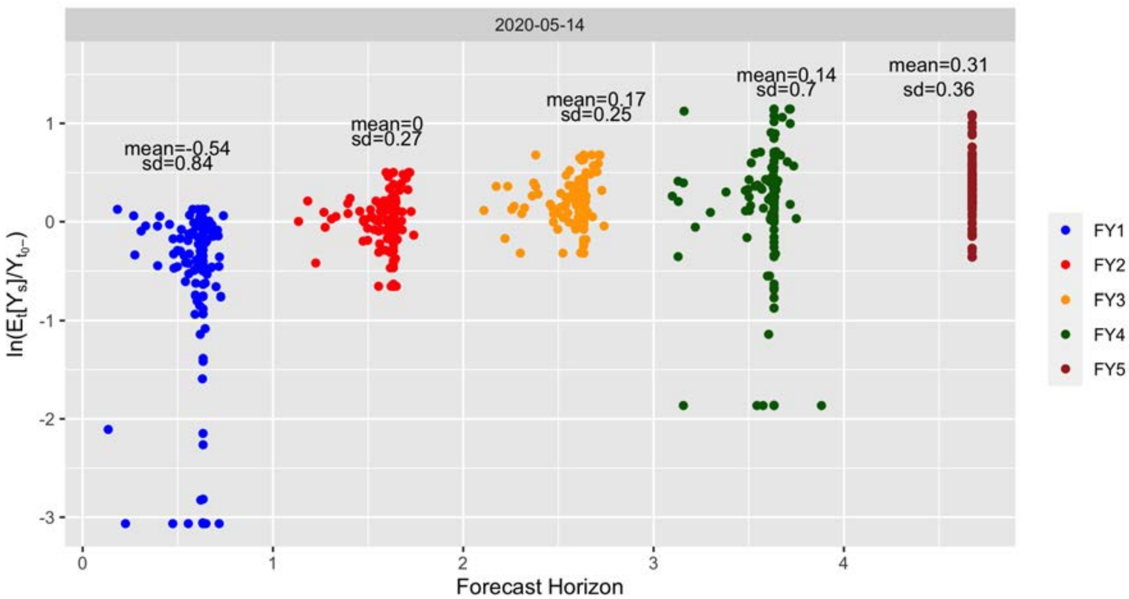
For the preceding example, $s - t_0 = (10 - 2)/12$ (the event time t_0 is February 2020 and time s in equation (16) is October 2020.) That is, 8/12 =2/3 of the annual earnings is after the pandemic arrival and the other 4/12=1/3 is non-pandemic. Our adjusted earnings forecast at t (in May for our empirical analysis) is then given by $FY1_t^{adj} = (3/2)FY1_t - (1/2)FY1_{t_0-} = FY1_t + 0.5 \times (FY1_t - FY1_{t_0-})$. That is, the adjusted annual earnings forecast $FY1_t^{adj}$ is equal to the unadjusted FY1 forecast $FY1_t$ plus a term, which accounts for the change of forecasts caused by the pandemic arrival. If pandemic is bad news for the firm, i.e., $FY1_t < FY1_{t_0-}$, this earnings forecast is adjusted downward by $0.5 \times (FY1_t - FY1_{t_0-})$, where the multiple 0.5 reflects the ratio between the non-pandemic 4- month duration and pandemic 8-month duration. In our sample, the non-pandemic forecast $FY1_{t_0-}$ is the FY1 forecasts in January and $FY1_t$ is the unadjusted FY1 forecasts in May.

We merge IBES forecasts with CRSP market capitalization data using historical 8-digit CUSIP identifiers.[11] We then merge in the 8-digit GICS code obtained from Compustat. On each date in our IBES sample, we set the negative values in adjusted FY1 to the lowest

[11]For the unmatched cases, we obtain additional matching using the official tickers and 6-digit CUSIP.

Figure 4: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ Over Forecast Horizons

This figure plots the natural log of the industry level I/B/E/S earnings forecasts divided by the non-pandemic earnings, $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$, against the horizons of the forecasts $(s-t)$. Y_{t_0-}, the non-pandemic earnings, is the FY1 forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The May 2020 cross section is plotted. Forecast horizons are marked with different colors. Forecast are defined by the distance between the forecast end date and the I/B/E/S statistical period.



positive observation in adjusted FY1 on that date. We also set the negative values of FY2 on each date to the lowest positive FY2 observation on each date. We repeat the same procedure for FY3, FY4 and FY5. We then aggregate the EPS forecasts, pre-pandemic growth rate forecasts, non-pandemic earnings, and time until fiscal year end to the 8-digit GICS industries using the end of 2019 market capitalization from CRSP as the weights. We winsorize these industry $\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}$ and $\widehat{g}$ at the 5% level.

The summary statistics for our dependent variables are presented in Table 1. In Panel A, we report the distribution of $\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}$ for the mid-May 2020 forecasts. The mean is 1.16 and the standard deviation is 0.54. The $\ln\left(\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}\right)$ has a mean of 0.01 with a large standard deviation of 0.61. The mean $(s-t)$ is 2.57 for the May 2020 forecasts.

In Figure 4, we take a closer look at the standard deviation of these forecasts by plotting the industry forecast revisions separately for FY1 to FY5 forecasts. We can see that the

Table 1: Summary Statistics

This table summarizes the mean, standard deviation, and the quartiles of the key variables used in our main analysis at 8-digit GICS industry level. $\mathbb{E}_t[Y_s]/Y_{t_0-}$ is the earnings forecasts in month t divided by the non-pandemic earnings Y_{t_0-}, which is the FY1 forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$. $s-t$ is the horizon of the earnings forecasts in month t, which is the difference between the date of the forecast period end and the I/B/E/S statistical period in month t. We include the May sample of I/B/E/S summary statistics in 2020 in our analysis. The sample includes the earnings forecasts with horizons up to 5 years. Panel A presents the summary statistics of $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ and $s-t$ in May 2020. Panel B contains the summary statistics of other key variables. Face-to-Face Score is first constructed at the occupation level using O*Net Main database and then aggregated to industry level using the BLS Industry-occupation matrix data (from 2018). Market Leverage is calculated at the end of 2019 using the following formula, (long-term debt+ debt in current liabilities)/(fiscal year end market capitalization + total assets - common equity). $\widehat{g}$ is the I/B/E/S forecasts of growth rates in January 2020. All the firm level variables are aggregated to the industry level using 8-digit GICS code, weighted by the market values of the companies in each industry at the end of 2019. $\mathbb{E}_t[Y_s]/Y_{t_0-}$ is winsorized at 5% level on each date within each horizon. Forecasts horizons are defined by the distance between the forecast end date and the I/B/E/S statistical period. $\widehat{g}$ is also winsorized at 5% level.

(a) Panel A: Distribution of $\mathbb{E}_t[Y_s]/Y_{t_0-}$ and $s-t$ in May 2020

	Mean	SD	P0	P25	P50	P75	P100
$\mathbb{E}_t[Y_s]/Y_{t_0-}$	1.16	0.54	0.05	0.86	1.10	1.39	3.14
$\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$	0.01	0.61	-3.07	-0.15	0.10	0.33	1.14
$s-t$	2.57	1.45	0.13	1.56	2.62	3.63	4.67

(b) Panel B: Distribution of other variables used in analysis

	Mean	SD	P0	P25	P50	P75	P100
Market Leverage	0.20	0.10	0.03	0.13	0.19	0.25	0.72
Face-to-Face Score	3.94	0.14	3.59	3.85	3.90	4.01	4.33
Customer Score	3.45	0.45	2.54	3.09	3.44	3.80	4.48
Blinder Score	2.97	0.24	2.57	2.75	2.95	3.13	3.76
$\widehat{g}$	0.10	0.09	-0.05	0.06	0.08	0.13	0.35

FY1 forecast within twelve months before forecast end are significantly revised down: 54% on average for the May 2020 forecasts across the industries in our sample. This is consistent with a significant negative jump on average in our model. But we can also see that the FY2 forecasts farther out are not nearly as impacted.

3.2 Leverage, Face-to-Face, and Customer Interaction Measures

We obtain the GICS code and calculate the market leverage of each firm using Compustat. Market Leverage is calculated at the end of 2019 using the following formula: long-term debt (dlttq) plus debt in current liabilities (dlcq) all divided by the sum of market capitalization (prccq $\times$ cshoq) and total assets (atq) net common equity (ceqq).

We then use the O*Net Main database in the U.S. about occupational information to construct the face-to-face exposures of different industries. O*Net collects information on 974 occupations. They are based on the Standard Occupational Classification (SOC), the last update of which was done in 2010. O*Net surveys people in these occupations, asking about the knowledge, skills, and abilities used to perform the activities and tasks of their occupations. Our face-to-face measure is based on Montenovo, Jiang, Rojas, Schmutte, Simon, Weinberg, and Wing (2020).

They use questions taken from the 2019 Work Context module. The questions used in face-to-face measure are: (1) How often do you have face-to-face discussions with individuals or teams in this job? And (2) To what extent does this job require the worker to perform job tasks in close physical proximity to other people? These measures are typically provided on a 1-5 scale, where 1 indicates that a task is performed rarely or is not important to the job, and 5 indicates that the task is performed regularly or is important to the job.

There is also a direct question that asks people to rate how much they work with customers in the O*Net survey. The question is: How important is it to work with external customers or the public in this job? We take the average score for each occupation for this alternative measure.

One issue with this customer measure is that it does not necessarily capture face-to-face contact. To this end, we have also constructed a customer measure from Blinder (2009) based on the following questions: (1) establishing and maintaining personal relationships, (2) assisting and caring for others, (3) performing for or working directly with the public, (4) selling or influencing others, and (5) social perceptiveness.

The O*Net provides two ways that people weight how an occupation uses these characteristics: Importance and Level. That is, people in an occupation are asked to rate how important the characteristic is in their job and the level of use of the characteristic in their job. We use the Importance score of each characteristic and take the simple average of the Importance scores to make what we call the Blinder index for each occupation. The social perceptiveness question is in the Social Skills part of the O*Net. The other four measures are in the Work Activities part of the O*Net.

We have occupation-level measures of face-to-face and the two customer measures. We then convert them to an industry-level measure. To do this, we use the BLS Industry-occupation matrix data (from 2018).[12] In the BLS data, for every industry, they measure what percentage of workers work in a given occupation. (They also use the SOC occupation codes just like the O*Net). So we take the O*Net occupation measures and for each industry weight them by the percentage of workers in that industry that work in the occupation. We take a weighted-average to come up with the industry measures. One issue is that the BLS uses NAICS codes for industries. We convert these to 8-digit GICs codes using a crosswalk.[13]

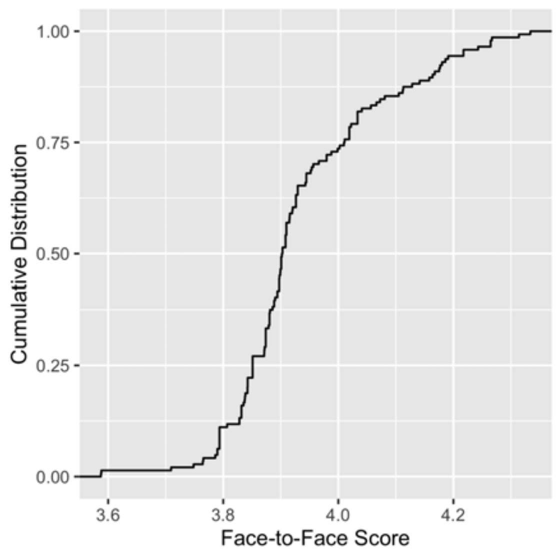
The summary statistics for leverage and these three face-to-face measures are provided in Panel B of Table 1. The mean Market Leverage ratio is 0.2 with a standard deviation of 0.1. The mean Face-to-Face Score is 3.94 with a standard deviation of 0.14. The mean Customer Score is 3.45 with a standard deviation of 0.45, while the Blinder Score has a mean of 2.97 and a standard deviation of 0.24. These measures are correlated (around 0.4 to 0.5 in pairwise correlations). The statistics for $\widehat{g}$ are also displayed — the mean (annual) non-pandemic growth rate is 10% with a standard deviation of 9%.

In our empirical analysis, we will work with percentiles of these measures as opposed to the values themselves. Figure 5 show the empirical cumulative distribution of our Face-to-

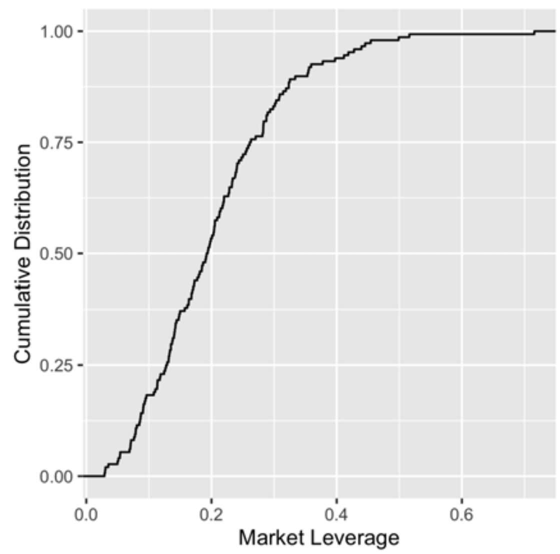
[12]See https://www.bls.gov/emp/tables/industry-occupation-matrix-industry.htm
[13]See https://sites.google.com/site/alisonweingarden/links/industries

Figure 5: The Empirical Distributions of Face-to-Face Scores and Market Leverage

This figure plots the empirical cumulative distributions of Face-to-Face Scores and Market Leverage of industries defined by 8-digit GICS codes. Subfigure (a) is the cumulative distribution of Face-to-Face Scores. Face-to-Face Score is first constructed at the occupation level using O*Net Main database and then aggregated to the industry level using the BLS Industry-occupation matrix data (from 2018). Subfigure (b) is the cumulative distribution of Market Leverage. Market Leverage is calculated at the end of 2019 using the following formula, (long-term debt+ debt in current liabilities)/(market capitalization + total assets - common equity). The variables are from Compustat. In Compustat variable names, the formula is the following, Market Leverage = (dlttq + dlcq)/(atq - ceqq + prccq * cshoq).



(a) The Cumulative Distribution of Face-to-Face Scores



(b) The Cumulative Distribution of Market Leverage

Face Score and Market Leverage measures, respectively. The correlation at the industry level of face-to-face ranks and leverage ratio ranks is 0.4. There are a number of good economic reasons why these two industry attributes are correlated. Airline and hotels for instance have high Face-to-Face Scores and are also industries that have physical assets such as land or planes that are used for collateralized borrowing. Our goal in this paper is not to disentangle these two effects. Hence we will use both of these measures interchangeably to model latent growth rates in our baseline specifications. We will consider the two customer measures in our robustness exercises.

Table 2: NLS Results Using the I/B/E/S Sample in May 2020

This table presents the coefficients and bootstrap confidence intervals from non-linear least square regressions of Equation (14). The regressions are run using I/B/E/S summary statistics in May 2020. $\mathbb{E}_t[Y_s]/Y_{t_0-}$ is the earnings forecasts divided by the non-pandemic earnings. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$. Y_{t_0-}, the non-pandemic earnings, is the FY1 forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The explanatory variables include the horizon of the earnings forecasts $s-t$ and the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$. λ is the vaccine arrival rate. g_0 represents the proportional change in the growth rate. n_0 governs the size of the jump in earnings. Columns (1)-(3) present the results from three different restrictions on the model parameters. Column (1) contains the results of the unconstrained regression. Column (2) contains the results restricting $\lambda = 0$. Column (3) contains the results restricting $g_0 = 1$. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score, and Market Leverage. The 95% bootstrap confidence intervals are reported in square brackets. We also present the likelihood ratio test statistics for the restricted models.

	(1)	(2)	(3)
λ	1.354		0.538
	[0.78,1.71]		[0.39,0.74]
g_0	-1.203	0.850	
	[-2.25,-0.06]	[0.68,1]	
n_0	2.021	0.214	0.879
	[0.99,4.1]	[0.16,0.28]	[0.68,1.22]
Num.Obs.	633	633	633
Log.Lik.	-493.690	-534.685	-513.274
LR.Stat.		81.99	39.17

4 Empirical Results

4.1 Baseline Specification

In Table 2, we present the coefficients and bootstrap confidence intervals from non-linear least square regressions of equation (14) using May 2020 earnings forecasts. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$, i.e., the revision of forecasts between January and May 2020. The explanatory variables include the (remaining) duration of time-t earnings forecasts $(s-t)$ and the non-pandemic (January 2020) forecasts of the growth rate $\widehat{g}$.

Column (1) contains the results for our baseline and unconstrained model. The estimate of λ is 1.354 with 95% bootstrap confident interval of $[0.78, 1.71]$. So the vaccine that returns the earnings to normal is expected in 1/1.354 or 0.74 years.[14] The estimate of g_0 is -1.203, indicating that pandemic growth rates are lower than during the non-pandemic periods. The confidence interval is $[-2.19, -0.06]$. Moreover, industries experience a large downward jump in earnings level, captured by $n_0 = 2.021$, which has a confidence interval of $[0.99, 4.10]$. Notice that this parameter also captures the expected reflation in earnings for these industries when the vaccine does arrive. The jump in earnings level is given by $1 - e^{-n}$, which means that there is around an 80% drop in earnings immediately following the arrival of COVID-19.

Recall that the average earnings FY1 forecast revision in the summary statistics is nearly 50% with a fat left-tail. The nonlinear least squares model, which is equal-weighted, will fit this tail, giving a sizable estimate for the downward jump in earnings g_0. There is also a fat-left tail in further out forecasts, which will then impart an attribution of low of negative growth rates in the pandemic regime compared to the non-pandemic regime. Finally, the high λ estimate comes from the intuition discussed earlier that there is a sizable disconnect between downward revisions in FY1 forecasts compared to subsequent ones.

In column (2), we present the estimates for the constrained model where we set $\lambda = 0$, i.e. assuming there is no vaccine. The estimate for g_0 is 0.850 with a 95% bootstrap confidence interval of $[0.68, 1]$. There is also a much smaller earnings jump parameter of 0.214 with a confidence interval of $[0.16, 0.28]$. When λ is forced to be zero, the constrained model has to compensate with a positive g_0 to account for the higher levels of FY2-FY5 earnings forecasts compared to FY1. Moreover, the initial jump in earnings is $n_0 = 0.214$ with a confidence interval of $[0.16, 0.28]$. This implies a downward jump of $1 - e^{-n_0} = 0.20$ or 20%.

The estimates of the constrained model are nonsensical because they imply only a small impairment of growth rates and a small initial jump. Of course, we know from the summary statistics that the FY1 forecast revision for the median industry is nearly 50%. These

[14] There has been significant attention to the question of when vaccines will arrive and if they will return the economy to normal. For instance, see the *McKinsey Report* (July 29, 2020) "On pins and needles: Will COVID-19 vaccines save the world", and an article in the *Washington Post* (August 2, 2020), entitled "A coronavirus vaccine won't change the world right away". Our estimate of the vaccine arrival rate λ as far as we know is the first systematic attempt to speak to this question.

nonsensical estimates are of course coming from constraining λ, which is equivalent to an omitted variables bias where expectations of an imminent vaccine are ignored in estimating damage functions. This lack of fit is reflected in a log likelihood of -534.685, which is substantially higher than the log likelihood of -493.69 from the unconstrained model in column (1). The likelihood ratio test statistic is 81.99, clearly rejecting the constrained model in column (2) in favor of the unconstrained model in column (1).

In column (3), we present the estimates for the constrained model where we set $g_0 = 1$; i.e. there was no damage to growth rates. λ is now estimated to be 0.538 with a 95% confidence interval of $[0.39, 0.74]$, and n_0 is 0.879 with a 95% confidence interval of $[0.67, 1.22]$. Notice that since we are assuming there is no growth impairment, there is a lower estimated λ because the higher growth rate will explain more of the difference between revisions of long-horizon forecasts to short-horizon forecasts. The log-likelihood is -513.274. The likelihood ratio statistic comparing column (1) to (3) is 39.17, rejecting the constrained model in column (3) in favor of the unconstrained model.

Another way to see that the unconstrained model fits the data is to compare the predicted values as a function of our two main independent variables the forecast horizon $(s-t)$ and non-pandemic industry growth rate $\hat{g}_0^{(j)}$. These plots are in Figure 6. Panel (a) shows the fitted values for the unconstrained model from column (1), while panels (b) and (c) show the fitted values from the constrained models in columns (2) and (3), respectively. It is clear from these 3-D plots that only the unconstrained model can fit the data. The constrained models generate poor fits of the data.

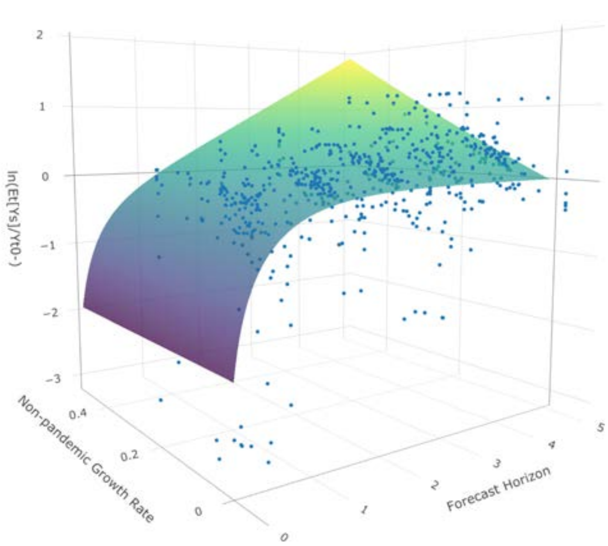
4.2 Robustness Exercises

We consider several robustness exercises. Since earlier work suggests that levered or face-to-face industries are particularly hit by COVID-19 and should be the most informative regarding the damage function,[15] we re-run our model using observations from just these

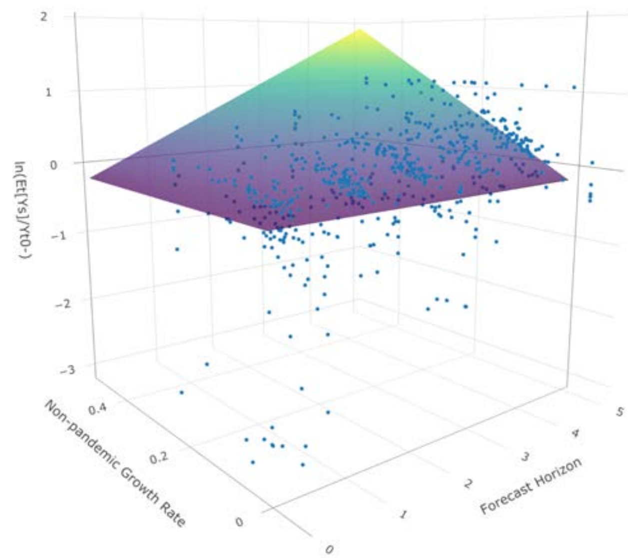
[15]The immediate impact of COVID-19 for stock prices was more negative for firms in these types of industries (Pagano, Wagner, and Zechner (2020), Ramelli and Wagner (2020), Alfaro, Chari, Greenland, and Schott (2020), Ding, Levine, Lin, and Xie (2020), Hassan, Hollander, van Lent, and Tahoun (2020), Favilukis, Lin, Sharifkhani, and Zhao (2020)).

Figure 6: The Surfaces of the Estimated Models

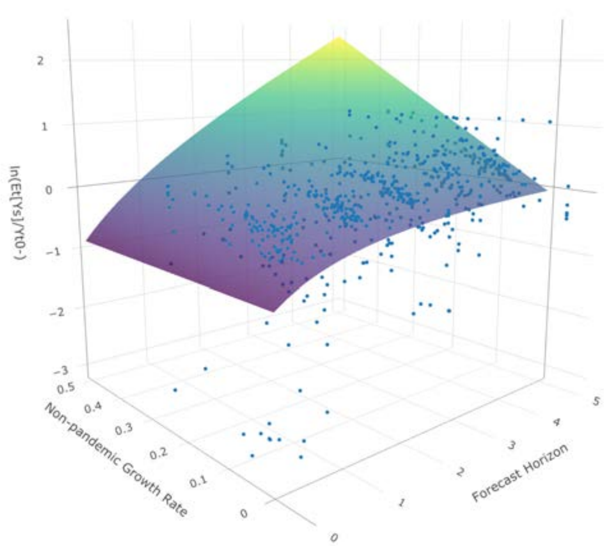
This figure plots the observations and fitted value of $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ using the parameter estimates of Equation (14) on the I/B/E/S sample from May of 2020. All the subfigures plot $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ and the fitted surface against the pre-pandemic growth rate and the horizons of forecasts. Subfigure (a) uses estimates from Column (1) in Table 2. Subfigure (b) uses estimates from Column (2) in Table 2. Subfigure (c) uses estimates from Column (3) in Table 2. The $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ observations are the blue dots.



(a) Unconstrained



(b) Constraint: $\lambda = 0$



(c) Constraint: $g_0 = 1$

industries. The results are presented in Table 3. In Panel A, we present the results for high face-to-face industries based on our main face-to-face measure. An industry is categorized in the high group if its face-to-face score is in the top tercile of the cross-sectional distribution. λ is precisely estimated to be 1.197, similar to our estimate of 1.354 from column (1) of Table 2. g_0 is estimated to be -2.123, which is smaller than the -1.203 figure from column (1) of Table 2. However, its confidence interval of $[-3.72, 0.54]$ is quite wide, including the -1.203 figure. Hence, there is not a statistical difference across the two sets of estimates. Similarly, the coefficient for n_0 is 3.115 which is larger than the 2.021 figure from Table 2. But again, they are not statistically different. In other words, the damage function estimated off of this subsample of firms is quite similar to the overall sample. The same can be said for the constrained models in columns (2) and (3). So overall, our earlier conclusions based on the overall sample continues to hold for this subsample.

In Panel B, we present the results for high leverage industries based on our main leverage measure. An industry is categorized in the high group if its leverage score is in the top tercile of the cross-sectional distribution. Our qualitative conclusions are quite similar to those from Panel A. We have also repeated these exercises by using a net market leverage measure where we deduct corporate cash and short-term investments and by replacing our baseline face-to-face measure with our two customer interaction measures. The conclusions are similar, pointing to the robustness of our damage function estimates.

In Table 4, we then consider a placebo exercise. We run exactly the same empirical procedure but using the forecasts in 2019 far before COVID-19. We report in Table 4 the regressions results with the constraint that $\lambda \geq 0$. Our estimates are zero for both the palcebo full sample and the placebo subsample of high face-to-face industries. For the placebo high leverage sample, the λ coefficient is 0.111, which is also very small. g_0 is 0.687 for the full sample with a tight 95% bootstrap confidence interval of $[0.52, 0.74]$. The point estimates are similar to the placebo subsample of high face-to-face and high leverage industries, though the confidence interval for the placebo high leverage subsample estimate is quite wide. n_0 is -0.068 with a tight confidence interval of $[-0.13, -0.04]$ for the full placebo sample. This is quite small in comparison to our earlier estimates. the same conclusions hold for the placebo

Table 3: NLS Results Using Subsamples

This table presents the coefficients and bootstrap confidence intervals from non-linear least square regressions of Equation (14) on subsamples of industries split by the terciles of Face-to-Face Scores and Market Leverage. The top tercile of the Face-to-Face Scores are classified as High Face-to-Face. The top tercile of the Market Leverage are classified as High Market Leverage. The regressions are run using I/B/E/S summary statistics in May 2020. $\mathbb{E}_t[Y_s]/Y_{t_0-}$ is the earnings forecasts divided by the non-pandemic earnings. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$. Y_{t_0-}, the non-pandemic earnings, is the FY1 forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The explanatory variables include the horizon of the earnings forecasts $s-t$ and the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$. λ is the vaccine arrival rate. g_0 represents the proportional change in the growth rate. n_0 governs the size of the jump in earnings. Panel A and B contain the results using the High Face-to-Face subsample and High Market Leverage subsample correspondingly. In each panel, Columns (1)-(3) present the results from three different restrictions on the model parameters. Column (1) contains the results of the unconstrained regression. Column (2) contains the results restricting $\lambda = 0$. Column (3) contains the results restricting $g_0 = 1$. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score, and Market Leverage. The 95% bootstrap confidence intervals are reported in square brackets. We also present the likelihood ratio test statistics for the restricted models.

(a) Panel A: NLS Results Using the High Face-to-Face Subsample

	(1)	(2)	(3)
λ	1.197		0.675
	[0.35,1.5]		[0.37,0.98]
g_0	-2.123	0.678	
	[-3.72,0.54]	[0.27,1.03]	
n_0	3.115	0.220	1.630
	[0.83,4.75]	[0.08,0.36]	[0.88,3.26]
Num.Obs.	201	201	201
Log.Lik.	-198.074	-217.778	-207.168
LR.Stat.		39.41	18.19

(b) Panel B: NLS Results Using the High Leverage Subsample

	(1)	(2)	(3)
λ	1.455		0.357
	[0.32,1.79]		[0.15,0.66]
g_0	-3.174	0.552	
	[-4.98,0.32]	[0.22,0.86]	
n_0	4.063	0.203	0.819
	[0.6,4.28]	[0.08,0.33]	[0.51,1.51]
Num.Obs.	182	182	182
Log.Lik.	-163.380	-175.836	-175.531
LR.Stat.		24.91	24.30

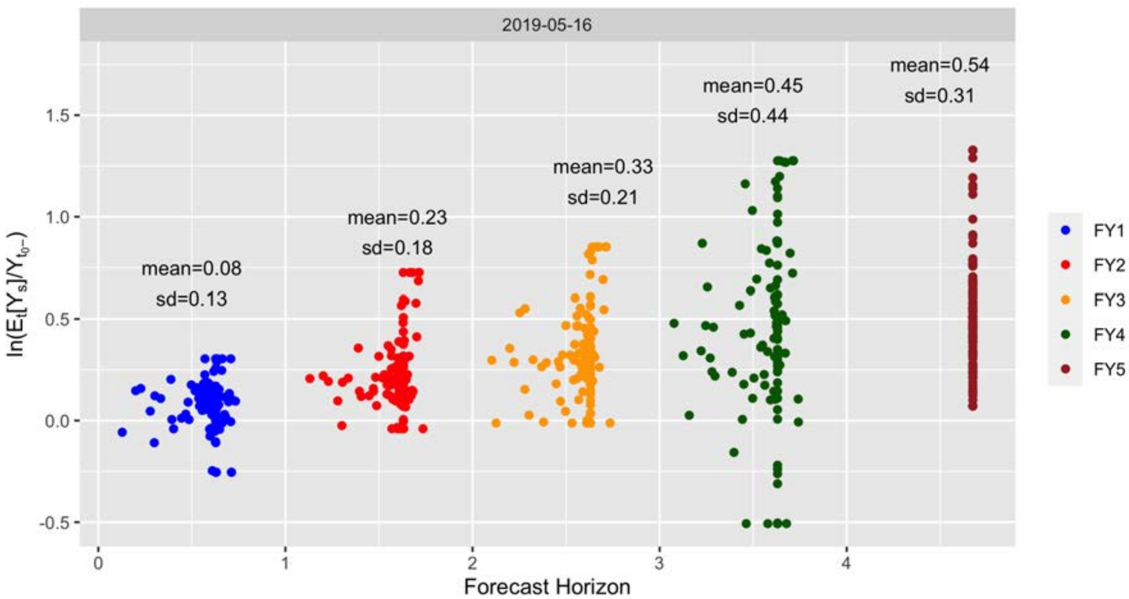
Table 4: Placebo Results Using the I/B/E/S Sample in May 2019

This table presents the coefficients and bootstrap confidence intervals from the placebo non-linear least square regressions of Equation (14) with the constraint that $\lambda \geq 0$. The regressions are run using I/B/E/S summary statistics in May of 2019. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$, where $\mathbb{E}_t[Y_s]/Y_{t_0-}$ is the earnings forecasts in May divided by the pseudo non-pandemic earnings. Y_{t_0-}, the pseudo non-pandemic earnings, are the FY1 forecasts in January 2019 discounted by the I/B/E/S growth rate forecasts in the same month. The explanatory variables include the horizon of the earnings forecasts $s-t$ and the January I/B/E/S forecasts of growth rate $\widehat{g}$ in 2019. λ is the vaccine arrival rate. g_0 represents the proportional change in the growth rate. n_0 governs the size of the jump in earnings. The first column contains the results using the full sample. The second column ("High Face-to-Face") shows the results using the subsample of industries with Face-to-Face Scores in the top tercile. The last column ("High Leverage") shows the results using the subsample of industries with Market Leverage in the top tercile at the end of 2018. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score, and Market Leverage. The 95% bootstrap confidence intervals are reported in square brackets.

	Full Sample	High Face-to-Face	High Leverage
λ	0.000	0.000	0.111
	[0,0.29]	[0,0.6]	[0,11.8]
g_0	0.687	0.676	0.793
	[0.52,0.74]	[0.39,0.78]	[-4.58,0.95]
n_0	-0.068	-0.107	-0.007
	[-0.13,-0.04]	[-0.25,-0.06]	[-3.56,0.06]
Num.Obs.	638	195	210

Figure 7: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ Over Forecast Horizons of the Placebo Sample

This figure plots the natural log of the industry level I/B/E/S earnings forecasts divided by the pseudo non-pandemic earnings, $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$, against the horizons of the forecasts $(s-t)$ using I/B/E/S summary statistics in May 2019. The pseudo non-pandemic earnings are the FY1 forecasts in January 2019 discounted by the I/B/E/S growth rate forecasts in the same month. Forecasts horizons are marked with different colors. Forecasts horizons are defined by the distance between the forecast end date and the I/B/E/S statistical period.



subsamples. These exercises indicate that our model estimates using the COVID-19 sample are informative.

In Figure 7, we plot the dependent variables, i.e., the forecasts revisions, for the placebo full sample that are analogous to those shown in Figure 4. We can see that the big difference between the COVID-19 period and the other placebo period is that one does not typically see such a large divergence in revisions across FY1 and FY2 forecasts. Understandably, in most periods, the relationship between FY1 and FY2 revisions should be more synchronized with the growth rate.

But of course, the COVID-19 period data suggests instead that there is a regime switch that might occur between over the roughly 1 to 2 year period of forecast horizons. As we said, the alternative is that the growth rates in the pandemic period are just much larger, which is counterfactual. Importantly, this is not an artifact of slow revisions of FY2 since analysts revise FY1 and FY2 at the same time and both sets of forecasts experienced significant revisions downward with the arrival of COVID-19.

5 Vaccine News and Time-Varying Damages

Finally, we extend our baseline model to allow for the possibility of time-varying arrival rates or vaccine news. This extension allows us to draw inferences for the June, July, and August 2020 forecasts. To this end, we now consider a vaccine model in which the vaccine arrives only after two jumps. We can interpret the two jumps as stages in the vaccine development process. For instance, the first stage can correspond to basic analysis on whether COVID-19 is a difficult virus to find a vaccine such as HIV or an easy one. The second stage is then the actual development of the particular treatment.

Let τ_η denote the arrival time of the first jump, which follows a Poisson process with arrival rate λ_η. Upon the arrival of the first jump, investors become informed about the arrival rate of the second jump (i.e., the first jump arrival reveals news about the second jump arrival rate, which can be either good (a high arrival rate λ_G) or bad (a low arrival rate λ_B.) Let π_B and π_G be the probability that the news is good and bad, respectively.

Let τ_v denote the vaccine arrival time: $\tau_v = \tau_G$ if news is good and $\tau_v = \tau_B$ if news is bad. The sequential order of the two jumps implies that $\tau_v > \tau_\eta$ with probability one in our model. Additionally, the news arrival time τ_η and the additional time required for vaccine arrival after news arrival, $\tau_v - \tau_\eta$, are independent. The expected vaccine arrival time at time t before news arrival (i.e., when $t < \tau_\eta$) is then given by

$$\mathbb{E}_t(\tau_v) = \mathbb{E}_t(\tau_\eta) + \mathbb{E}_t\left[\mathbb{E}_{\tau_\eta}(\tau_v - \tau_\eta)\right] = \frac{1}{\lambda_\eta} + \left(\frac{\pi_G}{\lambda_G} + \frac{\pi_B}{\lambda_B}\right), \tag{17}$$

where the first equality follows from the law of iterated expectation and the second equality uses the independence property of τ_η and $(\tau_v - \tau_\eta)$. The expected vaccine arrival time at time t where $t > \tau_\eta$, i.e., after the news arrival time, is simply $\mathbb{E}_t(\tau_v) = 1/\lambda_B$ if the news is bad and $\mathbb{E}_t(\tau_v) = 1/\lambda_G$ if the news is good.

The vaccine arrival-rate estimate of roughly one year from our baseline model using May 2020 forecasts essentially gives us an estimate of $\mathbb{E}_t(\tau_v)$, the LHS of Equation (17). Hence,

Table 5: Updated Estimates of the Vaccine Arrival Rate

This table presents the updated estimates of the vaccine arrival rate λ using I/B/E/S summary statistics in June, July, and August. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_t^{pred}$. Y_t^{pred} is the earnings predicted using the estimates in Column (1) of Table (2). The explanatory variables include the horizons of the earnings forecasts $s-t$ and the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$. λ is the vaccine arrival rate.

	June	July	August
λ	1.455	1.606	2.888
	[1.27,1.65]	[1.4,1.86]	[2.49,3.42]
Num.Obs.	632	632	630

we can interpret the expected arrival time as the sum of two arrival times: the news arrival time (stage 1) and then the subsequent vaccine development (stage 2).

A simple way then to check for the arrival of vaccine news is to re-estimate our baseline model for June, July, and August forecasts and check to see if the inferred vaccine arrival rates differ from that of the May forecasts.

More specifically, we take our model's predictions for Y_t for time t in the pandemic regime, Y_t^{pred}, by using the May 2020 estimates of n and g, which we denote by the subscript may (i.e. n_{may} and g_{may}). Then, with June, July or August forecasts, we can estimate λ with the same expectations formula as in our baseline model:

$$\begin{aligned}\frac{1}{Y_{j,t}^{pred}}\mathbb{E}_t[Y_s] &= \int_t^s \lambda e^{-\lambda(\tau-t)} e^{g_{may}(\tau-t)} e^{n_{may}} e^{\widehat{g}(s-\tau)} d\tau + e^{-\lambda(s-t)} e^{g_{may}(s-t)} \\ &= \frac{\lambda}{\lambda - g_{may} + \widehat{g}} \left[e^{\widehat{g}(s-t)} - e^{(g_{may}-\lambda)(s-t)}\right] e^{n_{may}} + e^{(g_{may}-\lambda)(s-t)}\end{aligned}$$

In the pandemic regime at time t, conditional on no news arrival, we expect our estimate of λ using these other months to be the same as that obtained from the May 2020 forecasts. That is, the estimate of λ in July conditional on no news arrival implies a value of $1/\lambda$ that is about the value of $1/\mathbb{E}_t(\tau_v)$ given in equation (17). On the other hand, if there is news, the estimated value of λ will differ — the estimated λ at t conditional on news arrival (i.e., $t > \tau_\eta$) should then be close to either λ_G or λ_B.

We report the results of this estimation in Table 5, where we fix the estimates n_0 and g_0 from column (1) of Table 2 and estimate λ using June, July and August forecasts. First, our inference of λ using the June and July forecasts are similar to those obtained using May. We estimate λ to be 1.443 for the June forecasts and 1.613 for the July forecasts, respectively. These estimates are close to the May estimates. However, we find that the estimated arrival rate increased when using the August 2020 forecasts. The estimated λ is 2.888 with a 95% confidence interval of $[2.49, 3.42]$. This confidence interval does not overlap with the 95% confidence interval attached to the 1.354 estimate of λ based on May forecasts from Table 2. It also does not overlap with the confidence intervals for the estimates based on June and July forecasts. This is evidence of time-varying vaccine arrival rates and hence a time-varying damage function.

6 Conclusion

Despite a large theoretical literature on the inherent nonlinearity of pandemic damage functions, there has been relatively little work in estimating them. To address this challenge, we propose a parsimonious damage function that we take to the data using timely measures of expected damage given by revisions of industry-level earnings forecasts. The structure of our model suggests a natural set of identifying restrictions related to forecast rationality that allow for estimation using nonlinear least squares. Forecast revisions in mid-May 2020 imply a significant negative earnings jump in levels and that a vaccine is expected in 0.74 years. Growth rates are significantly lower until the vaccine arrives.

Our estimates have implications for a number of policy questions. Notably, there is a timely debate on when and whether a vaccine will be a silver bullet for COVID-19 that reverts the economy to normal. Our estimates derived from analysts earnings forecasts provide a potential answer. Moreover, there are several natural inquiries based on our model and estimates. For instance, one can combine these estimates with an asset pricing model to assess the extent to which stock prices particularly for distressed industries such as airlines or hotels, are efficient. One can also consider the pricing of vaccine risk. We leave these inquires for future research.

References

Acemoglu, D., V. Chernozhukov, I. Werning, and M. D. Whinston, 2020, "A multi-risk SIR model with optimally targeted lockdown," working paper, National Bureau of Economic Research.

Alfaro, L., A. Chari, A. N. Greenland, and P. K. Schott, 2020, "Aggregate and firm-level stock returns during pandemics, in real time," Working Paper 26950, National Bureau of Economic Research.

Alvarez, F. E., D. Argente, and F. Lippi, 2020, "A simple planning problem for COVID-19 lockdown," Working Paper 26981, National Bureau of Economic Research.

Andersen, A. L., E. T. Hansen, N. Johannesen, and A. Sheridan, 2020, "Pandemic, shutdown and consumer spending: lessons from Scandinavian policy responses to COVID-19," Working paper.

Anderson, R. M., and R. M. May, 1992, *Infectious diseases of humans: dynamics and control.* Oxford university press.

Arnold, R., Y. Galloway, A. McNicholas, and J. O'Hallahan, 2011, "Effectiveness of a vaccination programme for an epidemic of meningococcal B in New Zealand," *Vaccine*, 29(40), 7100–7106.

Bailey, N. T., et al., 1975, *The mathematical theory of infectious diseases and its applications.* Charles Griffin & Company Ltd.

Ball, F., and D. Sirl, 2018, "Evaluation of vaccination strategies for SIR epidemics on random networks incorporating household structure," *Journal of Mathematical Biology*, 76(1-2), 483–530.

Behncke, H., 2000, "Optimal control of deterministic epidemics," *Optimal control applications and methods*, 21(6), 269–285.

Black, F., and M. Scholes, 1973, "The pricing of options and corporate liabilities," *Journal of political economy*, 81(3), 637–654.

Blinder, A. S., 2009, "How many US jobs might be offshorable?," *World Economics*, 10(2), 41.

Cameron, A. C., and P. K. Trivedi, 2005, *Microeconometrics: methods and applications*. Cambridge University Press.

Coibion, O., and Y. Gorodnichenko, 2012, "What can survey forecasts tell us about information rigidities?," *Journal of Political Economy*, 120(1), 116–159.

Ding, W., R. Levine, C. Lin, and W. Xie, 2020, "Corporate immunity to the COVID-19 pandemic," Working Paper 27055, National Bureau of Economic Research.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt, 2020, "The macroeconomics of epidemics," Working Paper 26882, National Bureau of Economic Research.

Elenev, V., T. Landvoigt, and S. Van Nieuwerburgh, 2020, "Can the COVID bailouts save the economy?," Working Paper 27207, National Bureau of Economic Research.

Farboodi, M., G. Jarosch, and R. Shimer, 2020, "Internal and external effects of social distancing in a pandemic," Working Paper 27059, National Bureau of Economic Research.

Favilukis, J. Y., X. Lin, A. Sharifkhani, and X. Zhao, 2020, "Labor force telework flexibility and asset prices: evidence from the COVID-19 pandemic," Working paper.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus, 2020, "Inside the mind of a stock market crash," Working Paper 27272, National Bureau of Economic Research.

Gormsen, N. J., and R. S. J. Koijen, 2020, "Coronavirus: impact on stock prices and growth expectations," Working Paper 27387, National Bureau of Economic Research.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun, 2020, "Firm-level exposure to epidemic diseases: COVID-19, SARS, and H1N1," Working Paper 26971, National Bureau of Economic Research.

Hong, H., and J. D. Kubik, 2003, "Analyzing the analysts: career concerns and biased earnings forecasts," *The Journal of Finance*, 58(1), 313–351.

Hong, H., N. Wang, and J. Yang, 2020, "Implications of stochastic transmission rates for managing pandemic risks," *Review of Financial Studies*, forthcoming.

Keane, M. P., and D. E. Runkle, 1998, "Are financial analysts' forecasts of corporate profits rational?," *Journal of Political Economy*, 106(4), 768–805.

Kruse, T., and P. Strack, 2020, "Optimal control of an epidemic through social distancing," Working paper.

Landier, A., and D. Thesmar, 2020, "Earnings expectations in the COVID crisis," Working Paper 27160, National Bureau of Economic Research.

Laster, D., P. Bennett, and I. S. Geoum, 1999, "Rational bias in macroeconomic forecasts," *The Quarterly Journal of Economics*, 114(1), 293–318.

Lee, B. Y., B. A. Norman, T.-M. Assi, S.-I. Chen, R. R. Bailey, J. Rajgopal, S. T. Brown, A. E. Wiringa, and D. S. Burke, 2010, "Single versus multi-dose vaccine vials: an economic computational model," *Vaccine*, 28(32), 5292–5300.

Leland, H. E., 1994, "Corporate debt value, bond covenants, and optimal capital structure," *The Journal of Finance*, 49(4), 1213–1252.

Merton, R. C., 1974, "On the pricing of corporate debt: the risk structure of interest rates," *The Journal of Finance*, 29(2), 449–470.

Montenovo, L., X. Jiang, F. L. Rojas, I. M. Schmutte, K. I. Simon, B. A. Weinberg, and C. Wing, 2020, "Determinants of disparities in COVID-19 job losses," Working Paper 27132, National Bureau of Economic Research.

Nordhaus, W. D., 1987, "Forecasting efficiency: concepts and applications," *The Review of Economics and Statistics*, pp. 667–674.

Pagano, M., C. Wagner, and J. Zechner, 2020, "Disaster resilience and asset prices," Working paper.

Ramelli, S., and A. F. Wagner, 2020, "Feverish stock price reactions to COVID-19," *The Review of Corporate Finance Studies*, forthcoming.

Wickwire, K., 1977, "Mathematical models for the control of pests and infectious diseases: a survey," *Theoretical Population Biology*, 11(2), 182–238.