Aggregate and Firm-Level Stock Returns During a Pandemic*

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Preliminary and Incomplete. Comments Welcome.

Abstract

We model investor beliefs about the severity of a pandemic in real time using standard models of infectious disease. We show that changes in these models' predicted infections as the crises unfold explain day-to-day aggregate market returns, even after controlling for the most recent change in infections. Our analysis currently is confined to four countries battling COVID-19. Future drafts will extend our investigation to additional countries and other pandemics, and examine the relationship between firms' returns and their exposure to pandemics along domestic and international input-output channels.

*This paper is preliminary and incomplete, and missing citations to existing research to be added in future drafts.

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1 Introduction

Pandemics inflict a substantial human toll. They also roil economies and equity markets. In this paper, we examine the relationship between changes in investor beliefs about the severity of a public health crisis and stock returns. We assume market participants gauge the economic severity of a pandemic using the parameters of standard models of infectious disease, updating the parameters of these models day by day as the number of new infections is revealed. In contrast to the daily change in cases, or even the daily acceleration of cases, estimated model parameters allow investors to update their beliefs about the eventual number of people that will be infected, and the rapidity with which that number will be reached.

We show that changes in the *model-predicted* number of infections, driven by daily updates in model parameters, predict daily aggregate market returns. Furthermore, we find that these changes retain their explanatory power even after controlling for the most recent increases in actual cases. This finding implies that markets may recover even while the number of infections is rising, as investors become increasingly certain of the trajectory of the outbreak.

At present, we find these relationships for four countries battling the COVID-19 virus: China, South Korea, Italy and the United States. In subsequent drafts, we will extend the analysis to other countries and pandemics, and investigate at the firm level the link between returns and exposure to the pandemic via domestic and international input and output linkages.

This paper adds to several literatures. First, our results contribute to the large body of research in corporate finance which uses event studies to understand market dynamics.[1] In a typical event study, researchers choose events that are thought to coincide with substantial changes in investor beliefs, and analyze the behavior of asset prices around these events.[2] Here, we show that our setting is amenable to modeling investor beliefs directly, and show the these beliefs predict daily changes in aggregate stock prices.

Second, our paper contributes to the very large literature in public health, based on models pioneered by Richards (1959), which attempts to model the trajectory of cases during an during an infectious disease outbreak. In contrast to that research, we link changes in the estimated parameters and predictions of these models in real time to economic outcomes. An interesting question for further research is the extent to which feedback from predicted economic consequences affects future infections. For example, dire enough anticipated economic consequences might influence the set of policies used to combat the outbreak, thereby altering its trajectory.

Finally, this paper relates to a rapidly emerging literature studying the economic consequences of COVID-19, and a more established literature investigating earlier pandemics. Barro et al. (2020), for example, argue that the decline in output during the 1918 to 1920 "Spanish Flu" epidemic provide a plausible mode of the economic consequences of COVID-19.

This paper proceeds as follows. Section 2 provides a brief description of infectious disease models. Section 3 explains our assumed link between the predictions of these models and asset prices. Section 4 applies our framework to COVID-19. Section 5 concludes.

[1]Pioneered by Ball and Brown (1968) and Fama et al. (1969), event studies are used in over 565 articles appearing in the top finance journals through 2006 (Khotari and Warner (2006)). Wolfers and Zitzewitz (2018) provide a recent summary.

[2]Bianconi et al. (2018) and Greenland et al. (2019), for example, find that industries and firms subject to greater import competition with China exhibited relatively high stock returns after President Trump's March 22, 2018 memorandum signifying the start of a "trade war" between the US and China.

2 Epidemiological Models of Infectious Diseases

Exponential and logistic growth models are frequently used in biology and epidemiology to model infection and mortality. An exponential model,

$$C_{it} = a_i e^{(r_i t)} \tag{1}$$

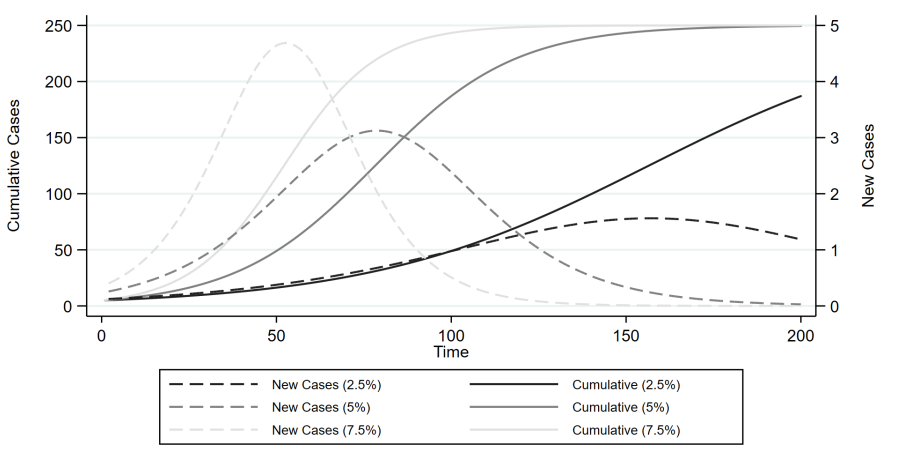
predicts the cumulative number of cases in country i on day t, C_{it}, as a function of the growth rate of infections in that country, r_i, the initial number of infected persons a_i, and time. In an exponential model, the number of infections per day continues to climb indefinitely. While clearly unrealistic ex-post, the exponential growth model is consistent with early stage pandemic growth rates.

In a logistic model (Richards, 1959), by contrast, the growth in infections grows exponentially initially, but then declines as the stock of infections approaches the population's "carrying-capacity," i.e., the cumulative number of people that ultimately will be infected. Carrying capacity is generally less than the full population. In a logistic model, the cumulative number of infections for country i on day t is given by:

$$C_{it} = \frac{k_i}{1 + c_i e^{(-r_i t)}}, \tag{2}$$

where k_i is the carrying capacity for country i, c_i is a shift parameter (characterizing the number of initially infected persons in country i) and r_i is the growth rate. Figure 1 provides an example of logistic infections for three different growth rates (2.5%, 5% and 7.5%) assuming $k_i = 250$ and $c_i = 50$. For each growth rate, we plot both the cumulative number of cases as of each day (left axis) and the number of new cases each day (right axis). As indicated in the figure, higher growth rates both shorten the time required to reach carrying capacity, and increase the peak number of infections.

Figure 1: Disease Outbreak with Different Rates of Infection



Source: authors' calculations. Figure compares new and cumulative infections from days 1 to 200 assuming a logistic model with $k_i = 250$ and $c_i = 50$ and noted growth rates (r_i).

Given data on the actual evolution of infections, the two parameters in equation 1 and the three parameters in equation 2 can be updated each day using the sequence of infections up to that date.

We estimate these sequences using STATA's nonlinear least squares command (`nl`).[3] STATA's `nl` command requires a vector of starting values, one each for each parameter to be estimated.

We encounter two problems during our estimation of logistic functions in our COVID-19 application below. First, final estimates for each day t are sensitive to the choice of starting values for that day, particularly in the initial days of the pandemic. This feature of the estimation is not surprising: when the number of cases is relatively small, the data are consistent with a wide range of logistic curves, and the objective function across them may be relatively flat.

To increase the likelihood that our parameter estimates represent the *global* solution, we estimate 500 epidemiological models for each day, 250 for the logistic case, and 250 for the exponential case. In each iteration we use a different vector of starting values. For each day t, our first starting values are the estimated coefficients from the prior day, if available.[4] In the case of the logistic model, we then conduct a grid search defined by all triples $\{r, c, k\}$ such that

$$r \in \{0.01, 0.21, 0.41, 0.61, 0.81\}$$
$$c \in \{\widehat{c_i^{t-1}}, 2 * \widehat{c_i^{t-1}}, 4 * \widehat{c_i^{t-1}}, \ldots, 10 * \widehat{c_i^{t-1}}\}$$
$$k \in \{\widehat{k_i^{t-1}}, 2 * \widehat{k_i^{t-1}}, 3 * \widehat{k_i^{t-1}}, \ldots, 10 * \widehat{k_i^{t-1}}$$

where hats over variables indicate prior estimates, and superscripts indicate the day on which they are estimated. If more than one of these initial starting values produces estimates, we choose the parameters from the model with the highest adjusted R^2. We estimate the exponential model similarly.

The second, more interesting, problem that we encounter during estimation of the logistic outbreak curves is that STATA's `nl` routine may fail to converge. This failure generally occurs in the transition from relatively slow growth initially to an obviously exponential pattern over time. We believe this problem reflects the fact that, during this phase of the outbreak, the growth in the number of new cases each day is too large to be captured by a logistic function, i.e., the drop in the growth of new cases necessary to estimate a carrying capacity has not yet occurred. As a result, and as discussed further below, we estimate both exponential and logistic models for each day of the outbreak, and assume that investors switch between them once their predictions become sufficiently distinct.

Figure 2 provides an example of simulated "actual" cumulative cases and an estimate of the underlying logistic function for 200 days, using equation 1 to simulate actual data.[5] The predicted values use the cumulative information as of day 200 to estimate $\widehat{k_i^{200}}$, $\widehat{c_i^{200}}$, and $\widehat{r_i^{200}}$ and thereby generate predicted cases for each day. The inflection point of the logistic cumulative cases curve – a crucial moment in the evolution of the outbreak – occurs at the peak of the new cases curve.

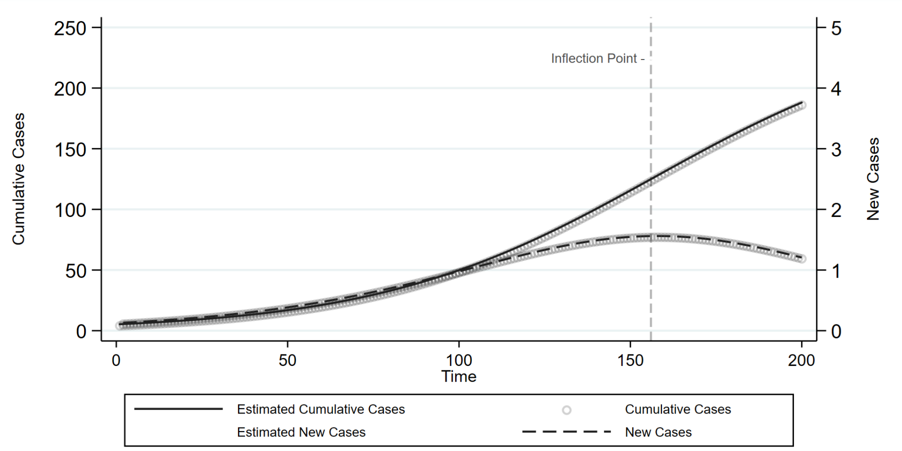
In our application below, we assume investors re-estimate the parameters of the exponential and logistic curves each day. That is, for the logistic curve, they estimate $\widehat{k_i^t}$, $\widehat{c_i^t}$, and $\widehat{r_i^t}$ at each day t using the sequence of infections observed up to day $t-1$. Figure 3 illustrates how the logistic parameters evolve over time using the simulated data from Figure 2. As shown in the figure, in this example, estimates are highly volatile in the early stage of the outbreak, are not available due to lack on convergence for days 47 through 78, and then begin to settle down shortly thereafter.

[3] We are exploring other estimation procedures for use in a future draft, including use of a SIR model (Atkeson (2020)).

[4] If the prior day did not converge, we use the most recent prior day for which we have estimates.

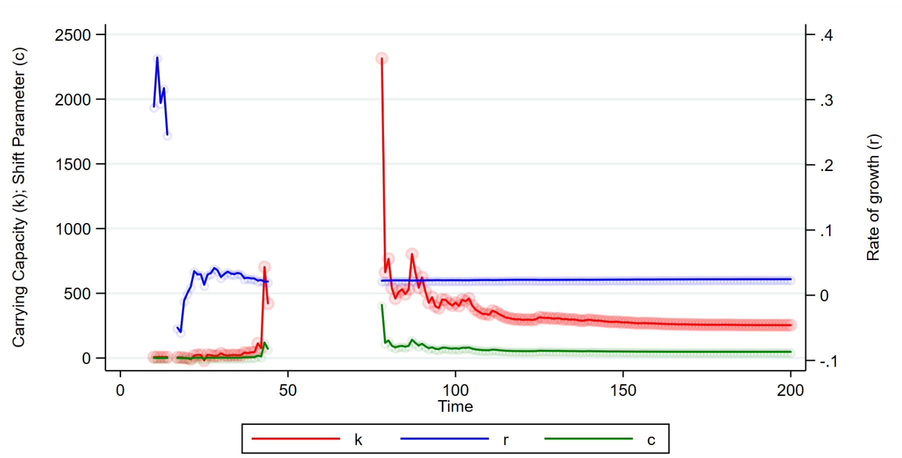
[5] Simulated data are created by computing $C_{it} = \frac{k_i}{1+c_i e^{(-r_i t)}} + |\epsilon_t|$, assuming $k_i = 250$, $r_i = .025$, $c_i = 50$ and $|\epsilon_t|$ is the absolute value of a draw from a standard normal distribution.

Figure 2: Disease Outbreak Simulation



Source: authors' calculations. Figure compares estimated new and cumulative cases for each day (circles) against "actual" values of those quantities using the simulation procedure noted in the main text. The "actual" data for all 200 days are used to perform the estimation.

Figure 3: Logistic Parameter Estimates During Simulation

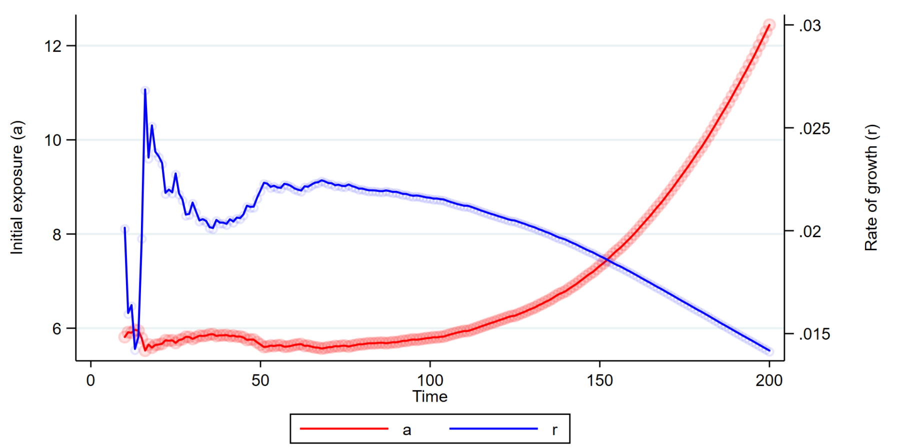


Source: authors' calculations. Figure plots the sequence of logistic parameters $\widehat{k_{i_t}}$, $\widehat{c_{i_t}}$ and $\widehat{r_{i_t}}$ estimated using the information up to each day t on the simulated data displayed in Figure 7. Missing estimates indicate lack of convergence (see text). In the figure, circle markers represent estimates, and solid lines connect those estimates.

Figure 4, by contrast, reports the analogous evolution of the parameters of the exponential estimation. Here, estimates are also volatile in the early days of the pandemic, and settle down near day 50. In contrast to the logistic estimation, parameters are available for each day, i.e., the estimation does not suffer from a lack of convergence. The intuition for the increase in $\widehat{a_{i_t}}$ and decline in $\widehat{r_{i_t}}$ as days near 200 is as follows: because the data are logistic, the only way to reconcile them with an exponential function is to assume that the initially exposed ($\widehat{a_{i_t}}$) is larger, and that the infection spread with a lower growth rate, $\widehat{r_{i_t}}$.

We assume investors base their economic forecasts on changes in underlying model parameters. That is, they predict the cumulative number of cases on day t given the actual cumulative cases known on day $t-1$, $\widehat{C_{it}^{t-1}}$, where the superscript $t-1$ refers to the timing of the information used

Figure 4: Exponential Parameter Estimates During Simulation

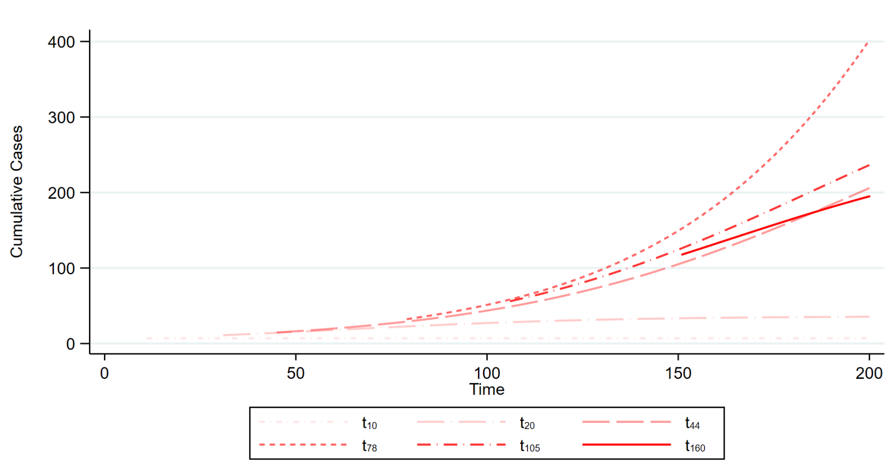


Source: authors' calculations. Figure plots the sequence of exponential parameters $\widehat{a_{i_t}}$ and $\widehat{r_{i_t}}$ estimated using the information up to each day t on the simulated data displayed in Figure 7. In the figure, circle markers represent estimates, and solid lines connect those estimates.

to make the prediction. They then compare this prediction to one generated for day t based on the cumulative number of cases observed one day earlier, $\widehat{C_{it}^{t-2}}$.

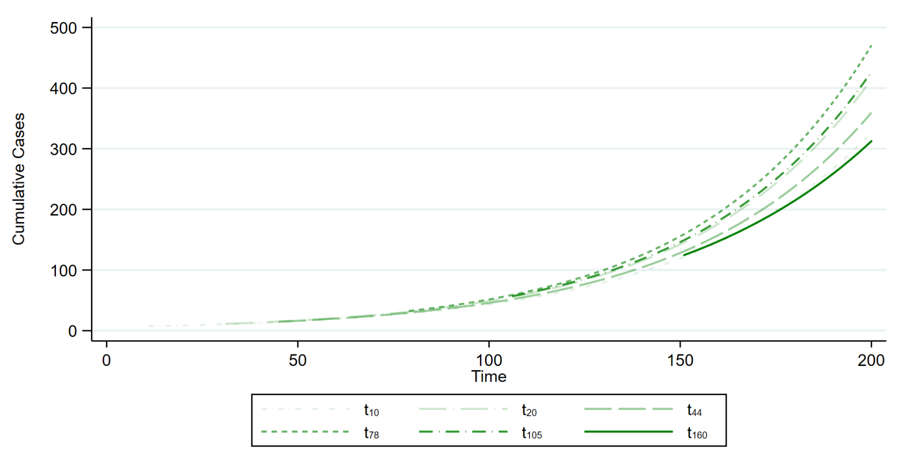
In Figure 5, we compare predicted infections up to day 200 under the logistic model using the parameters estimated on days $t \in \{32, 38, 53, 73, 92, 199\}$. In each case, predictions are displayed for all days after the information upon which they are based. As indicated in the figure, early predictions can differ substantially from later predictions. The prediction for day 44 is the final one available until day 78 due to lack on convergence. Comparison of Figures 3 and 5 reveals that the change in parameter estimates and predicted infections between days 44 and 78, i.e., before and after lack of convergence – are far more distinct for the logistic model than the exponential model (Figures 4 and 6). As indicated in these figures, both sets of estimates exhibit wide variation in the number of cases expected at day 200.

Figure 5: Logistic Predicted Outbreak Profiles Estimated At Different Dates



Source: authors' calculations. Figure plots the predicted sequence of cumulative infections using parameter estimates from the noted day reported in Figure 3.

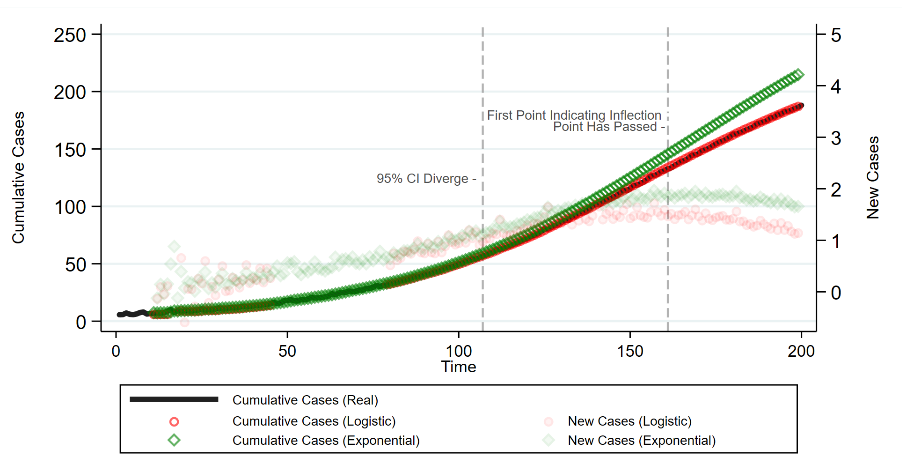
Figure 6: Exponential Predicted Outbreak Profiles Estimated At Different Dates



Source: authors' calculations. Figure plots the predicted sequence of cumulative infections using parameter estimates reported in Figure 4.

Finally, Figure 7 compares the exponential (green) and logistic (red) predictions for cumulative and new cases for each day t based on the information available up to day $t-1$.[6] As illustrated in the figure, the exponential and logistic series line up very well through the initial phase of the pandemic, but begin to diverge at $t = 104$, when the 95% confidence intervals for both predictions no longer overlap. It is after this point that the logistic model's predictive power begins to exceed that of the exponential model. Indeed, while the exponential model continues to project an ever-increasing number of infections, the logistic model's predictions head towards the estimated carrying capacity.

Figure 7: Comparison of Daily Predictions for Logistic and Exponential



Source: authors' calculations. Figure compares simulated "actual" cumulative infections as of day 200 to the predicted infections using parameters estimated on day 200.

While separation of the 95 percent confidence intervals of the two models' predictions might be one decision rule that is used to switch from the exponential to the logistic model in real time, another might be when the logistic model's estimates first indicate that its inflection point, i.e.,

[6] As discussed further in the next section, we assumed investors compare these predictions in real time in assessing the economic consequences of the pandemic.

when new cases are at their highest – has passed. In the logistic model, this point is given by $ln(\widehat{c_{it}})/\widehat{r_{it}}$. It is noted in Figure 7 by the second dashed vertical line.

3 Investors' Beliefs

We assume that investors model the economic implications of an infectious disease outbreak using either the exponential or logistic models of infectious disease described in the previous section. More precisely, we assume their assessment of the impact of an outbreak on aggregate market value is a function of changes in these models' estimated parameters. For example, a jump in estimated carrying capacity suggests a larger ultimate supply shock in terms of lost labor supply, while a jump in the estimated growth rate has implications for healthcare capacity constraints.[7]

We assume the following timing. At the beginning of day t, i.e., before markets open, investors observe the number of infections occurring on day $t-1$. Using this day $t-1$ information, they predict the number of cases for day t, denoted $\widehat{C_{it}^{t-1}}$, where the $t-1$ superscript denotes the day of the information upon which the prediction is based.

In our application to COVID-19 below, we currently compare the change in daily market return, $\Delta ln\,(MV_{it})$, to the log change in the number of predicted cases for day t using information from days $t-1$ and $t-2$,

$$\Delta ln\,(MV_{it}) = \alpha + \beta_1 * \Delta ln\left(\widehat{C_{it}^{-1,-2}}\right) + \beta_2 X_{it} + \epsilon_{it} \tag{3}$$

where

$$\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right) = ln\left(\widehat{C_{it}^{t-1}}\right) - ln\left(\widehat{C_{it}^{t-2}}\right). \tag{4}$$

Intuitively, $\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right)$ captures the unanticipated growth in cases due to a change in the estimated severity of the epidemic. Since both $\widehat{C_{it}^{t-2}}$ and $\widehat{C_{it}^{t-1}}$ are forecasting the cumulative number of cases at time t, the difference between them captures the impact of the new information revealed about the epidemic between $t-2$ and $t-1$. That is, $\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right)$ is the change in expected cumulative cases due to the updated epidemiological model. If markets are efficient, this new information will be priced into the market on day t. In particular, we assume that $\Delta(\widehat{C_{it}^{-1,-2}}) > 0$ would lead to a reduction in market returns.[8]

4 Application to COVID-19

In this section we provide real-time estimates of the outbreak parameters and case projections for COVID-19 in China, South Korea, Italy and the United States. We then estimate equation 3 for the US – estimates for other countries are forthcoming.

[7] As noted in the introduction, the evolution of these parameters may also trigger policy "events" either directly or as a result of their economic consequences, which may alter the underlying parameters of the outbreak. We do not currently account for such feedback, but plan to do so in a future draft.

[8] We are currently exploring more flexible specifications, as well as specification that would capture investors switch between and exponential and logistic models.

4.1 Data

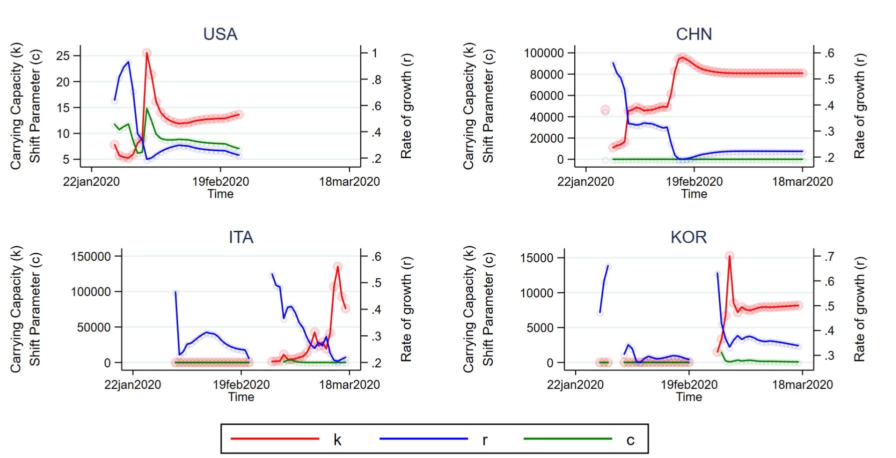
Data on the cumulative number of COVID-19 cases in each country as of each day are from the Johns Hopkins Coronavirus Resource Center.[9] Data tracking each country's daily aggregate stock market performance are downloaded from Yahoo Finance. The aggregate market indexes we use are the SSE (Shanghai Stock Exchange composite index) for China, the KOSPI (Korea Composite Stock Price Index) for South Korea, the FTSE-MIL for Italy, and the Wilshire 5000 index for the United States. We begin our sample period on the first day for which parameter estimates converge for each series and the markets are open.

The first COVID-19 case appeared in China in November of 2019, while the first cases in the United States and Italy appeared on January 20, 2020. All of our analysis, however, begins on January 22, 2020, the first day the World Health Organization began issuing situation reports detailing new case emergence internationally. The number of cases in each country across our sample period are displayed in Appendix Figure A.1.

4.2 Outbreak Estimates

We estimate equations 1 and 2 by day for each country as discussed in Section 2. The daily parameter estimates for the baseline logistic estimation, $\widehat{k_i^t}$, $\widehat{c_i^t}$ and $\widehat{r_i^t}$ are displayed graphically for each country in Figure 8. Figure 9 displays exponential function estimates for each country. Gaps in the time series in either figure represent lack of convergence.

Figure 8: Logistic Parameter Estimates

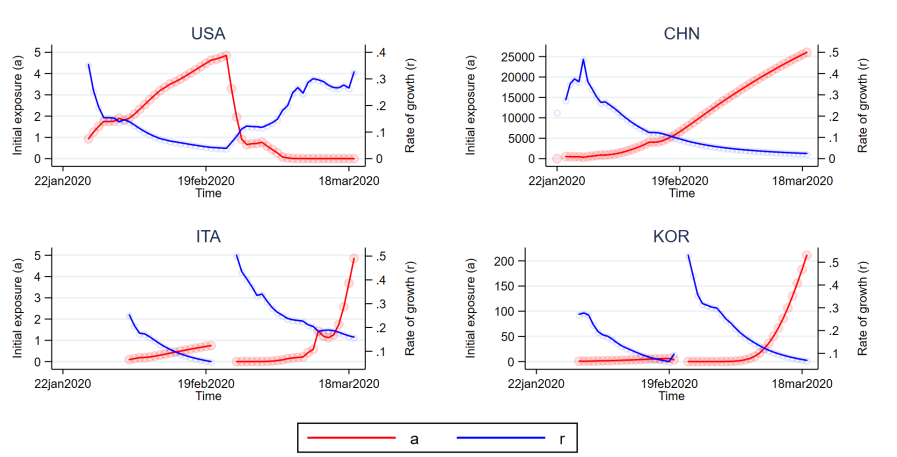


Source: Johns Hopkins Coronavirus Resource Center and authors' calculations. Figure displays the estimated growth rates and carrying capacities using observed cumulative cases up to each day. Missing estimates indicate lack of convergence (see text).

Logistic parameter estimates for the United States fail to converge beginning on February 24, when the number of cases jumps abruptly from 15 to 51. That no parameter estimates are available after this date suggests that growth in new cases observed thus far (as of March 20) is inconsistent with a carrying capacity, at least according to our estimation method. The exponential model, by contrast, converges for every day thus far. As a result, use of the exponential model to predict growth seems best at present. This conclusion appears warranted given the close relationship between actual and predicted exponential cases in Figure 10.

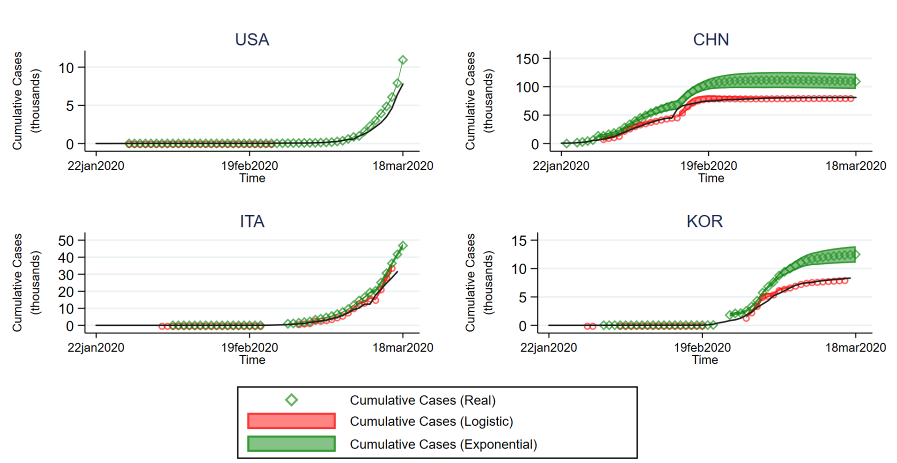
[9] These data can be downloaded from https://github.com/CSSEGISandData/COVID-19 and visualized at https://coronavirus.jhu.edu/map.html.

Figure 9: Exponential Parameter Estimates



Source: Johns Hopkins Coronavirus Resource Center and authors' calculations. Figure displays the estimated growth rates and carrying capacities using observed cumulative cases up to each day. Missing estimates indicate lack of convergence (see text).

Figure 10: Predicted Cases for Exponential and Logistic



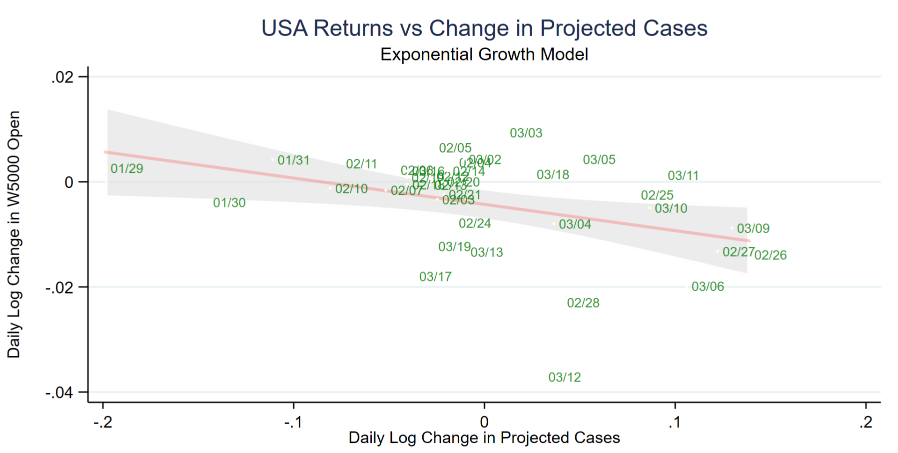
Source: Source: Johns Hopkins Coronavirus Resource Center and authors' calculations. Figure displays the projected cases according to both the logistic and exponential models and provides a 95% confidence interval. Predictions are based on the parameter estimates from the prior day.

For South Korea, we find that parameter estimates for the logistic model converge during the initial phase of the pandemic, but fail to converge in mid February. Here, too, the exponential model converges more frequently. However, when compared to actual cases (Figure 10), the exponential model's predictions begin to diverge on March 1, when the the 95% confidence intervals of the exponential and logistic models no longer overlap. From that point forward, the exponential model clearly and substantially over-estimates observed cases.

4.3 Financial Market Reactions

We find that the changes in expected cumulative infections are related to aggregate stock market performance in the United States.[10] Figure 11 plots the daily log change in the Wilshire 5000 index against $\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right)$.[11] Visually we can see that days with larger upward revisions $\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right)$ tend to have larger downward revisions in market value.

Figure 11: Changes in Predicted Cases vs Aggregate Market Returns



Source: Johns Hopkins Coronavirus Resource Center and authors' calculations. Figure displays the daily log change in the Wilshire 5000 index against the log change in projected cases at time t.

To ensure that this result is not driven solely by the most recent changes in cases – i.e., that modeling the pandemic is important – we turn to the regressions estimated in Table 1. Between each of the 37 days for which we obtain parameter estimates, we calculate the daily log changes in the opening (i.e., day $t-1$ to day t open) and closing values of the Wilshire 5000, the log change in actual observed cases, and the log change in model-predicted cases, $\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right)$.

[10] We will include results for China, South Korea and Italy in a future draft.

[11] Results are qualitatively similar for other US market indexes. We prefer the Wilshire 5000 as it is among the broadest.

Table 1: Exponential Growth Model: USA

	(1) ΔLn(Open)	(2) ΔLn(Close)	(3) ΔLn(Open)	(4) ΔLn(Close)	(5) ΔLn(Open)	(6) ΔLn(Close)
$\Delta Ln(\widehat{C_{it}^{-2,-1}})$	-0.113***	-0.139*	-0.050***	-0.059**	-0.045**	-0.054*
	(0.031)	(0.072)	(0.014)	(0.025)	(0.020)	(0.027)
$\Delta Ln(C_{it}^{-2,-1})$					-0.016	
					(0.024)	
$\Delta Ln(C_{it}^{-1,0})$						-0.007
						(0.007)
Constant	-0.010**	-0.010	-0.004***	-0.004	-0.003*	-0.002
	(0.004)	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	36	36	36	36	35	36
R^2	0.125	0.061	0.150	0.073	0.155	0.086

Notes: Data from Johns Hopkins Coronavirus Resource Center, Yahoo! Finance, and authors' calculations. $\Delta Ln(Open_t)$ and $\Delta Ln(Close_t)$ are the daily log changes in the opening (i.e., day $t-1$ to day t open) and closing values of the Wilshire 5000. $\Delta ln\left(\widehat{C_{it}^{-1,-2}}\right)$ is the change in predicted cases. $\Delta ln\left(C_{it}^{-2,-1}\right)$ is the change in actual observed cases between days $t-2$ and $t-1$. $\Delta ln\left(C_{it}^{-1,0}\right)$ is the change in actual observed cases between days $t-1$ and t. Robust standard errors in parenthesis. Columns 1 and 2 divide all variables by the number of days since the last observation (i.e. over weekends). Columns 3 and 4 do not make this adjustment for the log change in open or close.

In columns 1 and 2 we present univariate estimates of our predictions. Column 1 indicates that a doubling of predicted cases leads to an average decline of 11.3% for opening and 13.9% for closing prices. These effects are significant at the 1% and 10% respectively.

In columns 3 and 4 we repeat this analysis but divide both the dependent and independent variables by the number of days since the last market opening. We do this to ensure that changes in predictions that transpire across weekends and holidays are not spuriously large compared to trading days. This makes no meaningful difference in our results.

Finally, in columns 5 and 6 we include the lagged or contemporaneous change in realized cases, $\Delta ln\left(C_{it}^{-2,-1}\right)$ and $\Delta ln\left(C_{it}^{-1,0}\right)$. That their inclusion has no significant impact on our point estimates suggests that the primary role new cases play in affecting financial markets is through their impact on investor expectations about the estimated overall severity and timing of the epidemic. This implies that as investors become more certain about the underlying parameters of the outbreak, subsequent case growth will have less of affect on the market. Indeed, markets are most sensitive to new cases while investor beliefs are most fluid.

5 Conclusion

This paper shows that day-to-day changes in the predictions of standard models of infectious disease can predict changes in aggregate stock returns across four countries currently battling the COVID-19 pandemic. In future updates to this paper, we plan to extend the analysis to other countries and pandemics, and to investigate the link between individual firms' returns and their exposure to public health crises via domestic and international input and output linkages.

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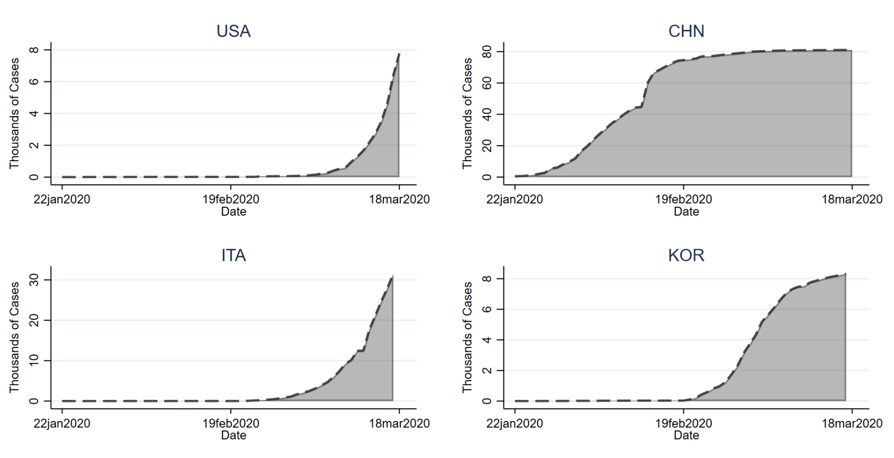
Figure A.1: Actual COVID-19 Cases, By Country



Source: Johns Hopkins Coronavirus Resource Center and authors' calculations. Figure displays the COVID-19 up to March 22.