Pandemics, Vaccines and Corporate Earnings *

Harrison Hong[†] Jeffrey D. Kubik[‡] Neng Wang[§] Xiao Xu[¶]
Jinqiang Yang[‖]

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Abstract

We estimate a model of damage to corporate earnings from COVID-19. A pandemic decreases earnings due to costly mitigation and lower growth rates. The arrival of a vaccine, modeled as a Poisson process, reverts earnings to normal. We fit our model to timely measures of expected damage given by revisions of industry-level consensus earnings forecasts. In mid-May 2020, a vaccine is expected to return earnings to normal in one year. Levered and face-to-face industries will benefit the most from a vaccine. We then extend our framework to account for time-varying vaccine arrival rates. August 2020 forecasts imply a return to normal in six months, consistent with good news on the effectiveness of multiple vaccines announced in November 2020.

Keywords: COVID-19, pandemics, vaccines, damages, corporate earnings, analyst forecasts

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[†]Columbia University and NBER. E-mail: hh2679@columbia.edu
[‡]Syracuse University. E-mail: jdkubik@maxwell.syr.edu
[§]Columbia University and NBER. E-mail: neng.wang@columbia.edu
[¶]Columbia University. E-mail: xx2251@columbia.edu
[‖]Shanghai University of Finance and Economics. E-mail: yang.jinqiang@mail.sufe.edu.cn

1 Introduction

We estimate a model of damage to corporate earnings from the COVID-19 pandemic. The unexpected arrival of a pandemic results in a downward jump of earnings for a typical corporation due to costly mitigation by both customers and firms.[1] Damage depends on when an effective vaccine (or other medical interventions such as therapeutics) is expected to arrive. When the vaccine arrives, these costs no longer need to be paid and there is an upward jump in earnings. Growth rates during a pandemic are lower than historical growth rate forecasts before the arrival of COVID-19 due the adverse direct effects of infections. Our model—a parsimonious version of Hong, Wang, and Yang (2020)—boils down to a regime-switching model of earnings with just a few parameters: vaccine arrival rate, jump in earnings (both on pandemic impact and reflation upon vaccine arrival), and differential growth rates across normal (or non-pandemic) versus pandemic regimes.

We fit our model to timely measures of expected damage to corporate earnings given by revisions of industry-level consensus earnings forecasts.[2] 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 at different horizons the parameters of the earnings process taking into account the effects of COVID-19. Our estimation methodology allows for potential heterogeneity in damages across industries, such as technology firms even benefitting from the need for social distancing.

We associate a medical intervention which 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. According to Bloomberg News article "Trump administration dips into

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

[2] The only caveat is that stock-level forecasts might be biased due to conflicts of interest (Michaely and Womack (1999), Hong and Kubik (2003)). But Landier and Thesmar (2020) find that May 2020 industry-level earnings forecast revisions following COVID-19 explain stock price performance across industries, suggesting that bias is not a concern when it comes to COVID-19.

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). Nonetheless, our regime-switching model can be applied to other countries where it might be the arrival of therapeutics or testing that return these countries to normal. For instance, rigorous testing has played a bigger role in Asian countries. 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.

Our contribution is to develop a methodology to infer key structural parameters affecting cumulative damage to corporate earnings from COVID-19. Our estimates naturally address several related questions of interest to policy makers and practitioners. First, when will a vaccine return the economy to normal? This issue has received significant attention in consulting reports and mass media. But a systematic method to generate quantitative estimates does not yet exist. Second, which industries will benefit most from a vaccine? Only the question of which industries have been the most damaged has received attention thus far. Third, what accounts for damage to corporate earnings — jumps in earnings due to costly mitigation versus the growth rate effect in a pandemic regime due to the unexpected course of the pandemic?

We show that our method is a useful complement to surveys that attempt to answer these questions.[3] While analysts are not directly responsible for issuing vaccine forecasts, they are highly incentivized when it comes to making earnings forecasts. And their forecasts ought to integrate not only scientific evidence on the development of effective vaccines but also logistical issues surrounding their distribution as well as macroeconomic consequences, i.e. whether consumers and firms return to normal.

To begin with, 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

[3] An example is a survey from *Good Judgment* on "When will enough doses of FDA-approved COVID-19 vaccine(s) to inoculate 25 million people be distributed in the US?".

parameters and several independent variables. Our baseline model follows the literature on the arrival of vaccines in assuming 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)). 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 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.

The growth rates in the pandemic regime are latent and can vary across industries. For the sake of parsimony, we model these latent pandemic growth rates as a multiple of non-pandemic growth rates. Moreover, the jump in earnings can potentially depend on industry characteristics. For these characteristics, we focus on leverage of the firms in an industry and the exposure of an industry to face-to-face interactions either with customers or other employees. We map face-to-face exposure measures based on occupational surveys (Montenovo, Jiang, Rojas, Schmutte, Simon, Weinberg, and Wing (2020)) to the industry level by using occupation shares for each industry. We take these industry characteristics as given and do not model the relationship between labor and financing frictions (see, e.g. Whited (2019)). Our model can be estimated using non-linear OLS and standard errors

[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.

calculated using the bootstrap method.

First, we have the following findings regarding the vaccine arrival rate. Using forecast revisions in May 2020, we estimate that vaccine arrival rate is 0.999 with a 95% bootstrap CI [0.45,1.64]. Our estimates should be interpreted as not when a vaccine is approved but when the vaccine has been successfully adopted and the economy returns to normal. These estimates imply that the vaccine is expected in 1 year (or 1/0.999) with a 95% bootstrap confident interval of between 0.61 and 2.22 years.

To see how we estimate these parameters, consider the plot in Figure 3 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.

Second, highly levered and face-to-face industries experience greater damage in the form of jumps in earnings following COVID-19 and hence are also expected to be the biggest beneficiaries of a vaccine when earnings reflate more for these sectors. Although leverage and face-to-face scores at the industry level are highly correlated (0.4), leverage is the most significant in our specifications. Moreover, we find that industry leverage that nets out corporate cash and liquid investments performs slightly better than our baseline gross leverage measure in explaining pandemic damage to corporate earnings. Our baseline face-to-face scores (Montenovo, Jiang, Rojas, Schmutte, Simon, Weinberg, and Wing (2020)) include interactions with both employees and customers. We also consider face-to-face scores meant to capture just interactions with customers such as in Blinder (2009). But these scores perform worse in explaining pandemic damage than our baseline overall face-to-face interaction measure.

Third, pandemic growth rates are estimated to be lower than the non-pandemic growth rates, especially for levered industries. However, our confidence interval for this attribution is much wider than for our vaccine arrival or jump estimates.[5] Growth rates during a pandemic being lower on average points to the value of mitigation for corporate earnings even in the absence of health considerations (as modeled in Hong, Wang, and Yang (2020)).

One way to show that our model explains analyst earnings forecast revisions 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 (or a vaccine is expected to arrive in an infinite number of years) using this placebo sample. And the estimates for the jump and growth rates do not yield significant results.

We then extend our model to account for vaccine news, which then allows us to draw inferences using the June, July, and August 2020 forecasts (the latest data we have available on IBES). 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

[5] One reason perhaps is that mitigation government policies to stabilize the economy (see, e.g., Elenev, Landvoigt, and Van Nieuwerburgh (2020)) — growth rates would no doubt be worst absent these other interventions.

informed 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 six months, or the Spring of 2021. In other words, our model's estimates indicate that there was good news on vaccines in the late summer, consistent with qualitative narratives in the stock market.[6] In other words, analysts' expectations imply that the vaccines expected to be widely distribute by the Spring of 2021, which would then be collectively a silver bullet for corporate earnings. Our estimates are also consistent with news on Pfizer, Moderna and AstraZeneca vaccine effectiveness in November 2020, though it remains to be seen if the vaccines are indeed widely distributed by the Spring of 2021 and if the economy will return to normal then.

Our paper proceeds as follows. We review the related literature in Section 2. We present our model of earnings in Section 3. Section 4 describes the dataset and main variables. Estimates of our baseline model are presented in Section 5. We extend the model to account for vaccine news in Section 6. We conclude in Section 7.

2 Related Literature

Our analysis is related to Landier and Thesmar (2020) who document that industry-level forecast revisions explain stock price movements. Our contribution is to model the determinants of these analyst revisions. Our analysis also complements Gormsen and Koijen (2020), who use dividend strips to back out the negative impact of COVID-19 on dividend growth. Our finding of a quick arrival of a vaccine that returns earnings to normal is consistent with Giglio, Maggiori, Stroebel, and Utkus (2020), who surveyed retail investors and found that the average investor became more pessimistic about the short-run performance of both the stock market and the economy after COVID-19, even as their corresponding long-run ex-

[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".

pectations remained unchanged. Our results suggest that analysts view gloomier scenarios outlined by the Federal Reserve Board or in academic work on long-term scarring as unlikely.

We focus on face-to-face and leverage characteristics of industries because a number of papers (see, e.g., 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)) find that the immediate impact of COVID-19 for stock prices was more negative for firms in these types of industries.[7] Our findings are qualitatively similar to these papers in terms of the heterogeneous initial impact of COVID-19 across different industries. Our estimates, however, are obtained with the restriction that the initial jump is reversed when the vaccine arrives. Hence, we can interpret these estimates as implying that levered and face-to-face industries would benefit the most from a vaccine arrival.

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 effect in a pandemic regime. The initial jump in earnings corresponds to costly mitigation measures (e.g. social distancing) meant to keep the virus at bay. When a vaccine arrives, there is then a reversal of this jump. But a lower growth rate in the pandemic regime subsequent to the downward jump in earnings (i.e. should a vaccine not arrive yet) would be indicative of negative direct effects associated with a pandemic.

Finally, in our empirical work, we focus on earnings forecasts made by security analysts, even though our estimation method can be applied to macroeconomic forecasts such as GDP to the extent macroeconomic aggregates and stock market earnings are correlated. After all, models of the impact of COVID-19 on the broader economy more generally such as in Eichenbaum, Rebelo, and Trabandt (2020) follow a similar logic.

3 Model

We propose a parsimonious version of Hong, Wang, and Yang (2020). We assume that the economy can be in one of the two regimes: the normal (or non-pandemic) and pandemic

[7] Related measures utilize additional O*NET questions to measure telework felxibility (Favilukis, Lin, Sharifkhani, and Zhao (2020)).

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.

3.1 Normal Regime

We let $\widehat{Y}_t$ denote the earning process of the asset in the normal regime. We assume that $\widehat{Y}_t$ follows a commonly used geometric Brownian motion process:

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

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.

3.2 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 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 in Hong, Wang, and Yang (2020), 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.

3.3 Transition from Normal to Pandemic Regime

In Hong, Wang, and Yang (2020), 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.

3.4 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:

$$\frac{1}{Y_t}\mathbb{E}_t[Y_s] = \int_t^s \lambda e^{-\lambda(\tau-t)} e^{g(\tau-t)} e^n e^{\widehat{g}(s-\tau)} d\tau + e^{-\lambda(s-t)} e^{g(s-t)} \tag{5}$$

$$= \frac{\lambda}{\lambda - g + \widehat{g}} \left[e^{\widehat{g}(s-t)} - e^{(g-\lambda)(s-t)} \right] e^n + e^{(g-\lambda)(s-t)} . \tag{6}$$

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.

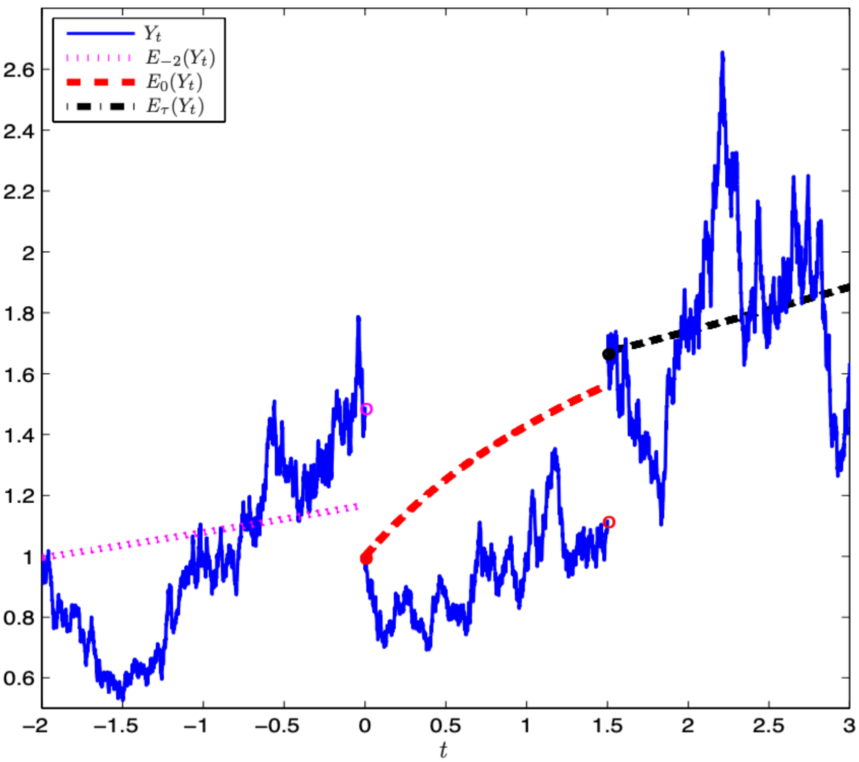
The first term of equation (5) is conditioned on a vaccine arriving in the interval between t and s. Inside the first term, the density of the stochastic vaccine arrival time τ is $\lambda e^{-\lambda(\tau-t)}$. Before the vaccine arrives (from t to τ) the cumulative (gross) growth is $e^{g(\tau-t)}$. 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 $g \leq \widehat{g}$ 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]

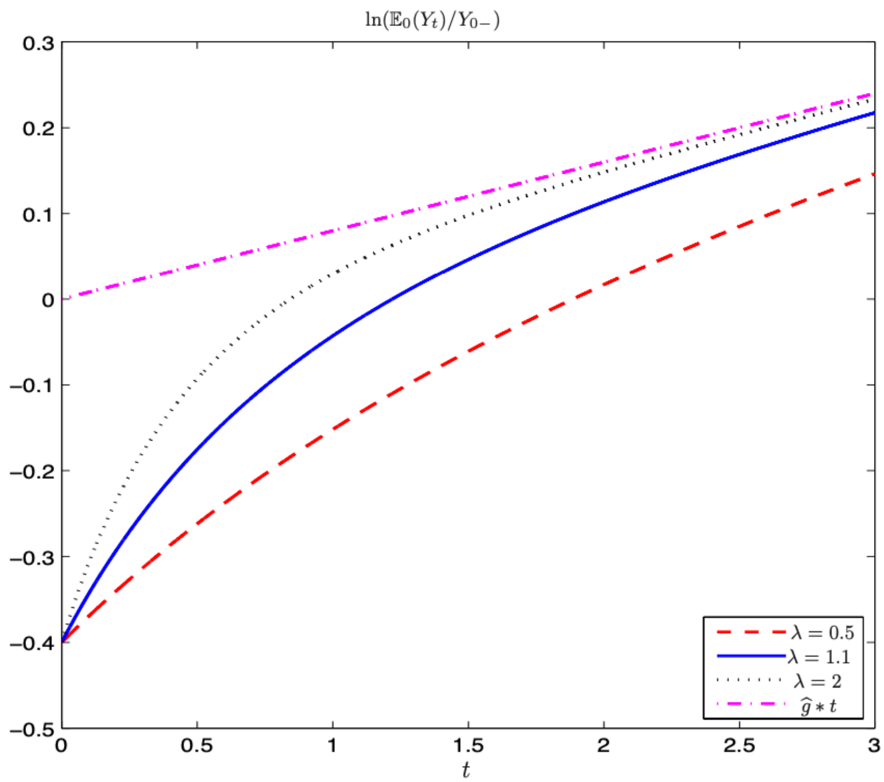
$$\frac{1}{Y_{t_0-}}\mathbb{E}_{t_0}[Y_s] = \frac{Y_{t_0}}{Y_{t_0-}}\frac{1}{Y_{t_0}}\mathbb{E}_{t_0}[Y_s] \quad = \quad \frac{\lambda}{\lambda - g + \widehat{g}}\left[e^{\widehat{g}(s-t_0)} - e^{(g-\lambda)(s-t_0)}\right] + e^{-n}e^{(g-\lambda)(s-t_0)}\,. \tag{7}$$

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.

3.5 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:

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

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

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

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

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

We estimate equation (10) using non-linear least squares (NLS).

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

$$n^{(j)} = n_0 + \mathbf{n}\mathbf{X}^{(\mathbf{j})}, \quad (11)$$

where $\mathbf{X}^{(\mathbf{j})}$ are industry characteristics and $\mathbf{n}$ is the corresponding parameter vector. The growth rate g for firms in industry j in the pandemic regime, $g^{(j)}$, is latent and can vary by industry. We parameterize $g^{(j)}$ as

$$g^{(j)} = (g_0 + \mathbf{g}\mathbf{X}^{(\mathbf{j})}) \cdot \widehat{g}^{(j)}\,. \quad (12)$$

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.

3.6 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.

4 Data and Variables

4.1 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 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 forecast as $FY1_t$. If the time gap is between 366 days and 730 days, we label the forecast as $FY2_t$. We also similarly collect FY3 and FY4 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.

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

[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.

in our empirical analysis) is adjusted as follows:

$$FY1_t^{adj} = FY1_t \cdot \left(\frac{1}{s-t_0}\right) + FY1_{t_0-} \cdot \left(1 - \frac{1}{s-t_0}\right), \tag{13}$$

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 (13) 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 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.

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

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

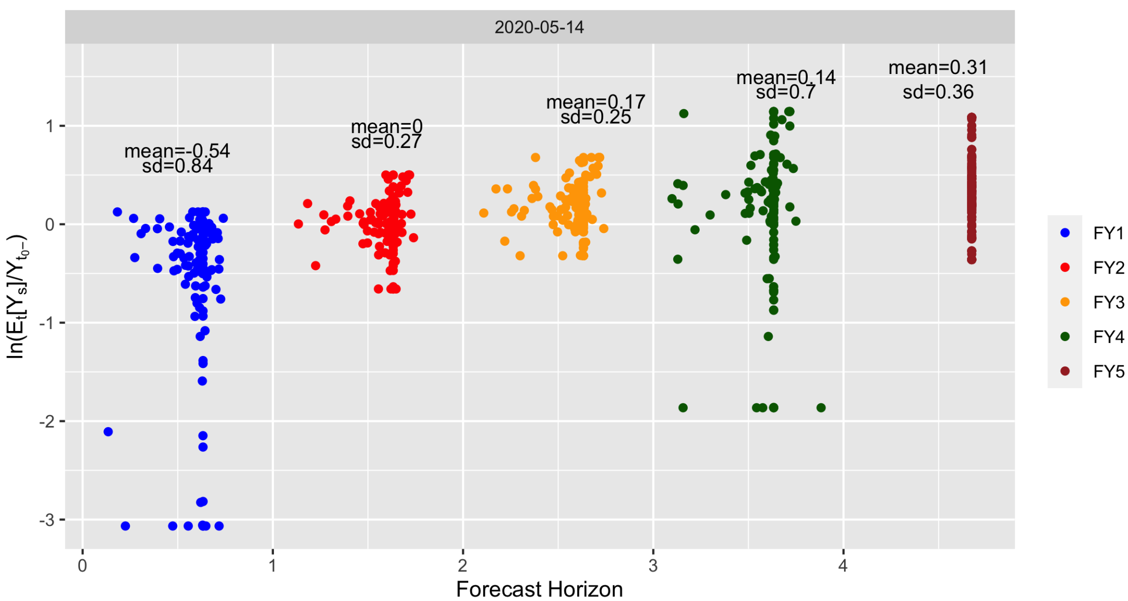
	Mean	SD	P0	P25	P50	P75	P100
$\mathbb{E}_t[Y_s]/Y_{t_0-}$	1.16	0.54	0.05	0.86	1.10	1.39	3.14
$\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$	0.01	0.61	-3.07	-0.15	0.10	0.33	1.14
$s-t$	2.57	1.45	0.13	1.56	2.62	3.63	4.67

(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

Figure 3: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ 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.



In Figure 3, 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 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.

4.2 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%.

[12]See https://www.bls.gov/emp/tables/industry-occupation-matrix-industry.htm

[13]See https://sites.google.com/site/alisonweingarden/links/industries

In our empirical analysis, we will work with percentiles of these measures as opposed to the values themselves. Figure 4 show the empirical cumulative distribution of our Face-to-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.

5 Empirical Results

5.1 Baseline Specification

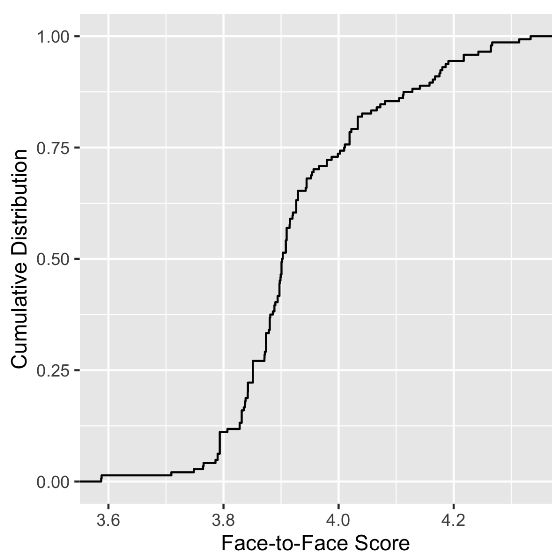
In Table 2, we present the coefficients and bootstrap confidence intervals from non-linear least square regressions of equation (10) using May 2020 earnings forecasts. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$, i.e. the revision of forecasts between January and May 2020. The explanatory variables include the (remaining) duration of time-t earnings forecasts $(s-t)$, the non-pandemic (January 2020) forecasts of the growth rate $\widehat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage.

Column (1) contains the results assuming that the earnings jump parameter n depends on Face-to-Face Score, $n = n_0 + n_1 \times$Face-to-Face Score Pct and similarly for the growth rate parameter, $g = g_0 + g_1 \times$ Face-to-Face Score Pct. Face-to-Face Score Pct is the percentile rank of the industry level Face-to-Face Score and n_1 is the effect on the jump in earnings from Face-to-Face Score, while g_1 is the influence of Face-to-Face score on pandemic regime growth rates.

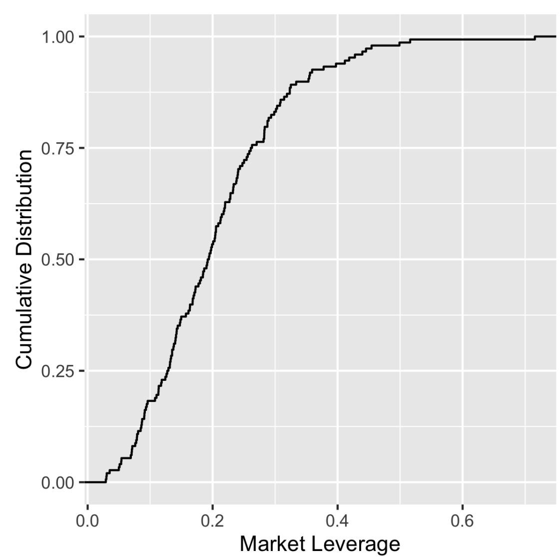
The estimate of λ is 0.880 with bootstrap standard errors of $[0.32, 1.63]$. So the vaccine that returns the earnings to normal is expected in 1/0.88 or 1.14 years. The estimates of

Figure 4: 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

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 (10). 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 $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. λ is the vaccine arrival rate. Columns (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}, and the growth rate in the pandemic regime, g. Column (1) contains the results assuming n and g depend on Face-to-Face Score, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct and $g = g_0 + g_1 \times$ Face-to-Face Score Pct. Face-to-Face Score Pct is the percentile rank of the industry level Face-to-Face Score. Column (2) contains the results assuming n and g depend on Market Leverage, i.e., $n = n_0 + n_2 \times$ Market Leverage Pct and $g = g_0 + g_2 \times$ Market Leverage Pct. Market Leverage Pct is the percentile rank of industry level Market Leverage at the end of 2019. Column (3) contains the results assuming n and g depend on both Face-to-Face Score and Market Leverage, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct and $g = g_0 + g_1 \times$ Face-to-Face Score Pct $+ g_2 \times$ Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score Pct, and Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets. All the regressions are weighted by industry market capitalization at the end of 2019.

	(1)	(2)	(3)
λ	0.880	1.090	0.999
	[0.32,1.63]	[0.49,1.68]	[0.45,1.64]
g_0	0.433	0.519	0.429
	[-1.11,1.47]	[-1.17,1.49]	[-1.29,1.66]
g_1	0.487		0.602
	[-2.97,3.06]		[-2.78,3.25]
g_2		-0.760	-0.887
		[-3.89,2.03]	[-4.25,1.59]
n_0	0.013	-0.073	-0.362
	[-0.77,0.57]	[-1.05,0.69]	[-1.54,0.39]
n_1	2.082		1.727
	[0.44,19.88]		[-0.6,7.7]
n_2		3.944	2.270
		[0.75,23.41]	[0.41,16.64]
Num.Obs.	633	633	633
AIC	-4561973.4	-4561999.0	-4562028.8
BIC	-4561946.7	-4561972.3	-4561993.2

g_0 and g_1 both indicate that pandemic growth rates are lower than during non-pandemic periods. But neither estimates are statistically significant even as the economic effects are large. Moreover, high face-to-face industries experience a significantly larger downward jump in earnings, captured by $n_1 = 2.082$. A 0.01 point increase in this measure leads to a 0.0208 downward jump in earnings. Notice that this parameter also captures the expected reflation in earnings for these industries when the vaccine does arrive.

In column (2), the jump e^{-n} depends on Market Leverage through the functional form $n = n_0 + n_2 \times \text{Market Leverage Pct}$, where Market Leverage Pct is the percentile rank of industry level Market Leverage at the end of 2019 and n_2 is the effect on the jump in earnings from Market Leverage. In column (2), the growth rate also depends on market leverage through the coefficient g_1. The vaccine arrival rate λ estimate is now 1.090 with standard error band of $[0.49, 1.68]$. Again, the estimates of g_0 and g_1 both indicate that pandemic growth rates are lower than during non-pandemic periods. But neither estimates are statistically significant. Highly levered industries experience a significantly larger downward jump in earnings, captured by $n_2 = 3.944$. A 0.01 point increase in this measure leads to a 0.0394 downward jump in earnings.

Column (3) contains the results assuming the jump and growth rate depend on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times \text{Face-to-Face Score Pct} + n_2 \times \text{Market Leverage Pct}$ and $g = g_0 + g_1 \times \text{Face-to-Face Score Pct} + g_2 \times \text{Market Leverage Pct}$. Our preferred specification is column (3) since this column has the lowest AIC and BIC scores, indicating goodness of fit, compared to columns (1) and (2). The vaccine arrival rate λ is 0.999 per annum with a bootstrap confidence interval of [0.45, 1.64]. This translates to an expected vaccine arrival time around 1 year with an early arrival of 0.61 years and a late arrival of 2.22 years. It is also clear from column (3) that the Market Leverage Pct is a stronger predictor of the jump than is Face-to-Face Pct. A 0.01 point increase in this measure leads to a 0.0227 downward jump in earnings. If we examine the coefficient n_1 in column (3), we see that it is also positive but no longer significant.

There has been significant attention to the question of when vaccines will arrive and if they will return the economy to normal.[14] Our estimate of the vaccine arrival rate λ as far as we know is the first systematic attempt to speak to this question.

5.2 Role of Industry Characteristics in Driving Inference of Vaccine Arrival Rates

To this end, we next delve a bit deeper into how we come up with our estimate. We next show that our inference of λ is sensibly being driven by the industries most affected by COVID-19. To see why, consider Panel (a) of Figure 5 where we plot the dependent variable against both the forecast horizon $(s - t)$ and the industry characteristic Face-to-Face Score Pct (i.e. fitted values from column (1) regression model in Table 2). We can see that the FY1 forecast within twelve months before forecast end are significantly revised down, especially for higher Face-to-Face score 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.

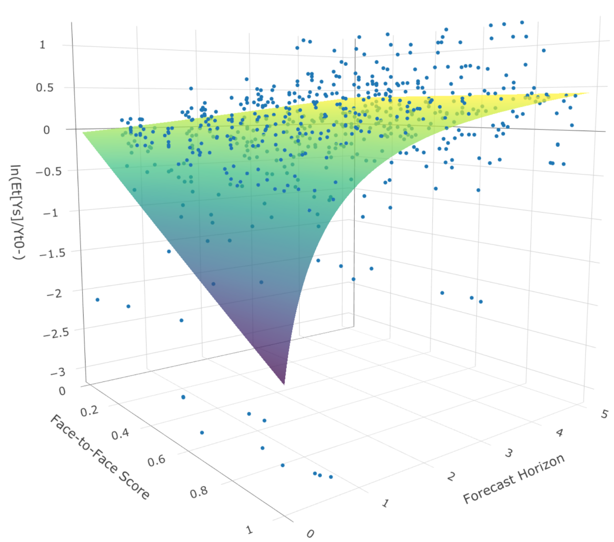
We see a similar pattern in Panel (b) of Figure 5 where we plot the dependent variable against both the forecast horizon $(s - t)$ and the industry characteristic Market Leverage Pct (i.e. fitted values from column (2) regression model in Table 2). It is also clear from Panel (b) of Figure 5 that it is important to properly account for different jump sizes for industries so as to efficiently estimate the arrival rate λ.

One important take-away from Figure 5 is that our estimate of λ is larger when we use Market Leverage as opposed to the Face-to-Face industry characteristics. The reason is that there is a much bigger difference in FY1 versus FY2 revisions for high Market Leverage industries. As such, one needs a much larger λ to fit that portion of the data, which ultimately means that our estimate of λ is being sensibly driven by observations of the most affected industries.

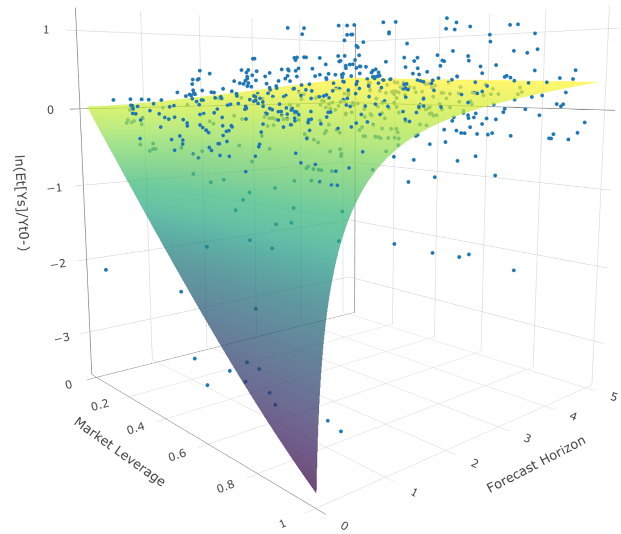
[14] For instance, see the *McKinsey Report* (July 29, 2020) "On pins and needles: Will COVID-19 vaccines save the world", and an article in the *Washington Post* (August 2, 2020), entitled "A coronavirus vaccine won't change the world right away".

Figure 5: The Surfaces of the Estimated Models Using Data in May 2020

This figure plots the observations and fitted value of $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ using the parameter estimates of Equation (10) on the I/B/E/S sample from May of 2020. Subfigure (a) plots $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ and the fitted surface against the percentile rank of Face-to-Face Score and the horizons of forecasts. The estimates used correspond to Column (1) in Table 2. Subfigure (b) plots $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ and the fitted surface against the percentile rank of Market Leverage and the horizons of forecasts. The estimates used correspond to Column (2) in Table 2. $\widehat{g}$ is set to be 0.09, the median value, when generating the surface plots. The $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ observations are the blue dots.



(a) Against Face-to-Face Score and Forecast Horizons



(b) Against Market Leverage and Forecast Horizons

5.3 Net Market Leverage and Customer Interaction Measures

We next show how our baseline results differ when we use a different market leverage measure. In Table 3, we report the results using a net market leverage measure where we deduct corporate cash and short-term investments. In column (1), we find that the vaccine arrival rate is now estimated to be 1.158 with a standard error band of $[0.52, 1.65]$. This estimate is somewhat larger than out baseline estimate which is close to one. The parameters driving the latent pandemic growth rate are similar to those obtained earlier but not statistically significant. Moreover, the parameter $n_2 = 4.829$ is statistically significant and larger than that obtained in our baseline estimate.

In column (2), when we run the specification with both Face-to-Face and Net Market Leverage scores, we find that the vaccine arrival rate is 1.113 per annum with a standard error band of $[0.54, 1.58]$. Net Market Leverage is again more significant in explaining jumps in earnings than the Face-to-Face score. These results, in columns (1) and (2), then suggest that Net Market Leverage is marginally better than Market Leverage in capturing pandemic damage to corporate earnings.

We next replace our baseline face-to-face measure with our two customer interaction measures. In Panel (a) of Table 4, we use the Customer Score. From column (1), we see that the vaccine arrival rate is 0.732 with a standard error band of $[0.16, 1.83]$. This estimate is lower than the baseline estimate in column (1) from Table 2. Moreover, this Customer Score does not seem to explain much of the pandemic growth rate nor the earnings jump on the arrival of COVID-19. From column (2), the conclusion is similar — compared to our baseline face-to-face measure, this Customer Score explains less of the pandemic damage to corporate earnings. In Panel (b) of Table 4, we use the Blinder Score. There is not much of a difference across these two customer scores and both explain less of the damage to earnings than our Face-to-Face Score.

The contrast between the baseline face-to-face industry results with the customer interaction measures suggest that the pandemic damage is not being simply driven by the demand side (i.e. customers going away until a vaccine returns). The supply-side effects in terms of

Table 3: NLS Results Using Net Market Leverage

This table presents the coefficients and bootstrap confidence intervals from non-linear least square regressions of Equation (10). 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 $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. λ is the vaccine arrival rate. Columns (1)-(2) present the results from two different specifications of the jump in earnings, e^{-n}, and the growth rate in the pandemic regime, g. Column (1) contains the results assuming n and g depend on Net Market Leverage, i.e., $n = n_0 + n_2 \times$ Net Market Leverage Pct and $g = g_0 + g_2 \times$ Net Market Leverage Pct. Net Market Leverage Pct is the percentile rank of industry level Net Market Leverage at the end of 2019. Column (2) contains the results assuming n and g depend on both Face-to-Face Score and Net Market Leverage, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Net Market Leverage Pct and $g = g_0 + g_1 \times$ Face-to-Face Score Pct $+ g_2 \times$ Net Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score Pct, and Net Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets. All the regressions are weighted by industry market capitalization at the end of 2019.

	(1)	(2)
λ	1.158	1.113
	[0.52,1.65]	[0.54,1.58]
g_0	0.464	0.391
	[-1.13,1.67]	[-1.6,1.81]
g_1		0.405
		[-3.62,3.33]
g_2	-0.570	-0.657
	[-3.74,2.15]	[-3.86,2.25]
n_0	-0.090	-0.406
	[-0.98,0.61]	[-2.9,0.41]
n_1		1.649
		[-1.13,15.49]
n_2	4.829	3.543
	[0.85,27.9]	[0.64,23.58]
Num.Obs.	633	633
AIC	-4561985.5	-4562013.8
BIC	-4561958.8	-4561978.2

Table 4: NLS Results with Alternative Face-to-Face Scores

This table presents the coefficients and bootstrap confidence intervals from non-linear least square regressions of Equation (10). The regressions are run using I/B/E/S summary statistics in May of 2020. 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 divided by the non-pandemic earnings. Y_{t_0-}, the non-pandemic earnings, is the FY1 forecasts in January 2020 discounted by the January I/B/E/S growth rate forecasts in 2020. The explanatory variables include the horizon of the earnings forecasts $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A reports the results of NLS using Customer Score as the Face-to-Face Score of an industry. The Customer Score is based on the question about how much they work with customers in the O*Net survey. Panel B reports the results using Blinder Score as the Face-to-Face Score of an industry. The Blinder (2009) Score is another customer measure based on five questions in the O*Net survey. λ is the vaccine arrival rate. For each panel, Columns (1)-(2) present the results from two different specifications of the jump in earnings, e^{-n}, and the growth rate in the pandemic regime, g. Column (1) contains the results assuming n and g depend on Face-to-Face Score, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct and $g = g_0 + g_1 \times$ Face-to-Face Score Pct. Face-to-Face Score Pct is the percentile rank of the industry level Face-to-Face Score. Column (2) contains the results assuming n and g depend on both Face-to-Face Score and Market Leverage, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct and $g = g_0 + g_1 \times$ Face-to-Face Score Pct $+ g_2 \times$ Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score Pct, and Market Leverage Pct.The 95% bootstrap confidence intervals are reported in square brackets. All the regressions are weighted by industry market capitalization at the end of 2019.

(a) Panel A: NLS Results Using Customer Score as Face-to-Face Score

	(1)	(2)
λ	0.732	1.099
	[0.16,1.83]	[0.54,1.6]
g_0	0.662	0.222
	[-1.58,1.94]	[-2.1,1.91]
g_1	0.214	0.663
	[-2.79,3]	[-2.86,4.26]
g_2		-0.900
		[-4.39,1.86]
n_0	0.424	-0.527
	[-0.38,1.21]	[-1.84,0.38]
n_1	0.503	0.975
	[-0.65,10.31]	[-0.8,5.76]
n_2		4.275
		[0.95,14.71]
Num.Obs.	633	633
AIC	-4561929.4	-4562023.4
BIC	-4561902.7	-4561987.8

(b) Panel B: NLS Results Using Blinder Score as Face-to-Face Score

	(1)	(2)
λ	0.739	1.097
	[0.16,1.78]	[0.49,1.59]
g_0	0.623	0.292
	[-1.4,1.89]	[-1.98,1.95]
g_1	0.284	0.544
	[-2.81,2.94]	[-2.74,4.19]
g_2		-0.899
		[-4.31,1.88]
n_0	0.331	-0.509
	[-0.45,1.14]	[-2,0.47]
n_1	0.728	1.011
	[-0.48,9.55]	[-0.97,6.51]
n_2		4.160
		[0.93,14.11]
Num.Obs.	633	633
AIC	-4561948.6	-4562028.8
BIC	-4561921.9	-4561993.2

firms having to mitigate to protect their workforce also appear to be important, consistent with the modeling specifications in Hong, Wang, and Yang (2020).[15]

5.4 Placebo Analysis

In Table 5, we 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 5 the regressions results with the constraint that $\lambda \geq 0$. The constraint is binding, i.e. our estimate is zero, which means that the unconstrained regression (unreported for brevity) gives a non-economically sensible negative estimate. In Figure 6, we plot the dependent variables, i.e. the forecasts revisions, that are analogous to those shown in Figure 3. 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

[15]For instance, *MarketWatch* reported on May 2, 2020 that even a technology company like Amazon will spend $4 billion or more on COVID-19 mitigation responses such as testing for its workers, potentially wiping out the company's Q2 profit.

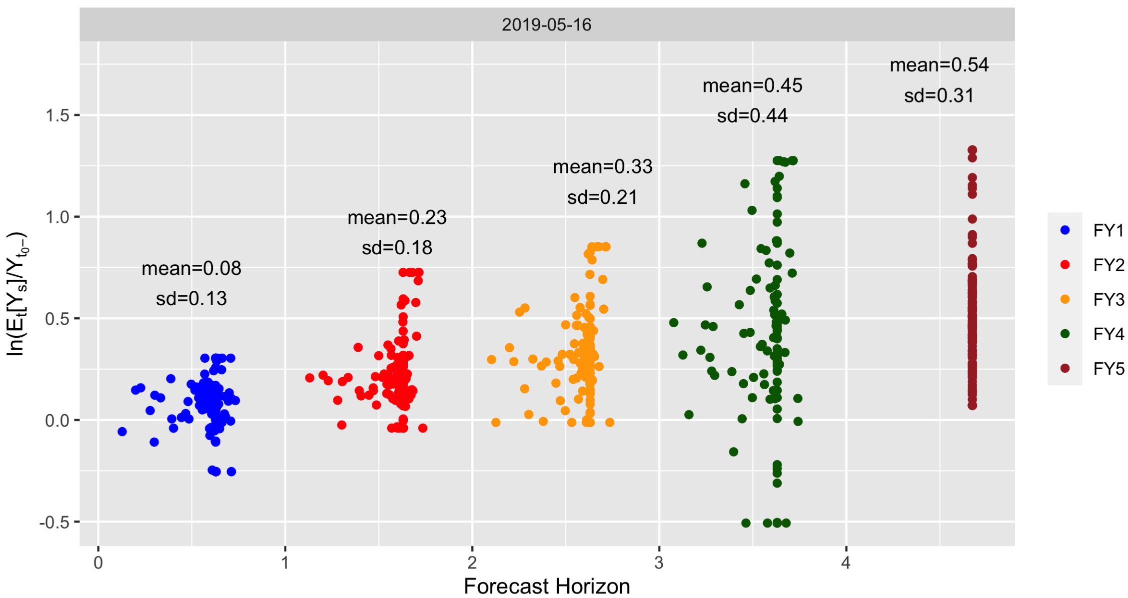
Table 5: Placebo Results Using I/B/E/S Sample in May 2019

This table presents the coefficients and bootstrap confidence intervals from the placebo non-linear least square regressions of Equation (10) 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 $s-t$, the January I/B/E/S forecasts of growth rate $\widehat{g}$ in 2019, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. λ is the vaccine arrival rate. Columns (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}, and the growth rate in the pandemic regime, g. Column (1) contains the results assuming n and g depend on Face-to-Face Score, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct and $g = g_0 + g_1 \times$ Face-to-Face Score Pct. Face-to-Face Score Pct is the percentile rank of the industry level Face-to-Face Score. Column (2) contains the results assuming n and g depend on Market Leverage, i.e., $n = n_0 + n_2 \times$ Market Leverage Pct and $g = g_0 + g_2 \times$ Market Leverage Pct. Market Leverage Pct is the percentile rank of industry level Market Leverage at the end of 2018. Column (3) contains the results assuming n and g depend on both Face-to-Face Score and Market Leverage, i.e., $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct and $g = g_0 + g_1 \times$Face-to-Face Score Pct$+ g_2 \times$Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\widehat{g}$, Face-to-Face Score Pct, and Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets. All the regressions are weighted by industry market capitalization at the end of 2018.

	(1)	(2)	(3)
λ	0.000	0.000	0.000
	[0,0.91]	[0,0.73]	[0,0.66]
g_0	0.680	0.788	0.722
	[0.12,0.88]	[0.46,0.92]	[0.19,0.94]
g_1	0.134		0.118
	[-0.34,0.8]		[-0.3,0.87]
g_2		-0.163	-0.148
		[-0.71,0.22]	[-0.72,0.24]
n_0	-0.066	-0.081	-0.076
	[-0.26,0.03]	[-0.25,-0.03]	[-0.29,0.04]
n_1	-0.011		-0.049
	[-0.23,0.23]		[-0.26,0.19]
n_2		0.022	0.055
		[0,0.24]	[-0.17,0.29]
Num.Obs.	638	638	638
AIC	-4548171.5	-4548182.0	-4548219.5
BIC	-4548144.7	-4548155.3	-4548183.8

Figure 6: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ 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.



by 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.

6 Accounting for Vaccine News

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

$$\mathbb{E}_t(\tau_v) = \mathbb{E}_t(\tau_\eta) + \mathbb{E}_t\left[\mathbb{E}_{\tau_\eta}(\tau_v - \tau_\eta)\right] = \frac{1}{\lambda_\eta} + \left(\frac{\pi_G}{\lambda_G} + \frac{\pi_B}{\lambda_B}\right), \tag{14}$$

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 (14). Hence, 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 (14). 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 6. First, our inference of λ using the June and July forecasts are similar to those obtained using May. For instance, In Panel A, where we use the estimates of n and g from column (1) of Table 2, we estimate λ to be 0.948 for the June forecasts and 1.075 for the July forecasts, respectively. These estimates are close to 1. The same holds for Panels B and C where we use estimates from columns (2) and (3) from Table 2, respectively. The estimates here are slightly higher at 1.2 to 1.4. But the standard error bands of these estimates overlap with those of our May 2020 estimates. For instance, the standard error band for column (3) of Table 2 is $[0.45, 1.64]$.

However, we find that the estimated arrival rate increased when using the August 2020 forecasts. Across Panels A-C, the estimated λ now varies from 2.005 to 2.374. The standard error band for the August 2020 estimate from Panel B does not overlap with the standard error band for the May 2020 estimate. The August 2020 forecasts suggest that a vaccine is expected in 6 months, or the Spring of 2021. In other words, our model's estimates indicate that there was good news on vaccines in the late summer, consistent with qualitative narratives in the stock market. Our estimates anticipate good news on Pfizer, Moderna and AstraZeneca vaccine effectiveness announced in November. But it remains to be seen if the

Table 6: 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 from the estimates in Table 2. The explanatory variables include the horizons of the earnings forecasts $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\widehat{g}$, the pandemic growth rate predicted from the estimates in Table 2, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A presents the estimates of λ after plugging in the parameter estimates from Column (1) of Table 2. Panel B presents the estimates of λ after plugging in the parameter estimates from Column (2) of Table 2. Panel C presents the estimates of λ after plugging in the parameter estimates from Column (3) of Table 2. The 95% bootstrap confidence intervals are reported in square brackets. All the regressions are weighted by industry market capitalization at the end of 2019.

(a) Panel A: Plugging in Estimates From Column (1) of Table 2

	June	July	August
λ	0.948	1.075	2.005
	[0.66,1.33]	[0.76,1.51]	[1.29,3.12]

(b) Panel B: Plugging in Estimates From Column (2) of Table 2

	June	July	August
λ	1.244	1.447	2.374
	[0.92,1.67]	[1.07,1.97]	[1.7,3.54]

(c) Panel C: Plugging in Estimates From Column (3) of Table 2

	June	July	August
λ	1.132	1.323	2.180
	[0.83,1.5]	[0.98,1.79]	[1.52,3.16]

vaccines are indeed widely distributed by the Spring of 2021 and if the economy will return to normal then.

7 Conclusion

We estimate a parsimonious model of pandemic damage to corporate earnings developed in Hong, Wang, and Yang (2020). We infer from analysts' earnings forecasts that, as of mid-August 2020, an effective vaccine that returns corporate earnings to normal is expected to arrive in six months. Levered and face-to-face industries would benefit the most from a vaccine arrival. Analysts expectations imply that the vaccines are expected to collectively be a silver bullet for corporate earnings by the Spring of 2021.

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.

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