Pandemics, Vaccines and Corporate Earnings

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Abstract

We estimate a model of damage to corporate earnings from COVID-19. An unexpected pandemic lowers current earnings due to costly mitigation and reduces growth rates. Damage depends on the expected arrival of a vaccine that reverts earnings to normal. Using this model, we infer from analysts' earnings forecasts that, as of mid-May 2020, an effective vaccine is expected in 0.96 years (95% bootstrap CI [0.72,1.72]). Growth rates are on average 25% lower during the pandemic. Levered and face-to-face industries would benefit the most from a vaccine arrival. Analysts' expectations imply that the vaccine expected for the middle of 2021 is a silver bullet for corporate earnings.

Keywords: Covid-19, pandemic, damage function, corporate earnings, analyst forecasts, vaccine arrival

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1 Introduction

We estimate a parsimonious continuous-time model of damage to corporate earnings from the COVID-19 pandemic. Our model is adapted from Hong, Wang, and Yang (2020a). The unexpected arrival of a pandemic results in a downward jump of the earnings for a typical corporation due to costly mitigation — on the part of both customers and firms. Damage depends on when an effective vaccine is expected to arrive. When the vaccine arrives, these costs no longer need to be paid and we expect 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 simplified version of Hong, Wang, and Yang (2020a) boils down to a stochastic regime switching model of earnings (non-pandemic versus pandemic regimes) that depends on just a few key parameters: the arrival rate of a vaccine, jump in earnings (both on pandemic impact and reflation on vaccine arrival), and differential growth rates across these regimes. We derive an estimation method based on earnings forecasts. Our method allows for potential heterogeneity in damages across firms. For example, technology firms, e.g., Zoom, even benefit from the need for social distancing.

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.[1] The underlying premise of our empirical analysis is that these forecasts are generated by the same rational economic considerations as in our model. This is a reasonable assumption given the reaction of the stock market to news of vaccine developments and speculation regarding earnings reflation scenarios conditioned on vaccine arrival. Indeed, Landier and Thesmar (2020) have already documented substantial revisions in consensus analyst forecasts by May 2020 that reflect damage to a broad range of industries.

We view our contribution as estimating key structural parameters affecting cumulative damage to corporate earnings from COVID-19. Broadly, the vaccine arrival rate moderates

[1] Our method can also be applied to other contexts to the extent earnings might be thought of as being in a different regime.

the persistence of the COVID-19 shock to earnings. To the extent a vaccine is expected to arrive quickly, the shock should be mostly felt in near term as opposed to medium term earnings forecasts. Hence, we can infer from forecasts at different horizons the parameters of the perceived earnings process.

At the same time, our analysis also naturally addresses a couple of sets of questions posed by policy makers and practitioners. First, when is a vaccine expected to arrive and will it return the economy to normal? On the one hand, a number of experts surveyed in the *McKinsey Report* (July 29, 2020) "On pins and needles: Will COVID-19 vaccines save the world" believe that it is plausible that a couple of vaccines (likely Pfizer and Moderna) that are 60-75% effective will be widely distributed by the middle of 2021 and that they will then allow the economy to return to normal. In other words, standing in the Summer of 2020, the expected effective vaccine arrival is about one year.

On the other hand, an article in the *Washington Post* (August 2, 2020), entitled "A coronavirus vaccine won't change the world right away," summarizes skepticism among public health officials: "In popular conception, a vaccine is regarded as a silver bullet. But the truth — especially with the earliest vaccines — is likely to be far more nuanced." Yonatan Grad, an assistant professor of infectious diseases and immunology at the Harvard T.H. Chan School of Public Health, is quoted in the article as saying "It seems, to me, unlikely that a vaccine is an off-switch or a reset button where we will go back to pre-pandemic times."

Indeed, *Axios* reports on August 8, 2020 that Dr. Anthony Fauci told attendees at Brown University's School of Public Health during a Q&A session that, "The chances of it being 98% effective is not great, which means you must never abandon the public health approach." That is, even though there is a consensus that several vaccines will be approved by year end and distributed by the middle of 2021, the extent to which they can be effective is debatable.

Analysts' earnings forecasts are likely to integrate not only scientific evidence on the development of vaccines but also logistical issues surrounding their distribution as well as effectiveness, i.e. whether consumers and firms return to normal. Hence, we can compare our arrival rate estimate (using forecasts in April and May of 2020) to the widely-quoted one year figure, such as in the *McKinsey Report* cited above. To the extent our estimated vaccine arrival rate, which captures when earnings revert to normal, is smaller than this one year figure, we would conclude that analysts believe that it will take a while for vaccines to have an effect on earnings. In contrast, if our estimated arrival rate lines up with this one year figure, then it will imply that analysts believe the vaccines expected to arrive in the middle of 2021 will collectively be a silver bullet for earnings. Since earnings are an important part of the economy, we might also extrapolate that the vaccines expected in the middle of 2021 will be a silver bullet for the economy more generally.

Second, 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. Our analysis here complements Gormsen and Koijen (2020), who use dividend strips to back out the negative impact of COVID-19 on dividend growth. 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 and have important consequences for fiscal or monetary policy countermeasures (see, e.g., Elenev, Landvoigt, and Van Nieuwerburgh (2020)).

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 parameters and several independent variables. Our main dependent variable is the revision of earnings forecasts after the arrival date of COVID-19, which we take to be February 20, 2020, as in Gormsen and Koijen (2020) and others. To reduce measurement error, we work with industry portfolios by value-weighing median forecasts for stocks at the GICs 8-digit industry classification. There is naturally a lag in analyst revisions and we only begin to see significant revisions starting in April and May of 2020. For our baseline specifications, we pool together both industry FY1 (nearest fiscal year-end) and FY2 (next fiscal year-end) forecasts made in either April or May of 2020.

The main independent variables from our theory are the non-pandemic and pandemic regime growth rates. 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 focus on these characteristic 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. Face-to-face exposure measures are created using occupational surveys, which we map to the industry level by using occupation codes. The correlation at the industry level of face-to-face ranks and leverage ratio ranks is 0.4.

We then use non-linear OLS to make our inferences and present bootstrap standard errors. To see how we estimate these parameters, consider the plot in Figure 3 of consensus earnings forecasts standing 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, almost 50% 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) — 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. 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 and FY2 forecasts, are unrealistically high.

We have the following findings for our baseline specification. First, using forecast revisions in May 2020, we estimate that analysts expect a vaccine to arrive in 0.96 years with a 95% bootstrap CI [0.72, 1.72]. Estimates using April 2020 are similar. 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.

The mean estimate of 0.96 years is in line with general discussions in the media of the vaccine timeline. The 95% bootstrap confident interval is tight at between 0.72 years and 1.72 years. Hence, analysts' expectations imply that the vaccines expected for the Summer of 2021 are collectively a silver bullet for corporate earnings. Our finding of a quick arrival of a vaccine that returns earnings to normal is also 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 expectations remained unchanged.

Second, highly levered and face-to-face industries experience greater damage in the form of jumps in earnings following COVID-19. Leverage comes in particularly strong in our specifications and dominates face-to-face measures in explaining these jumps. These findings are similar qualitatively to the literature cited above on 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 levered and face-to-face industries would benefit the most from a vaccine arrival.

Third, growth rates during a pandemic are lower on average, consistent with direct negative effects of infections absent mitigation and a vaccine. Our point estimate is for the pandemic growth rates to be about 75% of the non-pandemic growth rates, though our confidence interval is much wider than for our vaccine arrival estimate. 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.

We then consider several robustness exercises. First, we 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. Second, we consider a different measure of industry leverage that nets out corporate cash and liquid investments. This measure yields similar results as our baseline specification except for April forecasts, when we obtain a quicker vaccine arrival rate of 0.56 year. Third, we consider alternative measures of face-to-face industries due to Blinder (2009). These measures emphasize interactions with customers as opposed to generalized face-to-face interactions that might encompass either customers or fellow employees. Our estimate for the vaccine arrival rate is similar.

Finally, we extend our analysis in two directions. First, we confront our implied growth rates to the observed growth rate forecasts in the pandemic regime. The median industry growth rate forecasts in May 2020 are around 20% lower than in January 2020, in line with but somewhat smaller than our point estimates which range from 25% to 40% lower. The difference might be due to growth rate forecasts picking up some of the earnings reflation should a vaccine arrive in a couple of years. Nonetheless, these figures suggests that growth rate forecasts in April or May of 2020 can essentially be viewed as expected growth rates that apply during a pandemic. Consistent with this view, when we simply use forecasts made in April or May 2020 as a proxy for pandemic growth rates, we retrieve similar coefficients for our other structural parameters.

Second, our estimates make the most sense for the months immediately following the arrival of a vaccine. As more forecasts come online, we need to allow for the possibility of time-varying arrival rates, which we then develop as an extension. But at this point, the inferences regarding arrival in the middle of 2021 seem in line with vaccine news.

Overall, our findings point to earnings returning to normal when a vaccine arrives in the middle of 2021, and hence an optimistic vaccine scenario is priced in stock markets. It is important to keep in mind that these forecasts might be wrong to the extent learning effects after disasters could lead to long-term scarring even after a vaccine arrives (see Kozlowski, Veldkamp, and Venkateswaran (2020) for possibility of scarring in COVID-19 or Hong, Wang, and Yang (2020b) for disasters more generally due to higher taxes to pay for mitigation in preparation for the next disaster).

Our paper proceeds as follows. We present our model of earnings in Section 2. Descriptions of the dataset and main variables are in Section 3. The empirical findings are presented in Section 4. We conclude in Section 5.

2 Model

In this section, we consider a simplified version of Hong, Wang, and Yang (2020a). 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.

2.1 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:

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

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:

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

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 $d\mathcal{J}_t = 1$ (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.[2] 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 (2020a), 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

In Hong, Wang, and Yang (2020a), 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 sudden increase in mitigation costs and decrease in earnings, means that the COVID-19 shock unexpectedly hits at t_0, the earnings drops by a fixed fraction δ:

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

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

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 let $\delta = n$. 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: $\tau- = t_0$, which occurs if $\lambda \to \infty$. For this case, earnings is not impacted at all by the jumps as $Y_\tau = e^n Y_{\tau-} = e^n Y_{t_0} = e^n e^{-n} Y_{t_0-} = Y_{t_0-}$.

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:

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

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

Recall that $\widehat{g}$ is pre-COVID growth (LTG) 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 $\mathbb{E}_t[Y_s]/Y_t$.

Below, 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 green dot $Y_{t_0-} = 1.492$ to the red 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 $Y_{\tau-} = 1.120$ to $Y_\tau = 1.672$.

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 $g = \widehat{g} \times 0.85 = 8\% \times 8.5\% = 6.8\%$.

[Figure 1 about here.]

In addition to plotting a sample path, we also plot the expected earnings $\mathbb{E}_0(Y_t)$ given the value of Y_0 at $t = 0$, i.e., immediately after the pandemic arrival (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 $Y_0 e^{gt}$ (see the pink dotted line.) The gap between the rational and naive forecasts of Y_t is due to 1.) $g \le \widehat{g}$ and 2.) earnings may jump by a fraction $(e^n - 1) > 0$ upon the vaccine arrival. The green 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 dotted line plots expected earnings Y_t immediately after the arrival of the vaccine at time τ, which is given by $\mathbb{E}_\tau = Y_\tau e^{\widehat{g}(t-\tau)}$. That is, the earnings processes in the normal regimes (both non-pandemic arrival and post-vaccine arrival) are the same. Notice that the post-pandemic growth rate for the dotted black line is equal to $\widehat{g}$, which is larger than the growth rate for the dotted red line, reflecting 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) and $Y_{t_0}/Y_{t_0-} = e^{-\delta}$ into (6) and assuming $\delta = n$, we obtain[3]

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

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. Notice that the revisions are naturally negative due to the downward jump in earnings upon the unexpected pandemic arrival but then because of the anticipated vaccine arrival increase towards zero at around 1 year. 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 pink dash-dotted straight line, $\widehat{g}\,t = 0.08t$.

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 2 about here.]

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, or just after the

[3]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.

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:

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

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 April 16 or 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

$$Y_{j,t_0-} = e^{-\widehat{g}_j(s-t_0-)}\mathbb{E}_{t_{0-}}[Y_{j,s}]\ . \qquad (9)$$

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

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

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

We parameterize the earnings jump parameter n for firms in industry j by

$$n_j = n_0 + \mathbf{n}X_j, \qquad (11)$$

where X_j are industry characteristics. The growth rate g for firms in industry j in the pandemic regime, g_j, is latent and can vary by industry. We parameterize it as

$$g_j = g_0 \cdot \widehat{g}_j\ . \qquad (12)$$

That is, the growth rate in the pandemic regime g_j is a multiple of $\widehat{g}_j$, the growth rate in the corresponding non-pandemic regime. The ratio between the two growth rates, $g_0 = g_j/\widehat{g}_j$, captures the average difference in growth rates across the two regimes.

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 either April or 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-, April or 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 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 $FY2_t$.

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 company 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 April 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 (April or May is 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 (either April or May in our empirical analysis) is adjusted as follows:

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

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 either April or 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 April or May.

We merge IBES forecasts with CRSP market capitalization data using historical 8-digit CUSIP identifiers.[4] 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 then aggregate the EPS forecasts, 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 at these industry $\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}$ and set $\widehat{g}$ at the 5% level.

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

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 0.89 and the standard deviation is 0.33. The $\ln\left(\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}\right)$ has a mean of -0.25 with a large standard deviation of 0.67. The mean $(s-t)$ is 1.09 for the May 2020 forecasts. In Panel B, we report the distribution of $\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}$ for the mid-April 2020 forecasts. The mean is now 1.00 and there is still a large standard deviation of 0.30. The $\ln\left(\frac{\mathbb{E}_{t_0}[Y_s]}{Y_{t_0-}}\right)$ has a mean of -0.07 with a large standard deviation of 0.44. The mean of $(s-t)$ is 1.16 with a standard deviation of 0.51.

[Table 1 about here.]

In Figure 3, we take a closer look at the standard deviation of these forecasts by plotting the industry forecast revisions separately for FY1 and FY2 forecasts. Panel A is the figure for the April 2020 forecasts and Panel B is the figure for the May 2020 forecasts. We can see that the FY1 forecast within twelve months before forecast end are significantly revised down, 26% on average for the April 2020 forecasts and 52% 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.

[Figure 3 about here.]

3.2 Leverage and Face-to-Face Industry 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).[5] In the BLS data, for every industry, they measure

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

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 this crosswalk.[6]

The summary statistics for leverage and these three face-to-face measures are provided in Panel C 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 0.13. The mean Customer Score is 3.44 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 11% with a standard deviation of 9%.

In our empirical analysis, we will work with percentiles of these measures as opposed to the values themselves. Figures 4 and 5 show the empirical cumulative density of our Market Leverage and Face-to-Face Score 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.

[Figure 4 about here.]

[Figure 5 about here.]

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

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 (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.

[Table 2 about here.]

Panel A reports the results of the unconstrained NLS, while Panel B reports the results where we impose theoretical restrictions on parameters from equations (11) and (12): $g_0 \leq 1$, $\lambda \geq 0$, $n_0 \geq 0$, $n_1 \geq 0$, and $n_2 \geq 0$. In both panels, Column (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}.

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. 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. In column (2), the jump e^{-n} depends on Market Leverage through the functional form $n = n_0 + n_2 \times$ 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. Column (3) contains the results assuming the jump depend on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct.

Our preferred specification is column (2) where we model the jump as a function of Market Leverage Pct. This column has the lowest AIC and BIC scores, indicating goodness of fit, compared to columns (1) and (3). The vaccine arrival rate λ is 1.05 per annum with a tight bootstrap confidence interval of [0.58, 1.38]. This translates to an expected vaccine arrival time around 0.96 years with an early arrival of 0.72 years and a late arrival of 1.72 years. In column (1), where the jump is modeled as a function of Face-to-Face score, the arrival rate is 0.88 per annum. In column (3), where the jump is modeled a function of both Market Leverage and Face-to-Face scores, the arrival rate is 1.10. In all three columns, the estimates come with fairly tight confidence intervals of between 0.72 years to 2.38 years.

It is also clear from column (2) that the jump really depends on the Market Leverage PCT, which is scaled to lie between 0 and 1. A 0.01 point increase in this measure leads to a 0.04 downward jump in earnings. If we examine the coefficient n_1 in column (1), we see that it is also positive and significant. That is Face-to-Face Percentile Ranks do also influence the size of the downward jump earnings. But the economic magnitude is smaller than leverage as witnessed by the AIC/BIC scores.

To see why column (2) is a better specification compared to column (1), we plot the dependent variable against the Face-to-Face Score in Figure 6 and against the Market Leverage Pct in Figure 7. The red dots represent FY2 forecasts while the blue dots represent FY1 forecasts. We can see that there is a much more pronounced jump for highly leveraged industries for the FY1 forecasts (blue dots).

[Figure 6 about here.]

[Figure 7 about here.]

To gain more intuition for how we estimate λ, consider Figure 8 where we plot the dependent variable against both $(s-t)$ and the industry characteristic (either Market Leverage of Face-to-Face score). We can see that the FY1 forecast within twelve months before forecast end are significantly revised down, especially for the levered 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.

[Figure 8 about here.]

It is clear from Figure 8 that it is important to properly account for different jump sizes for industries so as to efficiently estimate the arrival rate λ. To this end, when we put in both of these industry measures in column (3), we see that only Market Leverage is significant. One important take-away from Figure 8 is that our estimate λ is larger when we use market leverage as opposed to the face-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.

Finally, the growth rate we estimate for the pandemic regime is 0.75 of the non-pandemic growth rate, i.e., $g_0 = 0.75$. However, there is a wide confidence interval. But notice that when we impose the theoretical restrictions in Panel B, the estimates we obtain for column (2) are almost identical to what we obtained in Panel A. This is reassuring and says that our estimates from column (2) are stable. We can make a limited conclusion that there is a substantial negative direct effect to growth rates absent a vaccine.

In Table 3, we estimate our model using the April 2020 forecasts. Column (2) is again our preferred specification for the same reasons that we articulated in discussing Table 2. We can also compare the column (2) estimates across these two tables. The point estimate for the vaccine arrival rate is slightly higher, at 1.29 compared to 1.05 from Table 2 but the difference is not statistically significant. Moreover, we get fairly similar estimates for jumps and also g_0. The consistency across April and May 2020 is not surprising given that we did not have any major vaccine news per se and the memoryless property of our model should yield similar estimates. The caveat of course is that as we get additional months of forecasts going forward, we need to be more cognizant of how to interpret the arrival rates as we discuss in more detail below.

[Table 3 about here.]

4.2 Placebo Exercise

In Table 4, 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 4 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 9, we plot the dependent variables, i.e. the FY1 and FY2 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 by the growth rate.

[Table 4 about here.]

[Figure 9 about here.]

But of course, the COVID-19 period data suggests instead that there is a regime switch that might occur between over the roughly 2 year period of forecast maturities. 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.

4.3 Using Net Market Leverage

Second, we consider a net market leverage measure where we deduce corporate cash and short-term investments. The results for the constrained specification are in Table 5. For the May 2020 forecasts, the results are nearly identical to our baseline results. But for the April 2020 forecasts, we obtain a quicker vaccine arrival rate of 0.56 year. The reason is that the net market leverage measure is a much more powerful predictor for cross-industry heterogeneity in the downward jump than our original market leverage measure.

[Table 5 about here.]

4.4 Alternative Face-to-Face Industry Measures

Third, we consider instead of our Face-to-Face Score measures our two customer measures. These results are in Table 6. We can see that these two Customer Scores explain far less of the jump in earnings compared to Face-to-Face Scores. In any event, the Market Leverage Score measure is far more important as before.

[Table 6 about here.]

4.5 Confronting Growth Rate Forecasts during the Pandemic

We then confront our implied pandemic growth rates to the observed growth rate forecasts in the pandemic regime. In Table 7, we report the distributions of analyst growth rate forecasts for January 2020 and May 2020. Hence, we will refer to the January 2020 forecasts as non-pandemic growth rate forecasts and the May 2020 as the pandemic growth rate forecasts. We see that the growth rate forecasts for May 2020 are smaller than for January 2020: 0.09 in the non-pandemic period and 0.07 in the post-pandemic period. That is, the median industry growth rate forecast in May 2020 is around 20% lower than in January 2020. This is in line with but somewhat smaller than our point estimates of g_0 which range from 25% to 40% lower. The difference might be due to growth rate forecasts picking up some of the earnings reflation should a vaccine arrive in a couple of years. Nonetheless, these figures suggests that growth rate forecasts in April or May of 2020 can essentially be viewed as expected growth rates that apply during a pandemic.

[Table 7 about here.]

To this end, we simply use growth rate forecasts made in April or May 2020 as a proxy for the pandemic growth rates g. These results are reported in Table 8. In Panel A, using the May 2020 forecasts and the unconstrained specification, we obtain an (annual) arrival rate of vaccine around one, very similar to our baseline specification. Similarly, we find that levered industries will benefit more from a vaccine. The coefficients of the structural parameters are generally very close to our baseline. In Panel B, we present the constrained estimates. Our structural estimates are again very similar to the baseline results.

[Table 8 about here.]

4.6 Time-Varying Arrival Rates

Our estimates make sense for the months immediately following the arrival of a vaccine. As more forecasts come online, we need to allow for the possibility of time-varying arrival rates. We now develop just such an extension.

Let $\lambda(t)$ denote the vaccine arrival time at calendar time t. During the pandemic regime $(t_0 < t < \tau)$, we have

$$\frac{1}{Y_t}\mathbb{E}_t[Y_s] = \int_t^s \lambda(\tau) e^{-\int_t^\tau \lambda(u)du} e^{g(\tau-t)} e^n e^{\widehat{g}(s-\tau)} d\tau + e^{-\int_t^s \lambda(u)du} e^{g(s-t)} . \quad (14)$$

We employ the same approximation as before $Y_t/Y_{t_{0-}} \approx Y_{t_0}/Y_{t_{0-}} = e^{-\delta}$ to obtain the following relation:

$$\frac{\mathbb{E}_t[Y_s]}{Y_{t_0-}} = \frac{Y_t}{Y_{t_0-}}\frac{1}{Y_t}\mathbb{E}_t[Y_s] \approx e^{-\delta}\left[\int_t^s \lambda(\tau) e^{-\int_t^\tau \lambda(u)du} e^{g(\tau-t)} e^n e^{\widehat{g}(s-\tau)} d\tau + e^{-\int_t^s \lambda(u)du} e^{g(s-t)}\right] . \quad (15)$$

It then follows we have generalized our baseline specification to allow for time-varying arrival rates as follows:

$$\frac{\mathbb{E}_t[Y_{j,s}]}{e^{-\widehat{g}_j(s-t_0-)}\mathbb{E}_{t_{0-}}[Y_{j,s}]} \approx e^{-\delta}\left[\int_t^s \lambda(\tau) e^{-\int_t^\tau \lambda(u)du} e^{g_j(\tau-t)} e^n e^{\widehat{g}_j(s-\tau)} d\tau + e^{-\int_t^s \lambda(u)du} e^{g_j(s-t)}\right] . \quad (16)$$

5 Conclusion

There is a timely debate on whether a vaccine will be a silver bullet for COVID-19 that returns the economy back to normal. Even though there is a consensus that several vaccines will be approved by the end of 2020 and available for wide distribution in the middle of 2021, the extent to which they can be effective in returning the economy to normal is very much in doubt. Analysts earnings forecasts provide a potential answer. Broadly, a vaccine arrival rate ought to moderate the persistence of the COVID-19 shock to earnings. To the extent that it is expected to arrive quickly and be effective in returning earnings to normal, the COVID-19 shock should be mostly felt in near term as opposed to medium term earnings forecasts.

To this end, we use a simplified version of a pandemic damage model of earnings developed in Hong, Wang, and Yang (2020a) to infer from analysts' earnings forecasts that, as of mid-May 2020, an effective vaccine is expected to arrive in 0.96 years (95% bootstrap CI [0.72, 1.72]). Growth rates are on average 25% lower in the interim. Levered and face-to-face industries would benefit the most from a vaccine arrival. Analysts expectations imply that the vaccines expected in the middle of 2021 are collectively a silver bullet for corporate earnings. Since earnings are an important part of the economy, we might also extrapolate that these vaccines will be also a silver bullet for the economy more generally.

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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 $Y_t = 1.672$.

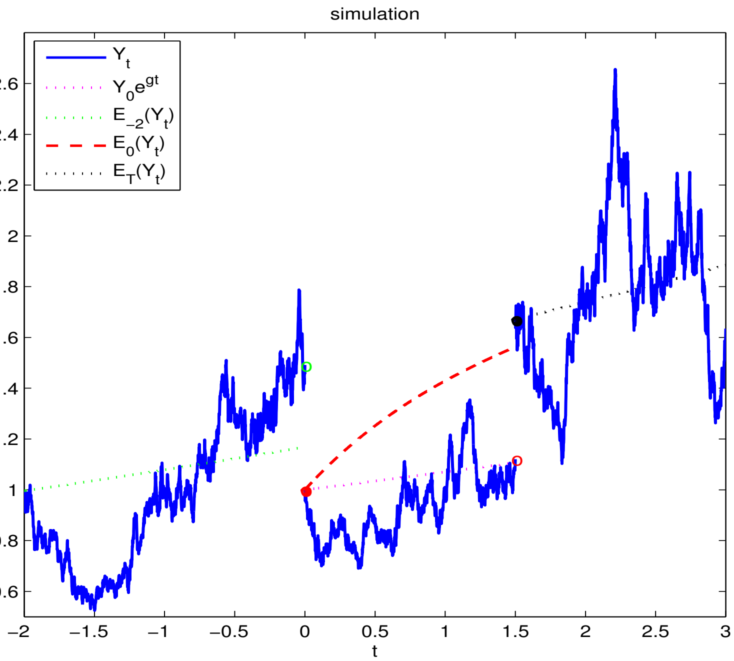


Figure 2: The Effect of the Vaccine Arrival Rate λ on $\ln\left[\mathbb{E}_0(Y_t)/Y_{0-}\right]$.

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

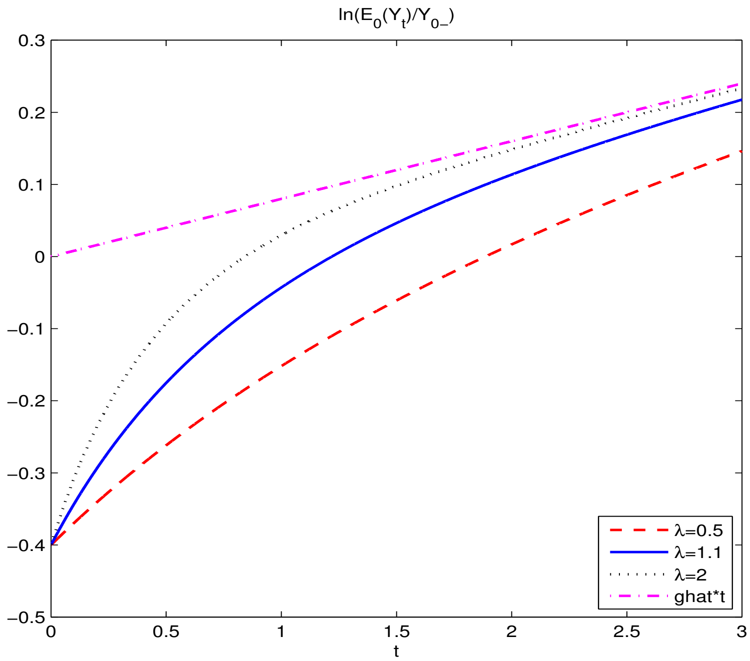


Figure 3: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ Over Forecast Maturities

This figure plots the natural log of the earnings forecasts divided by the non-pandemic earnings $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ against the maturities of the forecasts (s-t). Y_{t_0-}, the non-pandemic earnings, is the earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. Each panel plots a monthly cross section of our I/B/E/S sample, indicated by the date of each I/B/E/S statistical period on top of each panel. Forecasts with maturities less than 1 year are in blue. Forecasts with maturities between 1 and 2 years are in red.

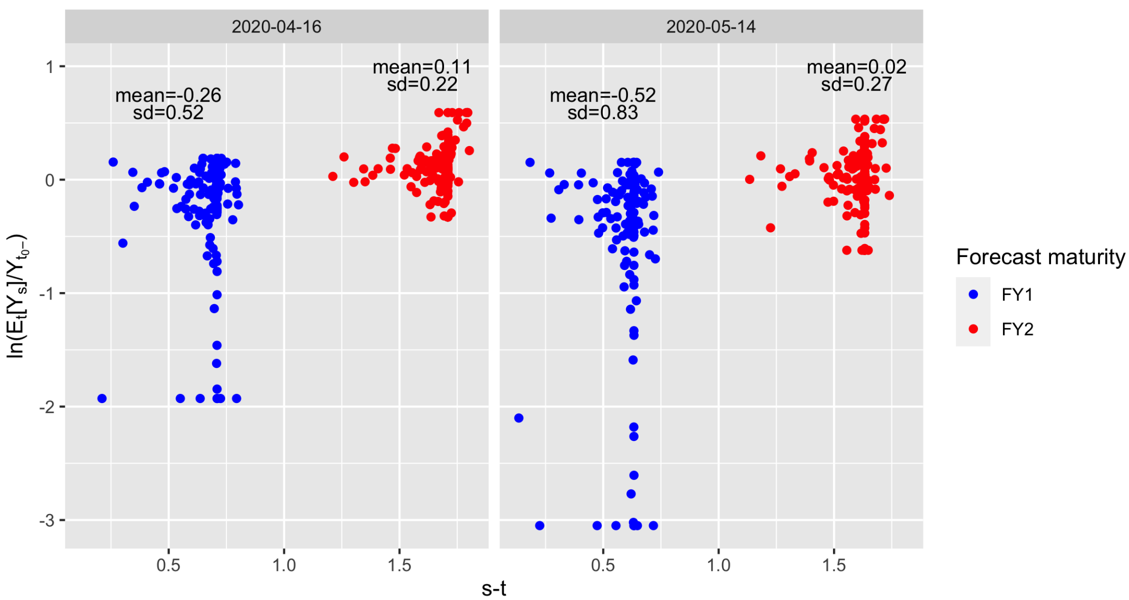


Figure 4: The Empirical Cumulative Density of Face-to-Face Score

This figure plots the empirical cumulative density of the Face-to-Face Score of 144 industries defined by 8-digit GICS codes. 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).

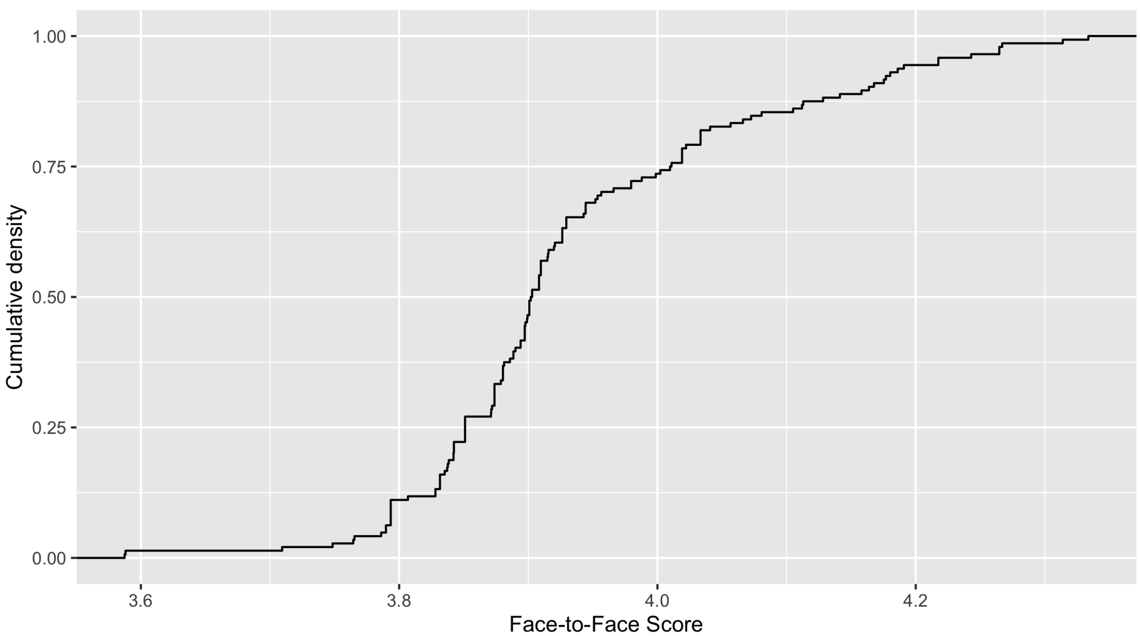


Figure 5: The Empirical Cumulative Density of Leverage

This figure plots the empirical density of the Market Leverage ratio of 148 industries defined by 8-digit GICS codes. 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).

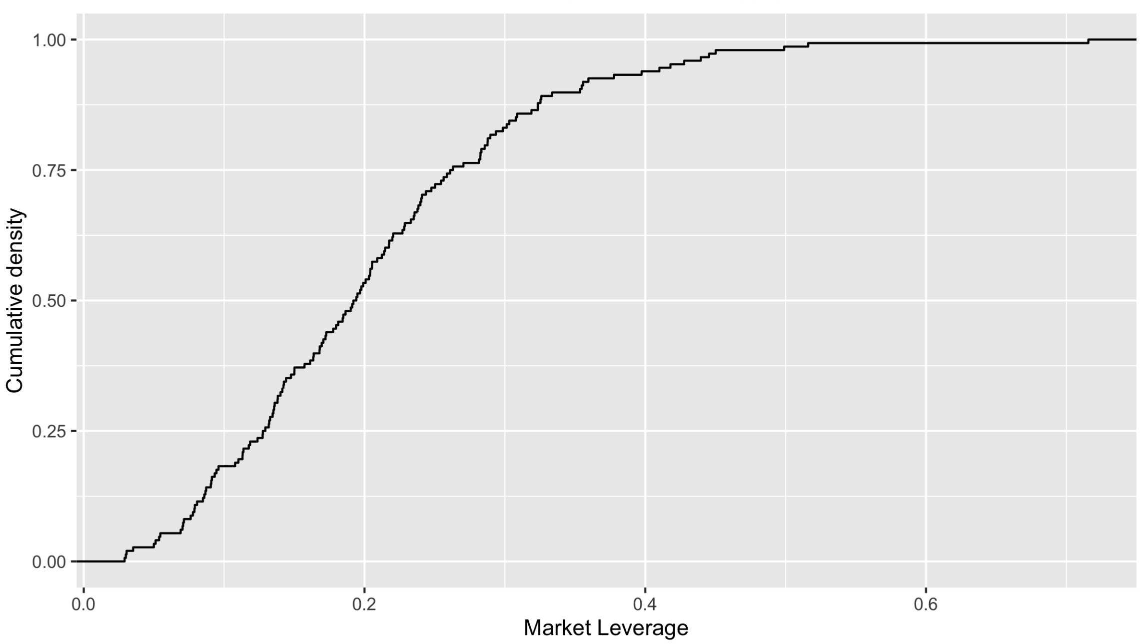


Figure 6: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ Over Face-to-Face Score

This figure plots the natural log of the earnings forecasts divided by the non-pandemic earnings $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ against the percentile rank of industry level Face-to-Face Score. Y_{t_0-}, the non-pandemic earnings, is the earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. Each panel plots a monthly cross section of our I/B/E/S sample, indicated by the date of each I/B/E/S statistical period on top of each panel. Forecasts with maturities less than 1 year (FY1) are in blue. Forecasts with maturities between 1 and 2 years (FY2) are in red. Linear fitted lines with 95% confidence interval are added for both FY1 and FY2 observations separately.

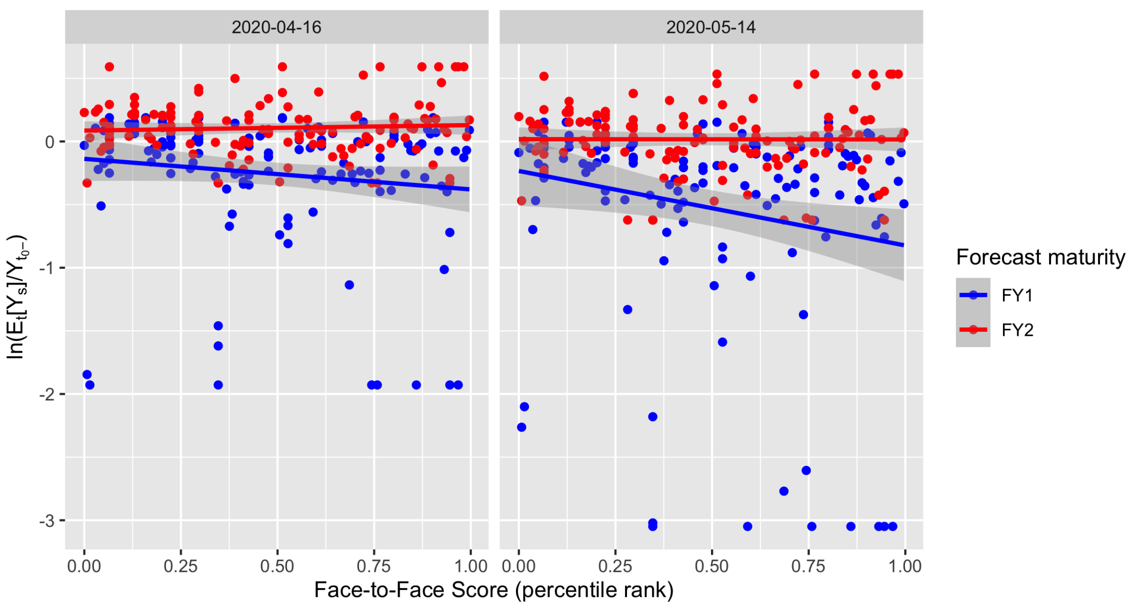


Figure 7: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ Over Market Leverage

This figure plots the natural log of the earnings forecasts divided by the non-pandemic earnings $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ against the percentile rank of industry level Market Leverage. Y_{t_0-}, the non-pandemic earnings, is the earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. Each panel plots a monthly cross section of our I/B/E/S sample, indicated by the date of each I/B/E/S statistical period on top of each panel. Forecasts with maturities less than 1 year (FY1) are in blue. Forecasts with maturities between 1 and 2 years (FY2) are in red. Linear fitted lines with 95% confidence interval are added for both FY1 and FY2 observations separately.

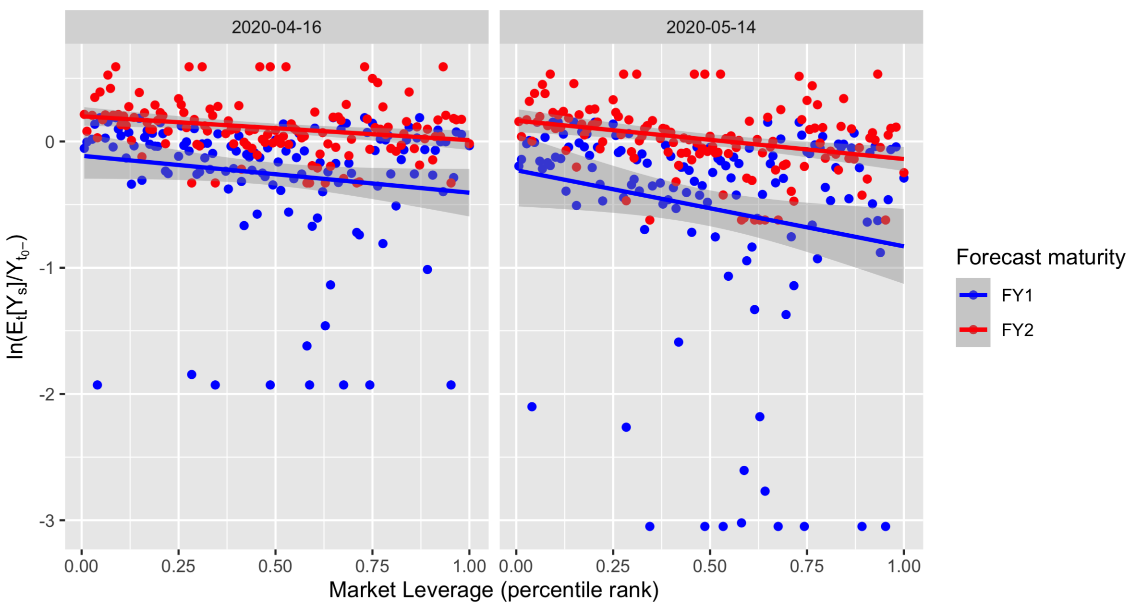
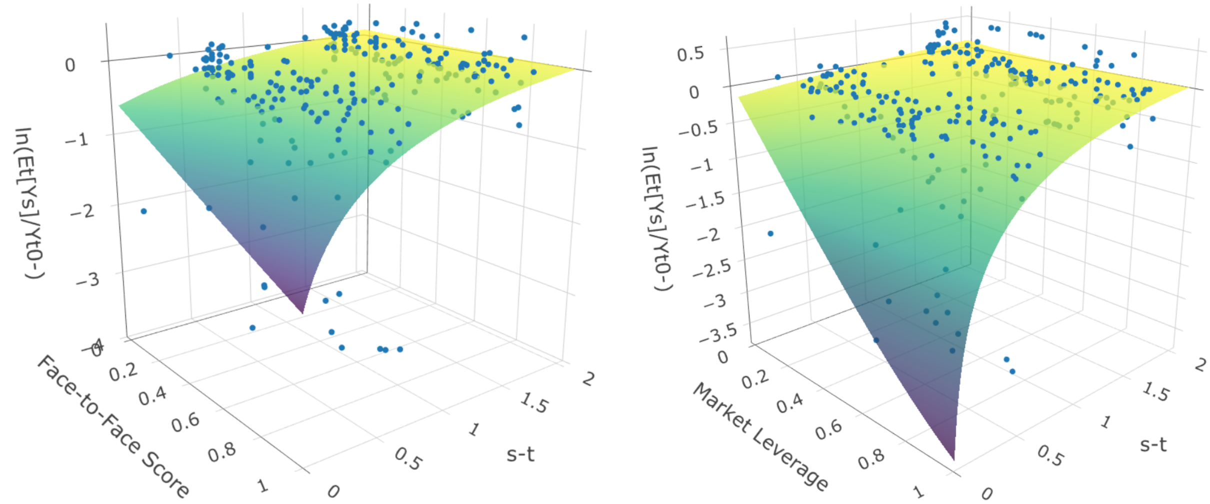


Figure 8: The Surfaces of the Estimated Models Using Data in May 2020

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 maturities of forecasts. The parameter estimates come from the specification that includes only Face-to-Face Score in modeling the jump in earnings. The estimates used corresponds to Column (1) of Panel B 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 maturities of forecasts. The parameter estimates come from the specification that includes only leverage in modeling the jump in earnings. The estimates used corresponds to Column (2) of Panel B in Table 2. $\hat{g}$ is set to be .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 Maturities

(b) Against Market Leverage and Forecast Maturities

Figure 9: $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ Over Forecast Maturities of the Placebo Sample

This figure plots $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$, the earnings forecasts in April and May of 2019 divided by the pseudo non-pandemic earnings, against the maturities of the forecasts (s-t) using I/B/E/S summary statistics in 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. Each panel plots a monthly cross section of the I/B/E/S 2019 sample, indicated by the date of each I/B/E/S statistical period on top of each panel. Forecasts with maturities less than 1 year are in blue. Forecasts with maturities between 1 and 2 years are in red.

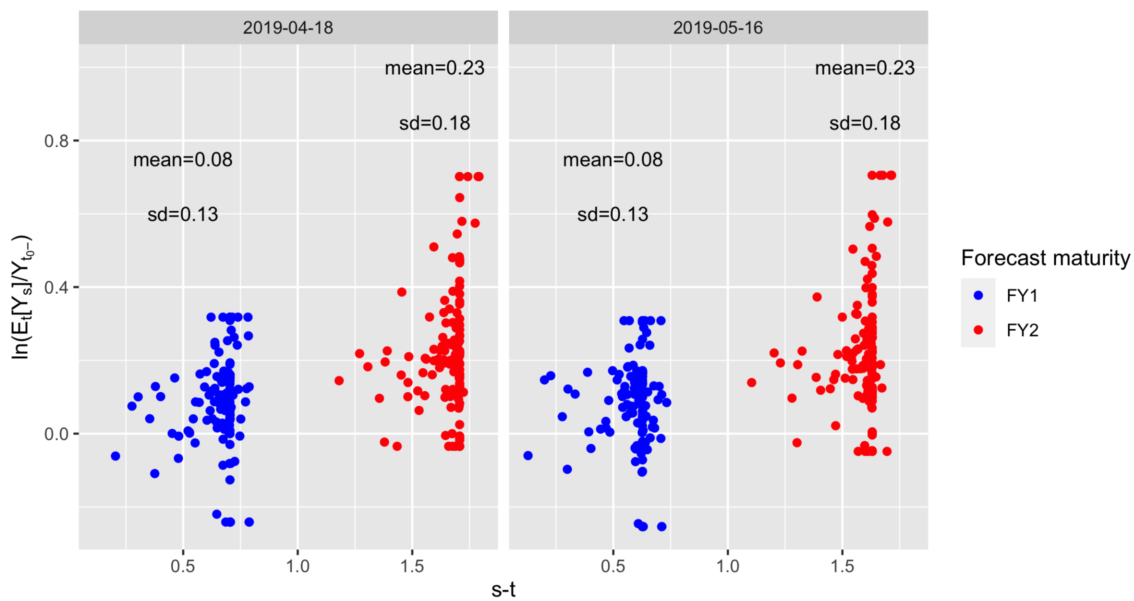


Table 1: Summary Statistics

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. $\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$ is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$. Y_{t_0-}, the non-pandemic earnings, is the earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. $s-t$ is the maturity 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 April and May sample of I/B/E/S summary statistics in 2020 in our analysis. Panel A includes 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 April 2020. Panel B includes 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 C 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). $\hat{g}$ 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 FY1 or FY2. Forecasts with maturities less than 1 year are FY1. Forecasts with maturities between 1 and 2 years are FY2. $\hat{g}$ 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
$\mathbb{E}_t[Y_s]/Y_{t_0-}$	0.89	0.33	0.05	0.71	0.92	1.07	1.70
$\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$	-0.25	0.67	-3.05	-0.34	-0.08	0.07	0.53
$s-t$	1.09	0.51	0.13	0.63	0.94	1.63	1.74

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

	Mean	SD	P0	P25	P50	P75	P100
$\mathbb{E}_t[Y_s]/Y_{t_0-}$	1.00	0.30	0.15	0.84	1.01	1.15	1.81
$\ln(\mathbb{E}_t[Y_s]/Y_{t_0-})$	-0.07	0.44	-1.93	-0.17	0.01	0.14	0.59
$s-t$	1.16	0.51	0.21	0.70	1.01	1.70	1.80

(c) Panel C: 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	0.13	3.59	3.85	3.90	4.00	4.33
Customer Score	3.44	0.45	2.54	3.08	3.44	3.79	4.48
Blinder Score	2.97	0.24	2.57	2.75	2.95	3.13	3.76
$\hat{g}$	0.11	0.09	-0.02	0.06	0.09	0.13	0.35

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 earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The explanatory variables include the maturity of the earnings forecasts $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\hat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A reports the results of the unconstrained NLS. Panel B reports the results where we impose restrictions on parameters. λ is the vaccine arrival rate. g_0 reflects the proportional change of growth rate in the pandemic regime. In both panels, Columns (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}. Column (1) contains the results assuming the jump depends on Face-to-Face Score, $n = n_0 + n_1 \times$ 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 the jump depends on Market Leverage, $n = n_0 + n_2 \times$ 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 the jump depends on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\hat{g}$, Face-to-Face Score Pct, and Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets.

(a) Panel A: Results of unconstrained NLS

	(1)	(2)	(3)
λ	0.875	1.046	1.097
	[0.42,1.34]	[0.58,1.38]	[0.6,1.38]
n_0	0.574	0.089	0.275
	[-0.03,1.22]	[-0.71,0.77]	[-0.49,1.14]
n_1	1.655		-1.153
	[0.39,10.8]		[-3.34,1.22]
n_2		4.118	5.636
		[1.12,15.07]	[1.19,14.3]
g_0	1.235	0.746	0.582
	[-0.37,2.26]	[-0.9,2.01]	[-1.15,1.84]
Num.Obs.	260	260	260
AIC	481.7	473.3	474.3
BIC	499.5	491.1	495.7

(b) Panel B: Results of constrained NLS

	(1)	(2)	(3)
λ	0.914	1.046	1.046
	[0.55,1.36]	[0.66,1.34]	[0.63,1.3]
n_0	0.564	0.089	0.089
	[0,1.18]	[0,0.72]	[0,0.68]
n_1	1.740		0.000
	[0.45,10.68]		[0,1.81]
n_2		4.119	4.118
		[1.38,9.8]	[1.1,7.89]
g_0	1.000	0.746	0.746
	[-0.66,1]	[-0.65,1]	[-0.66,1]
Num.Obs.	260	260	260
AIC	481.9	473.3	475.3
BIC	499.7	491.1	496.7

Table 3: NLS Results Using the I/B/E/S Sample in April 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 April of 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 earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The explanatory variables include the maturity of the earnings forecasts $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\hat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A reports the results of the unconstrained NLS. Panel B reports the results where we impose restrictions on parameters. λ is the vaccine arrival rate. g_0 reflects the proportional change of growth rate in the pandemic regime. In both panels, Columns (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}. Column (1) contains the results assuming the jump depends on Face-to-Face Score, $n = n_0 + n_1 \times$ 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 the jump depends on Market Leverage, $n = n_0 + n_2 \times$ 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 the jump depends on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\hat{g}$, Face-to-Face Score Pct, and Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets.

(a) Panel A: Results of unconstrained NLS

	(1)	(2)	(3)
λ	1.121	1.292	1.694
	[0.51,2.03]	[0.61,1.98]	[0.94,2.06]
n_0	0.594	0.383	0.704
	[0.17,1.57]	[-0.43,0.99]	[-0.09,2.34]
n_1	0.464		-2.179
	[-0.34,9.86]		[-5.59,0.11]
n_2		1.339	5.299
		[0.21,11.31]	[0.82,15.84]
g_0	0.996	0.826	0.417
	[-0.25,1.68]	[-0.46,1.64]	[-0.84,1.41]
Num.Obs.	260	260	260
AIC	253.4	249.1	248.0
BIC	271.2	266.9	269.4

(b) Panel B: Results of constrained NLS

	(1)	(2)	(3)
λ	1.121	1.292	1.292
	[0.63,2.04]	[0.73,1.95]	[0.72,1.94]
n_0	0.594	0.383	0.383
	[0.15,1.48]	[0,1.1]	[0,0.87]
n_1	0.464		0.000
	[0,11.13]		[0,2.06]
n_2		1.339	1.339
		[0.28,9.01]	[0.14,6.94]
g_0	0.996	0.826	0.826
	[-0.25,1]	[0,1]	[-0.33,1]
Num.Obs.	260	260	260
AIC	253.4	249.1	251.1
BIC	271.2	266.9	272.5

Table 4: Placebo Results Using I/B/E/S Sample in April or 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 April and May of 2019. The variables are constructed in the same way as in the baseline estimation but using the corresponding data in 2019. $\mathbb{E}_t[Y_s]/Y_{t_0-}$ is the earnings forecasts in April or May divided by the pseudo non-pandemic earnings. The dependent variable is the natural log of $\mathbb{E}_t[Y_s]/Y_{t_0-}$. 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 maturity of the earnings forecasts $s-t$, the January I/B/E/S forecasts of growth rate $\hat{g}$ in 2019, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A reports the results using the I/B/E/S sample in May. Panel B reports the results using the I/B/E/S sample in April. λ is the vaccine arrival rate. g_0 reflects the change of growth rate in the pandemic regime. In both panels, Columns (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}. Column (1) contains the results assuming the jump depends on Face-to-Face Score, $n = n_0 + n_1 \times$ Face-to-Face Score Pct. Face-to-Face Score Pct is the percentile rank of the industry Face-to-Face Score. Column (2) contains the results assuming the jump depends on Market Leverage, $n = n_0 + n_2 \times$ 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 the jump depends on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\hat{g}$, Face-to-Face Score Pct, and Market Leverage Pct.The 95% bootstrap confidence intervals are reported in square brackets.

(a) Panel A: Results of constrained NLS using sample from May 2019

	(1)	(2)	(3)
λ	0.000	0.000	0.000
	[0,3.24]	[0,3.05]	[0,1.01]
n_0	0.043	-0.037	-0.003
	[0.01,0.24]	[-0.19,0]	[-0.06,0.05]
n_1	-0.073		-0.103
	[-0.48,-0.03]		[-0.27,-0.05]
n_2		0.077	0.107
		[0.04,0.46]	[0.06,0.27]
g_0	1.036	1.004	0.996
	[0.87,1.22]	[0.86,1.18]	[0.86,1.14]
Num.Obs.	262	262	262
AIC	-348.8	-349.3	-362.0
BIC	-331.0	-331.5	-340.6

(b) Panel B: Results of constrained NLS using sample from April 2019

	(1)	(2)	(3)
λ	0.000	0.000	0.000
	[0,2.66]	[0,4.01]	[0,1]
n_0	0.050	-0.023	0.011
	[0.02,0.25]	[-0.25,0.02]	[-0.04,0.07]
n_1	-0.077		-0.102
	[-0.4,-0.04]		[-0.28,-0.06]
n_2		0.061	0.091
		[0.02,0.92]	[0.05,0.27]
g_0	1.032	1.006	0.998
	[0.87,1.17]	[0.83,1.16]	[0.87,1.13]
Num.Obs.	262	262	262
AIC	-377.7	-373.8	-387.8
BIC	-359.8	-356.0	-366.4

Table 5: Constrained 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 April or 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 earnings forecasts in January 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The explanatory variables include the maturity of the earnings forecasts $s-t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\hat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Net Market Leverage. Panel A reports the results of the constrained NLS using data of May 2020. Panel B reports the results of the constrained NLS using data of April 2020. λ is the vaccine arrival rate. g_0 reflects the proportional change of growth rate in the pandemic regime. In both panels, Columns (1)-(2) present the results from different specifications of the jump in earnings, e^{-n}. Column (1) contains the results assuming the jump depends on Net Market Leverage, $n = n_0 + n_2 \times$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 the jump depends on both Face-to-Face Score and Net Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct + $n_2 \times$ Net Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\hat{g}$, Face-to-Face Score Pct, and Net Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets.

(a) Panel A: Results of constrained NLS using May 2020 sample

	(1)	(2)
λ	1.090	1.090
	[0.75,1.34]	[0.68,1.34]
n_0	0.000	0.000
	[0,0.75]	[0,0.61]
n_1		0.000
		[0,1.88]
n_2	5.127	5.127
	[1.69,11.47]	[1.29,9.6]
g_0	0.732	0.732
	[-0.72,1]	[-0.61,1]
Num.Obs.	260	260
AIC	469.4	471.4
BIC	487.2	492.8

(b) Panel B: Results of constrained NLS using April 2020 sample

	(2)	(3)
λ	1.778	1.778
	[1.1,2.08]	[1.09,2.09]
n_0	0.000	0.000
	[0,0.96]	[0,0.8]
n_1		0.000
		[0,2.54]
n_2	5.988	5.988
	[0.82,17.57]	[0.53,17.02]
g_0	0.465	0.465
	[0,1]	[-0.59,1]
Num.Obs.	260	260
AIC	246.9	248.9
BIC	264.7	270.3

Table 6: 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. $\mathbb{E}_t[Y_s]/Y_{t_0-}$ 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 earnings forecasts in January 2020 discounted by the January I/B/E/S growth rate forecasts in 2020. The explanatory variables include the maturity of the earnings forecasts $s - t$, the non-pandemic (January 2020) I/B/E/S forecasts of growth rates $\hat{g}$, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A reports the results of the unconstrained 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. g_0 reflects the proportional change of growth rate in the pandemic regime. In both panels, Columns (1)-(2) present the results from two different specifications of the jump in earnings, e^{-n}. Column (1) contains the results assuming the jump depends on Face-to-Face, $n = n_0 + n_1 \times$ 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 the jump depends on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct. Market Leverage Pct is the percentile rank of industry level Market Leverage at the end of 2019. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, $\hat{g}$, Face-to-Face Score Pct, and Market Leverage Pct.The 95% bootstrap confidence intervals are reported in square brackets.

(a) Panel A: Results of unconstrained NLS using Customer Score as Face-to-Face Score

	(1)	(2)
λ	0.964	1.058
	[0.48,1.5]	[0.59,1.36]
n_0	1.547	0.445
	[0.69,6.89]	[-0.48,1.51]
n_1	-0.255	-0.789
	[-5.73,13.05]	[-2.4,0.58]
n_2		4.179
		[1.04,11.81]
g_0	1.067	0.638
	[-0.65,2.22]	[-0.99,1.88]
Num.Obs.	260	260
AIC	489.6	474.0
BIC	507.4	495.4

(b) Panel B: Results of unconstrained NLS using Blinder Score as Face-to-Face Score

	(1)	(2)
λ	0.994	1.063
	[0.5,1.51]	[0.59,1.36]
n_0	1.374	0.374
	[0.58,4.51]	[-0.58,1.42]
n_1	0.223	-0.754
	[-3.19,13.81]	[-2.54,0.78]
n_2		4.397
		[1.09,12.17]
g_0	1.047	0.633
	[-0.66,2.23]	[-0.99,1.89]
Num.Obs.	260	260
AIC	489.6	474.2
BIC	507.4	495.5

Table 7: Summary Statistics of I/B/E/S Growth Rate Forecasts

This table summarizes the quartiles of the non-pandemic and pandemic I/B/E/S growth rate forecasts at 8-digit GICS industry level. The data source is the I/B/E/S summary statistics. The non-pandemic date is January 2020, and the pandemic date is May 2020. We use the market value of firms at the end of 2019 to aggregate firm level growth rates to the industry level. Industry level data are winsorized at 5% level.

	P0	P25	P50	P75	P100
Non-pandemic Growth Rate Forecasts	-0.02	0.06	0.09	0.13	0.35
Pandemic Growth Rate Forecasts	-0.07	0.03	0.07	0.10	0.26

Table 8: NLS Results Using Pandemic I/B/E/S Growth Rate Forecasts

This table presents the coefficients and bootstrap confidence intervals from the non-linear least square regressions of Equation (10). The regressions are run using I/B/E/S summary statistics in May of 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 January earnings forecasts in 2020 discounted by the I/B/E/S growth rate forecasts in January 2020. The explanatory variables include the maturity of the earnings forecasts $s-t$, the pandemic (May 2020) I/B/E/S forecasts of growth rates g, the percentile rank of industry Face-to-Face Score, and the percentile rank of industry Market Leverage. Panel A reports the results using the unconstrained NLS results using May sample. Panel B reports the the constrained NLS results. λ is the vaccine arrival rate. In both panels, Columns (1)-(3) present the results from three different specifications of the jump in earnings, e^{-n}. Column (1) contains the results assuming the jump depends on Face-to-Face Score, $n = n_0 + n_1 \times$ 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 the jump depends on Market Leverage, $n = n_0 + n_2 \times$ 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 the jump depends on both Face-to-Face Score and Market Leverage, $n = n_0 + n_1 \times$ Face-to-Face Score Pct $+ n_2 \times$ Market Leverage Pct. We keep observations with non-missing $\mathbb{E}_t[Y_s]/Y_{t_0-}$, non-pandemic growth rate forecasts $\hat{g}$, g, Face-to-Face Score Pct, and Market Leverage Pct. The 95% bootstrap confidence intervals are reported in square brackets.

(a) Panel A: Results of unconstrained NLS using sample from May 2020

	(1)	(2)	(3)
λ	0.913	1.000	1.036
	[0.54,1.3]	[0.66,1.24]	[0.7,1.27]
n_0	0.597	0.086	0.268
	[0.03,1.34]	[-0.61,0.71]	[-0.5,1.08]
n_1	1.570		-1.000
	[0.22,7.54]		[-3.13,1.12]
n_2		3.958	5.216
		[1.31,13.16]	[1.58,14.6]
Num.Obs.	252	252	252
AIC	465.4	454.7	455.8
BIC	479.5	468.8	473.4

(b) Panel B: Results of constrained NLS using sample from May 2020

	(1)	(2)	(3)
λ	0.913	1.000	1.000
	[0.54,1.3]	[0.66,1.23]	[0.64,1.24]
n_0	0.597	0.086	0.086
	[0.02,1.32]	[0,0.71]	[0,0.65]
n_1	1.570		0.000
	[0.24,7.44]		[0,1.83]
n_2		3.959	3.959
		[1.33,8.95]	[1.05,7.88]
Num.Obs.	252	252	252
AIC	465.4	454.7	456.7
BIC	479.5	468.8	474.3