# COVID-19 Pandemic Risk and the Cross-Section of U.S. Stock Returns

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January 15, 2024

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**JEL classification:** G11, G12, I10.

**Keywords:** Asset Pricing, COVID-19, Stock Returns, Stock Markets, Pandemic.

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# 1 Introduction

The coronavirus (COVID-19) pandemic and subsequent lockdowns began in early 2020 have disrupted societies and economies worldwide. The COVID-19 crisis has also rattled global financial markets, including stock, bond, and commodity markets with heavy losses and extreme uncertainty, for instance, the S&P 500 index dropped by nearly 30 percent in 22 trading days from its peak on February 19, 2020. It is generally viewed that the pandemic impacts are not merely temporary, since the COVID-19 shock affects investors' beliefs about economic growth and stock prices (Giglio et al. (2020), Gormsen & Koijen (2020), Landier & Thesmar (2020)).

In this paper, we use COVID-19-related data on infections and deaths to investigate whether the COVID-19 pandemic is priced in the U.S. stock market. The number of infections and deaths is a key source of information regarding the severity of the COVID-19 pandemic and how rapidly it spreads that would determine whether and when a nation would get into a lockdown (Milcheva (2022)). Moreover, Schroders' latest Global Investor Study, carried out across 32 locations around the world between 30 April and 15 June 2020, shows that a significant majority of investors adjusted their portfolios as the pandemic unfolded.[1][2] Therefore, it highlights the pandemic's impact on investors' beliefs and investment decisions, and this may affect asset prices.

First, we examine our question by considering two aggregate measures of Covid-19, namely the daily change in the number of new infections and deaths, separately. We quantify the pandemic risk as the sensitivity of stock returns to these two aggregate measures and investigate whether COVID-19 is priced cross-sectionally by taking a portfolio-sort approach. We sort every day all common stocks trading in the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq into decile portfolios by the exposures of their daily returns to any given COVID-19 measure. We find that the daily change in the number of new infections is priced, whereas the daily change in the

[1] https://bit.ly/3uLuYEc

[2] Specifically, 53% of investors made adjustments to their portfolios by reallocating a significant portion or some of their portfolio to lower-risk investments. On the contrary, 35% of investors said that they shifted a significant proportion or some of their portfolios towards high-risk investments. Additionally, 8% of investors made changes to their portfolio composition while keeping the overall level of risk unchanged.

number of new deaths is not priced in the U.S. stock market. Stocks with high exposures to variations in the daily number of new infections exhibit low returns on average. Therefore, our results suggest that investors are only concerned about the daily change in the number of new infections. This is not surprising, since the number of infections reveals information about future deaths (e.g., a certain proportion of infected people is going to die), whereas any deaths have already been discounted in stock prices as soon as the number of infections has been announced (Alber (2020), Ashraf (2020), Raifu et al. (2021)). Furthermore, we show that our COVID state variable satisfies the requirements of the ICAPM and is a valid state variable under Merton (1973)'s ICAPM.

Second, as the pandemic may have different impacts on firms from different industries, we are curious about whether the pandemic beta effect may be driven by industry exposure. To explore this, we investigate the predictive abilities of the COVID-19 beta in different industries by dividing stocks into seven industry groups, based the Industry Classification Benchmark (ICB) system. Although the effect of the COVID-19 beta visibly differs across industries, the results indicate that this effect is not solely driven by a single industry.

Third, we follow Fama & French (1993) and Bali et al. (2017) and form a risk factor to capture the returns associated with the COVID-19 beta. Our findings confirm that the performance of our COVID-19 beta factor is not explained by other well-known risk factors.

Fourth, in addition to exploring how firms are affected by an epidemic disease and how they respond, it is of great importance to understand which characteristics may make firms resilient in the midst of a pandemic. To investigate how a firm's characteristics affects its stock price reaction to the COVID-19 shock, we examine the relation between (pre-pandemic) corporate characteristics and the reaction of stock returns to COVID-19 new infections. By considering potentially relevant characteristics, including firms' financial conditions, corporate social responsibility (CSR) activities, and corporate governance, our findings demonstrate that investors expected the shock induced by the COVID-19 pandemic to be amplified through financial channels. In particular, we find that US firms with stronger pre-pandemic financial condition–high cash, high profitability, and low leverage–experienced smaller declines in stock prices in response to the pandemic than other firms, as they are better able to avoid financial distress.

Finally, we conduct a number of robustness tests to confirm our baseline results. First, we repeat the portfolios sorts analysis by sorting stocks into quantile portfolios. We find consistent evidence that the difference between the average returns on the portfolios with the highest and lowest changes in the number of new infections beta remains negative and significant. Second, we estimate the price of COVID-19 risk factors by running Fama & MacBeth (1973) regressions and find that changes in new infections as a COVID-19 risk factor is priced across all of the specifications considered. Moreover, similar to our findings from individual stocks, the results indicate that changes in the number of new infections is negatively priced in the cross-section of equity portfolios as test assets (25 and 100 Fama-French portfolios sorted on size and book-to-market and 48 industry portfolios). Third, we demonstrate that how investors updated their beliefs and expectations about the economic consequences of the outbreak and became less responsive to the COVID-19 shock as the trajectory of the pandemic became less severe than initially expected. In particular, we document that investors gradually priced less exposure to pandemic risk after June 30, 2020, as the U.S. Federal Reserve have taken steps to mitigate the adverse effects of the pandemic by pumping massive amounts of money into the economy. Fourth, we perform several additional robustness checks to supplement our analyses. We repeat the univariate portfolio sorts analysis and re-examine the average return and alpha differences using two subsamples of big and liquid stocks, we estimate the COVID-19 beta using two alternative factor models to check whether alternative measures of the COVID-19 beta predict future stock returns, and we also investigate the predicting ability of our COVID-19 measure after controlling for the effect of economic policy uncertainty. All of these exercises validate the robustness of the COVID-19 beta as a reliable predictor of future stock returns. Finally, we explore the performance of the COVID-19 beta in an international setting to see whether other equity markets are afraid of variations in new infections. To do so, we replicate the same portfolio sorts exercise in 15 major

European stock markets. The aggregate results indicate that the COVID-19 beta is a reliable predictor of future equity returns across all European markets.

Our empirical findings contribute to the emerging literature on the stock market response to the COVID-19 pandemic. One stream of the literature examines the effect of COVID-19 to the firm-level equity returns. (e.g., Bretscher et al. (2020), Fahlenbrach et al. (2021), Martin & Nagler (2022), Glossner et al. (2022), Hassan et al. (2023), Pagano et al. (2023), Ramelli & Wagner (2020)), and a second stream investigates the effect of COVID-19 to the aggregate equity market (e.g., Alfaro et al. (2020), Baker et al. (2020), Croce et al. (2020)).

Our analysis is related to the first stream of literature and it complements it by employing an alternative state variable. Pagano et al. (2023) investigate whether pandemic resilience is priced in the stock market. Our study differs from that of Pagano et al. (2023) because they use a measure of the social distancing as a state variable, whereas we use the daily change in the number of new infections and deaths as state variables. This way, we address the question of whether the stock market is afraid of infections and deaths. To the best of our knowledge, this is the first study exploring the effect of the daily change in the number of new infections and deaths in the cross section of stock returns. Moreover, our findings confirm that the variations in the number of new infections beta as the COVID-19 pandemic beta can be seen as a reliable predicting variable of future equity returns in both the US and European stock markets.

Our paper also adds to the recent studies which seek to identify channels of firm exposure to COVID-19 through various firm characteristics (Albuquerque et al. (2020), Ding et al. (2021), Fahlenbrach et al. (2021)). We study how U.S. firms' pre-pandemic attributes affect their resilience to the COVID-19 shock. Our findings shed light on the importance of financial condition in general, and the role of low leverage, high cash holdings, and high profitability in particular, in enhancing U.S. firm value during the COVID-19 pandemic.

Our work is also related to the literature that examines the effect of rare disasters on asset prices. Early work by Rietz (1988) proposes a model that incorporates rare disasters into an asset-pricing model and argues that the model provides a possible explanation of the high equity risk premia. Barro (2006) extends the model by Rietz (1988) and calibrate disaster probabilities to explain the asset-pricing puzzles including the high equity premium, low risk-free rate and stock return volatility. Gabaix (2012) further extends the model by Rietz (1988) and Barro (2006) and adds a stochastic probability and severity of disasters and show that a time-varying severity of rare disasters can explain a number of finance puzzles, including the equity premium. Siriwardane (2015) utilizes options data to estimate a time series of a risk neutral probability of disaster and finds a negative and statistically significant relation between the probability of disaster and the cross section of stock returns. Our study can be viewed as complementary to the rare disaster literature by demonstrating how the COVID-19 pandemic, as a rare disaster, affects equity prices.

The rest of this study is organized as follows. In Section 2, we discuss the data. Section 3 provides a framework to examine the relation between COVID-19 and the cross- section of stock returns and presents empirical results obtained by sorting the cross section of stocks into decile portfolios based on exposures to COVID-19. Section 4 explores which characteristics makes some firms resilient in the face of the COVID-19 pandemic. Section 5 conducts a number of robustness checks. Section 6 concludes.

# 2 Data

We obtain the stock returns for all common stocks (the share codes of 10 and 11) listed at the NYSE, AMEX and NASDAQ (the exchange code of 1, 2, and 3) reported in the CRSP daily stock file via Wharton Research Data Services (WRDS). Also, we adjust returns for delisting to avoid survivorship bias, using the approach suggested by Shumway (1997). The sample period consists of 112 trading days from January 22 to June 30, 2020, spanning the first wave and the beginning of the second wave of the COVID-19 outbreak in the United States. There are two reasons which dictate the choice of our sample period up to June 30, 2020. First, most US states and European countries have begun to loosen social distance constraints and resume economic activities as of May 15, 2020 (Albulescu (2021)). Second, stock prices dropped 30% as a result of the COVID-19 situation and subsequent lockdowns, as well as a dramatic increase in US unemployment since March 2020. However, the U.S. Federal Reserve reacted to the COVID-19 crisis by injecting large amounts of money into the economy, causing the stock market to rapidly recover all of its losses by June 2020 (Sunder (2021)). Our sample consists of 402117 observations for 3673 stocks, for which we observe returns throughout the sample period. We also obtain data on daily stock index return, risk-free rate, and the factor mimicking portfolio returns for size, book to market, investment, and profitability and momentum factors, as well as the returns of the 100 and 25 Fama-French portfolios formed on size and book-to-market, and 48 industry portfolios, from the online data library of Kenneth French.[3]"

The first infections of COVID-19 were identified in Wuhan, China, in December 2019, while the first infections in the United States and South Korea were reported to the World Health Organization (WHO) on January 20, 2020.[4] The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020, as the number of reported cases worldwide increased.[5] The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University provides daily data on the cumulative number of COVID-19 infections and deaths in the United States from 22 January, 2020 onwards.[6] It is important to note that the first Coronavirus death was reported in the US on February 29, 2020, so the sample period for COVID-19 deaths runs from February 29, 2020 to June 30, 2020.

In the analysis that follows, we adjust the number of infections and deaths for the country's population. Table 1 reports basic descriptive statistics and the correlation matrix of the employed variables over the sample period.[7] The reported numbers for COVID-19's measures are normalized by the US population. As expected, the mean and standard de-

[3]The data can be downloaded from the Kenneth French data library at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[4]http://bit.ly/3RulQMU

[5]https://bit.ly/3tcxWkx

[6]The data can be downloaded from https://bit.ly/3uKDnb0.

[7] The sample period for COVID-19 deaths starts from February 29, 2020.

viation for the daily cumulative number of COVID-19 infections and deaths ($CInfections$ and $CDeaths$) are higher than those for the daily number of COVID-19 new infections and deaths ($NInfections$ and $NDeaths$). Moreover, the absolute value of the correlation coefficients between different variables are typically low, and there are no considerable correlations between COVID-19 factors and other control variables.

**[Insert Table 1]**

Figure 1 shows the daily cumulative number of COVID-19 infections and deaths per capita (per million of the US population) over the sample period. Also, in Figure 2, we plot the daily number of new COVID-19 infections and deaths normalized by the US population. In mid-March, the number of infections started to grow sharply, as the US testing capacity has increased considerably.[8] Several state and local governments enacted "stay-at-home" orders during March and early April, which reduced the country's growth rate of infections and deaths. After lifting “stay-at-home” restrictions in several states, a second surge of infections began in mid-June.

**[Insert Figure** 1**]**

**[Insert Figure** 2**]**

# 3 Empirical Analysis

In this section, we analyze whether the COVID-19 pandemic risk affects the stocks' risk premium. It is worth noting that the cumulative number of infections (deaths) and the number of new infections (deaths) are not stationary series, while the changes in new infections and deaths are both stationary variables. In the Supplementary Appendix, Figure A1 presents the autocorrelation functions (ACF) of the cumulative number of

[8]https://www.nytimes.com/2020/07/03/health/coronavirus-mortality-testing.html

infections, the number of new infections, and the daily change in new infections to justify our choice of the COVID-19 pandemic risk factor. For both the cumulative number of infections and the number of new infections, the results exhibit autocorrelation in the data. However, for the daily change in new infections, there is not the evidence of autocorrelation in the data.[9][10]

So, we only consider the daily change in new infections and deaths as COVID-19 measures to obtain consistent and reliable results. First, we estimate factor models for each company one by one over the sample period.[11] We run one of the following time series regressions on daily returns of each stock over the sample period to estimate its sensitivity to $\Delta NInfections$ and $\Delta NDeaths$. So, we first use the following equations:

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{COVID}^i COVID_t + \beta_F^i F_t + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the daily return for asset $i$ on day $t$, $R_{f,t}$ is the return of the risk-free asset. $COVID_t$ variable represents the daily change in the number of new infections ($\Delta NInfections$) and the daily change in the number of new deaths ($\Delta NDeaths$). $F_t$ is a vector of control variables and $\varepsilon_{i,t}$ is the error term. $F_t$ includes market excess returns ($R_{m,t} - R_{f,t}$), size (SMB), book-to-market (HML), momentum (UMD), investment (CMA), and profitability (RMW) factors of Fama & French (1993, 2015), and Carhart (1997).

We report the results from the first step of the methodology, which is based on Eq. (1), for the daily change in the number of new infections ($\Delta NInfections$) and ($\Delta NDeaths$) in Figure 3. The sample period for $\Delta NInfections$ is January 22 to June 30, 2020, and for $\Delta NDeaths$ is February 29 to June 30, 2020. Figure 3 plots the kernel density for $\Delta NInfections$ and $\Delta NDeaths$. In Panel A, we show the distribution of $\beta^i_{\Delta NInfections}$with and without controlling for common risk factors. We control for the market risk factor (MKT, i.e. $R_{m,t} - R_{f,t}$), the Fama & French (1993) pricing factors (FF3, i.e. MKT, SMB, and HML), the Fama & French (2015) pricing factors (FF5, i.e. MKT, SMB, HML,

[9]We obtain similar results (not presented to save space) when considering the cumulative number of deaths, the number of new deaths, and the daily change in new deaths.

[10]Also, the changes in new infections and deaths are both stationary time series when we perform the Augmented Dickey-Fuller (ADF) test.

[11]This approach follows Alfaro et al. (2020).

CMA, and RMW), and the Fama-French models augmented with the Carhart (1997)'s momentum factor (FF4 and FF6). Again, in Panel B, we plot the distribution of $\beta^i_{\Delta NDeaths}$ with and without control variables. As can be seen from this figure, when we estimate the regressions without control variables, we find that the majority of $\beta^i_{\Delta NInfections}$and $\beta^i_{\Delta NDeaths}$ are above zero, while the distribution shifts to the left and the majority of $\beta^i_{\Delta NInfections}$and $\beta^i_{\Delta NDeaths}$ oscillate around zero as we control for standard risk factors.[12]

**[Insert Figure 3]**

## 3.1 Univariate portfolio sorts on exposure to COVID-19

In this section, we examine whether COVID risk is priced in the cross-section of U.S. common stocks. For each COVID measure, at any given point in time, the stocks are sorted into decile portfolios based on their exposure to the respective COVID measure, where Decile 1 contains stocks with the lowest beta and Decile 10 contains stocks with the highest beta during the estimation period. We form both equal- and value-weighted portfolios. To construct value-weighted portfolios, each stock in the decile is weighted by its relative market capitalization within the decile at the end of the beta estimation period. After portfolio formation, we record one-day post ranking returns of each decile portfolio. We repeat the process by moving the beta estimation window forward by one day. We use a rolling window of 22 observations. We also compute daily post ranking returns for the spread portfolio, constructed as going long in the stocks of higher COVID-19 beta stocks (Portfolio 10) and short in the stocks of the lowest COVID-19 beta stocks (Portfolio 1). We term the COVID-19 factor to be priced if there is a monotonic relation between portfolio betas and average portfolio return, and the time series average return of the spread portfolio is statistically different from zero. We also estimate the Carhart (1997) four-factor and the Fama & French (2018) six-factor alphas of each decile portfolio, using post-ranking daily returns over the sample period. This way, we examine whether the effect of any COVID measure persist after controlling for standard risk factors, including

[12]Specifically, when we estimate the regressions without control variables, 81 percent of $\beta^i_{\Delta NInfections}$ and 85 percent of $\beta^i_{\Delta NDeaths}$are positive.

the market, size, book-to-market, momentum, profitability, and investment risk factors. We use a Newey-West standard error obtained from using a lag of three.

We first construct decile portfolios based on stocks' exposure to any COVID-19 measure and subsequently comparing the average returns and alphas of these portfolios.

$$\begin{aligned} R_{i,t} - R_{f,t} = \beta_0^{i,t} &+ \beta_{COVID}^{i,t} COVID_t + \beta_{MKT}^{i,t} MKT_t \\ &+ \beta_{SMB}^{i,t} SMB_t + \beta_{HML}^{i,t} HML_t + \beta_{UMD}^{i,t} UMD_t \\ &+ \beta_{RMW}^{i,t} RMW_t + \beta_{CMA}^{i,t} CMA_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

This specification (Eq.(2)) measures stocks' exposure to the COVID-19 measure ($COVID_t$), after controlling for exposure to the market ($MKT_t$), size ($SMB_t$), book-to-market ($HML_t$), momentum ($UMD_t$), profitability ($RMW_t$), and investment ($CMA_t$) factors simultaneously.

If COVID-19 is a priced risk factor, it is ideally expected to observe that a monotonic decreasing pattern exists in average returns and alphas from Decile 1 (lowest exposure) to Decile 10 (highest exposure) for portfolios sorted on their exposure to COVID-19. A high-low spread portfolio is expected to yield a negative average return. In other words, investors would increase (decrease) demand for positive (negative) beta stocks, thus increasing (decreasing) their prices and hence decreasing (increasing) their return. This is consistent with the intertemporal capital asset pricing model (ICAPM) of Merton (1973) and Campbell (1993, 1996). In this regard, an increase in the COVID-19 measure is generally associated with a deterioration in future investment and consumption opportunities. As a result, investors would prefer to hold the stocks with an increase in their returns during the COVID-19 outbreak to hedge against the unfavorable changes in their future investment and consumption opportunity sets.

The results of univariate portfolios sorted on $\beta^{\triangle NInfections}$ and $\beta^{\triangle NDeaths}$are reported in Panel A and B of Table 2, respectively. In Panel A of this table, for the equally-weighted portfolio, the average daily return decreases almost monotonically from 0.45% to -0.01% as we move from decile 1 to decile 10. Additionally, the average daily return of the High-Low portfolio of -0.46% is highly statistically significant with a t-statistic of

-2.91. Furthermore, the risk-adjusted returns (alphas) from the Carhart (1997) four-factor and the Fama & French (2018) models on the spread portfolio are also highly significant and equal to -0.57% with the t-statistics of -3.04 and -3.02, respectively. The average return per day on the value-weighted spread portfolio is -0.49% with a corresponding t-statistic of -2.27. Also, the four-factor and six-factor alphas for the value-weighted spread portfolios are equal to -0.61 with the t-statistics of -2.62 and -2.66, respectively.[13]

According to Harvey et al. (2016), the usual statistical significance cutoff (i.e., a t-statistic greater than 2.0) is too low and no longer appropriate in asset pricing studies due to the rising concerns associated with data mining. They argue that a new factor needs to pass a much higher hurdle, with a t-statistic above 3.0. The results in Table 2 indicate that for the four-factor and six-factor alphas on the equal-weighted spread portfolios, the absolute t-statistics exceed the t-statistic threshold of 3.0. Despite the fact that the four-factor and six-factor alphas on the value-weighted spread portfolios fails to pass this test, our findings confirm that the abnormal returns are not driven by small and illiquid stocks (see Table A6).[14]

The results when we sort all stocks based on $\beta^{\triangle NDeaths}$ are presented in Panel B of Table 2. For the equal-weighted and value-weighted portfolios, the average daily return difference between decile 10 and decile 1 is not statistically significant, indicating no difference in average returns between stocks with high $\beta^{\triangle NDeaths}$ and stocks with low $\beta^{\triangle NDeaths}$. Furthermore, for the equal-weighted and value-weighted portfolios, both the four-factor and the six-factor alphas of the spread portfolio are not statistically different from zero.

**[Insert Table 2]**

Overall, strong evidence exists that $\Delta NInfections$ is priced with a negative price of

[13] The average return and alphas on the spread portfolio are comparable to those values on the High-Low portfolio reported in the first version of the Pagano et al. (2023)'s paper.

[14] We also perform bivariate portfolio sorts to control for the effect of two well-known stock characteristics, market beta and size (see Tables A1 and A2).

risk, but there is no evidence that $\Delta NDeaths$ is priced. This is most likely due to the fact that investors know that infections lead to deaths, so they have already priced in deaths via infections. Also, the sample period for $\Delta NDeaths$ is shorter than $\Delta NInfections$.

To sum up, our findings from univariate portfolios sorts on different COVID-19 measures verify that there is a statistically significant and negative relation between the changes in new infections ($\Delta NInfections$) beta and future stock returns.

**Average stock characteristics of $\Delta NInfections$-sorted portfolios.** Table 3 reports the average stock characteristics across decile portfolios, computed in the portfolio formation day. We calculate the average portfolio characteristics by averaging them first within each decile portfolio and then over time. Table 3 presents the average share price, size or market capitalization (in millions of dollars), book-t-market ratio, market beta, idiosyncratic volatility, and Amihud's illiquidity measure of firms within each $\beta^{\triangle NInfections}$ decile portfolio. The characteristics indicate that both extreme-$\beta^{\triangle NInfections}$ portfolios (Decile 1 and 10) consist of relatively smaller market capitalization, less liquid stocks that also tend to have higher book-to-market ratios and idiosyncratic volatility and lower share prices than stocks in the middle portfolios. Therefore, these results confirm that the negative predictive ability of pandemic risk is not attributed to the differences in the various characteristics of individual stocks.

**-Is COVID risk premium consistent with the ICAPM?** Next, we examine whether the COVID factor is a valid state variable that is consistent with the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973). Maio & Santa-Clara (2012) argue that while the Merton (1973)'s ICAPM model does not directly recognize the state variables, it places restrictions on the time-series and cross-sectional behavior of state variables. They show that the cross-sectional return predictability of a given state variable must be compatible with its time-series predictability of changes in the investment opportunity set in order to be consistent with Merton (1973)'s ICAPM theory. Thus, for a given state variable to justifiable by the ICAPM framework, it should significantly forecast at least one dimension of the first two moments of the aggregate market return (i.e. stock market return and volatility) and its innovation should carry a significant price of risk with the correct sign in the cross-section. Specifically, if a state variable forecasts aggregate stock returns with a positive sign in the time-series, its innovation should carry a positive price of risk in the cross-section, and vice versa. Similarly, if a state variable predicts an increase (decrease) in the market volatility, its innovation should earn a negative (positive) risk premium in the cross-section.

However, Boons (2016) claims that this sign restriction is almost never fulfilled when the cross-sectional asset pricing test employs characteristics-sorted portfolios. Thus, in contrast to Maio & Santa-Clara (2012), Boons (2016) documents that the risk premium for the exposure to a given ICAPM-motivated state variable in the cross-section of individual stocks is consistent with how the state variable forecasts macroeconomic activity in the time-series and satisfies the sign restrictions in the time series.

Given the results discussed above and in section 5.2, the risk price estimates for the $\Delta NInfections$ factor are consistently negative in the cross-section of individual stocks. As a result, in order to be consistent with the ICAPM, the $NInfections$ factor should forecast a deterioration in future investment opportunities.

Following Maio & Santa-Clara (2012), to test whether $NInfections$ forecasts the market volatility (as a proxy of the investment opportunity set) at multiple horizons, we conduct the following predictive regressions:

$$svar_{t+1,t+q} = \alpha_q + \beta_q NInfections_t + u_{t+1,t+q} \tag{3}$$

where $svar_{t+1,t+q} \equiv svar_{t+1} + ... + svar_{t+q}$ and $svar_{\mathrm{t}}$ is the log of market realized volatility. $NInfections_t$ is the daily number of new infections. We use forecasting horizons of 5, 10, 15, 20, 30, and 45 days ahead. We compute the statistical significance of the regression coefficients using the Newey & West (1987) t-statistics with $q$ lags to correct for the serial correlation in the residuals.

In the Supplementary Appendix, Table A3 reports the estimation results for the single predictive regressions associated with stock market volatility. As shown, $NInfection$ positively predicts the stock market volatility and the associated coefficients are statistically significant at all horizons. This implies that the COVID state variable contains useful information about the aggregate investment opportunity set that is not fully captured by traditional state variables in the empirical ICAPM literature. Thus, these estimates are consistent with the negative risk price for $\triangle NInfection$.

**[Insert Table** A3**]**

Overall, the results of this section show that the negative risk price estimates associated with the $\triangle NInfection$ factor are consistent with the ICAPM, when future investment opportunities are measured by the stock market volatility. Thus, the COVID state variable satisfies the requirements of the ICAPM and is a valid state variable under Merton (1973)'s ICAPM.

## 3.2 Industry-level portfolio sorts

The firm's ability to deal with pandemic fears and uncertainties may be related to the nature of its business. Obviously, firms in face-to-face service industries such as food catering, travel, and tourism have been among the most severely affected sectors, as the nature of their business requires close interaction between customers and employees. Hence, the pandemic beta effect may be driven by industry effects.

In this subsection, we are curios to see whether the pandemic beta effect retains its predictive ability not only across industries but also within industries. To assure that the pandemic beta effect is not driven by any particular industry, we explore the predictive power of the $\Delta NInfections$ beta within different industry groups. To do this, stocks are sorted into quintile portfolios based on $\beta^{\Delta NInfections}$ within the 7 industries determined based on the Industry Classification Benchmark (ICB) system: Basic Materials; Consumer Staples and Discretionary; Energy; Financials and Real Estate; Health Care; Industrials and Utilities; Technology and Telecommunications.[15]

Table 4 reports the Fama & French (2018) six-factor alpha of the quintile portfolios as well as the alpha on the spread portfolio within the seven industries for the equal-

[15]See https://www.ftserussell.com/data/industry-classification-benchmark-icb for more details.

weighted (Panel A) and value-weighted (Panel B) portfolios. The results show that the six-factor alpha spreads are negative and statistically significant in most industries (in 4 out of 7 industries) for both equal- and value-weighted portfolios. It is fair to see that the statistical significance decreases relative to the full sample since we have a smaller sample of stocks within each industry. The six-factor alpha on the spread portfolio is statistically significant and economically largest for stocks in Basic Materials, Consumer Staples and Discretionary, Energy, and Health Care industry groups. On the other hand, the six-factor alpha on the long-short portfolio is statistically weak for stocks in Financials and Real Estate, Industrials and Utilities, and Technology and Telecommunications industry groups.

**[Insert Table 4]**

Overall, the results indicate that the COVID-19 effect is not driven by any single industry, and the predictive ability of the COVID-19 beta also works across most industries.

## 3.3 COVID-19 risk factor

Having demonstrated a significant negative cross-sectional relation between COVID-19 beta and expected stock returns which is not explained by well-known risk factors, we now follow a similar approach to Fama & French (1993) and Bali et al. (2017) to construct a risk factor to capture the returns associated with the COVID-19 beta and investigate whether other standard risk factors can explain the returns associated with the COVID-19 beta. To this end, we first independently sort all stocks into two groups based on their market capitalization (size) such that one group is composed of the stocks that account for 90% of the total stock market capitalization and the other group contains the stocks that comprise 10% of the total market capitalization. Second, we independently sort all stocks into three $\beta^{\Delta NInfections}$ groups using the 30th and 70th percentiles of $\beta^{\Delta NInfections}$ as breakpoints. Then, the intersections of the two size groups and the three $\beta^{\Delta NInfections}$ groups produce six portfolios. The $\beta^{\Delta NInfections}$ factor (COVID-19 risk factor) return is measured by taking the difference between the average return of the two high-$\beta^{\Delta NInfections}$ portfolios and the average return of the two low-$\beta^{\Delta NInfections}$ portfolios. According to Fama & French (1993), this factor-forming method seeks to capture returns associated with COVID-19 risk premium while maintaining neutral exposure to the firm's market value. We aim to investigate the performance of our COVID-19 risk factor.

Table 5 reports the average daily returns of the COVID-19 risk factor, as well as the alphas obtained using three different factor models for equal-weighted (Panel A) and value-weighted (Panel B) portfolios, respectively. For the equal-weighted portfolios, the results show that the average daily return of the COVID-19 risk factor portfolio is -0.34% with a t-statistic of -2.44. Furthermore, the risk-adjusted returns (alphas) of COVID-19 risk factor corresponding to three different factor models are in the range of -0.33 to -0.43 with statistically significant t-statistics ranging from -2.38 to -2.47. For the value-weighted portfolios, the average daily return of the COVID-19 risk factor portfolio of -0.25% is statistically significant with a t-statistic of -2.36. Also, the value-weighted alphas of COVID-19 risk factor corresponding to three different factor models are in the range of -0.25 to -0.35 with statistically significant t-statistics ranging from -2.32 to -2.48.

**[Insert Table** 5**]**

To sum up, the results confirm that the standard risk factors fail to explain the performance of our COVID-19 risk factor.

# 4 Corporate resilience to the pandemic risk

So far, our focus has been to examine whether firms' exposure to the COVID-19 pandemic contains any valuable information about future stock returns. In addition to studying how firms are exposed to COVID-19 and how they respond, it is also important to find out which attributes makes some firms resilient in the face of the COVID-19 pandemic. In other words, we explore how corporate characteristics shape stock price reactions to

COVID-19. Specifically, we examine the relation between pre-pandemic firm characteristics and stock price reactions of U.S. firms to the COVID-19 pandemic. To do so, we focus on three pre-2020 corporate characteristics: (1) financial conditions, such as leverage, cash ratio, and profitability, (2) corporate social responsibility (CSR) activities (3) corporate governance structure, such as managerial entrenchment, board structure, and executive compensation schemes.

To examine the relation between pre-2020 firm characteristics and stock price reactions to COVID-19, we follow Ding et al. (2021) as a reference for our regression model and run the following panel regression:

$$R_{i,t} = \beta_0 + \beta_1 COVID_t + \beta_2 X_{i,pre2020} \times COVID_t + \delta_i + \varepsilon_{i,t} \tag{4}$$

where $R_{i,t}$ is the daily stock return of firm $i$ on day $t$, $COVID_t$ is the daily change in the number of new infections, $X_{i,pre2020}$ includes a set of firms characteristics, including financial conditions, CSR activities, and corporate governance, and $\delta_i$ is two-digit SIC industry fixed effects to control for unobserved heterogeneity at the industry level.[16] We estimate Eq.(4) using ordinary least squares (OLS), where robust standard errors are clustered at the firm level.

**Financial conditions.** Several studies highlight the role of financial conditions for firm value as the COVID-19 crisis unfolded (Alfaro et al. (2020), Ding et al. (2021), Fahlenbrach et al. (2021), Pagano et al. (2023), Ramelli & Wagner (2020)). These papers discuss and provide evidence that the effect of the COVID-19 shock is amplified for firms with weaker financial flexibility. In particular, Fahlenbrach et al. (2021) discuss and demonstrate the importance of financial flexibility in light of the COVID-19 shock, which resulted in a sudden stop in firms' revenues.

First, we examine the economic effects of financial conditions on the sensitivity of stock returns to the pandemic. To do so, we obtain corporate accounting data in 2019 from Compustat North America. We consider four standard proxies for a firm's financial condition: Firm Size is the natural logarithm of the book value of total assets (Compustat

[16] We compute $COVID$ as $COVID_{\mathrm{t}} = ln(1 + NewInfections_t) - ln(1 + NewInfections_{t-1})$.

item *at*). Leverage is defined as book debt (*dlc+dltt*) divided by total assets (*at*). Cash ratio, which is defined as the total amount of cash and short-term investments (*che*) divided by total assets (*at*). ROA is the ratio of net income (*ni*) to total assets (*at*). To capture heterogeneity in firms' financial condition, we compute firms' Size, Leverage, Cash ratio and ROA based on the accounting data from the latest 2019 quarterly reports.

Table 6 reports the estimation results for the effect of pre-pandemic corporate financial conditions on stock price sensitivity to COVID-19. In Column 1, the association between COVID and stock returns is negative and statistically significant, implying that an increase in the daily growth rate of new infections leads to a drop in U.S. equity returns. As shown in Columns 2 and 3, the interaction between COVID and Cash ratio and ROA is positive and significant, whereas the interaction with Leverage is negative and significant, suggesting that market participants view firms with more cash, higher profitability, and less debt as more resilient to COVID-19 than other firms.

**[Insert Table** 6**]**

Overall, our findings indicate that US companies with stronger pre-pandemic financial condition–more cash, high profits, and low leverage–experienced milder stock price reactions in response to COVID-19 than other firms. In other words, investors consider companies with more cash, high profits, and less debt to be more disaster-resilient, as they are better positioned to cope with the real effects of the pandemic and sustain disaster-related losses. These results are broadly consistent with Albuquerque et al. (2020), Ding et al. (2021), and Ramelli & Wagner (2020), who also report evidence that cash holdings and profitability contribute to mitigate the impact of the COVID-19 shock on stock returns and find that leverage amplifies it.

**Corporate social responsibility (CSR) activities.** Second, we examine whether pre-pandemic CSR activities of US companies affect the response of their stock returns to the COVID-19 pandemic. Several recent papers investigate the relation between CSR activities and firms' value during the COVID crisis (Albuquerque et al. (2020), Demers et al. (2021), Ding et al. (2021), Garel & Petit-Romec (2021)). However, their findings on the effect of CSR efforts on firm value during times of crisis are inconclusive. In this regard, the mixed empirical findings highlight the challenge of determining how CSR activities affects corporate value.

To construct our sample, we obtain data on US firms' environmental, social, and governance (ESG) scores from Thomson Reuters Refinitiv, which contains environmental, social, and governance ratings of companies.[17] Thomson Reuters reports the three pillar scores and the final ESG score, which covers three categories: (1) environment concerns, including resource use, emissions, and innovation, (2) social themes, including workforce, human rights, community, and product responsibility, and (3) governance practices, including management, shareholders, and CSR strategy.[18]

In the Supplementary Appendix, Table A4 reports the estimation results. The interaction between COVID and the ESG score is positive, though not statistically significant. We also separately present results for the three pillars of the ESG score: i) Environmental, ii) Social, and iii) Governance scores. The results show that none of these three components affects stock returns in response to the pandemic. Overall, our findings provide no evidence that firms' pre-2020 CSR activities affected corporate immunity to the pandemic. These results are consistent with Demers et al. (2021), who also use a sample of U.S. firms and find no evidence that ESG is an "equity vaccine" against falling stock prices during the COVID-19 pandemic.

**Corporate governance.** Finally, we investigate whether the corporate governance structures of US companies affect their resilience to the COVID-19 shock. To do so, we consider pre-pandemic measures of managerial entrenchment, board structure, and executive compensation systems. Several studies document that governance provisions and managerial entrenchment reduce firm value (Bebchuk & Cohen (2005), Bebchuk et al. (2009), Cremers & Nair (2005), Gompers et al. (2003), Johnson et al. (2000)). In contrast, Eldar & Wittry (2021) argue that a negative relation between governance provisions and firm value does not hold under crisis and document that adopting poison pills plays an

[17] We match firms using their CUSIP numbers.

[18] When a firm's 2019 ESG scores are not available, we use the corresponding data from 2018.

important role in mitigating the adverse effect of an economic crisis on firm performance. Some studies also relate the firm performance to the structure of board of directors (Adams et al. (2010), Adams & Ferreira (2007), Erkens et al. (2012), Guo & Masulis (2015), Hermalin & Weisbach (1991), Nguyen & Nielsen (2010)) and executive compensation schemes (Murphy (2013)).

We retrieve information on firms' pre-pandemic measures of managerial entrenchment, board structures, and executive compensation policies from Thomson Reuters Refinitiv. To quantify managerial entrenchment, we use the number of antitakeover devices. Regarding the board structure, we measure Board Independence by the fraction of independent board members of a firm. To quantify executive compensation, we utilize Performance-based Compensation which equals one if the company has a performance-oriented compensation policy that attracts the senior executives and board members and Executive Compensation LT Objectives which equals one if managers and board remuneration is partially tied to long-term objectives and targets.

In the Supplementary Appendix, Table A5 report the estimation results of regressing stock returns on pre-crisis corporate governance measures and control variables. The coefficient estimate on the *Antitakeover Devices*COVID* is economically small and statistically insignificant, indicating that stock prices of firms do not react to the pandemic as a function of anti-takeover provisions. This result is consistent with mixed evidence on the link between managerial entrenchment and firm performance. Next, we consider the structure of corporate boards. Accordingly, we examine the link between stock price resilience to COVID-19 and corporate board independence. The interaction between *COVID* and *Board Independence* enters statistically insignificant. Therefore, we do not find a robust relation between stock price resilience to COVID-19 and the structure of corporate boards. Finally, we consider executive compensation policies. The the interactions between *COVID* and *Performance-based Compensation* and *Executive Compensation LT Objectives* are statistically insignificant. These results are consistent with Ding et al. (2021), who also find that both the structure of corporate boards and executive compensation policies do not affect stock price reactions to COVID-19. Overall, the results from Table A5 indicate that there is no evidence of differential stock price reactions to COVID-19 as a function of pre-pandemic corporate governance structures.

# 5 Robustness

In this section, we investigate whether our findings are robust to a battery of robustness checks.

## 5.1 Quintile portfolio sorts on delta new infections exposure

First, we repeat the same procedure in Section 3.1 by sorting the stocks into quantile portfolios instead of decile portfolios based on their exposure to $\Delta NInfections$, where Quantile 1 contains stocks with the lowest $\beta^{\Delta NInfections}$, and Quantile 5 contains stocks with the highest $\beta^{\Delta NInfections}$. Table 7 reports the results for quintile portfolio sorts. As shown in Panel A of this table, for the equal-weighted portfolio, the average daily return decreases monotonically from 0.34% to 0.05%, moving from quintile 1 to quintile 5. The average return on the spread portfolio (High-Low) which is long in the highest-$\beta^{\Delta NInfections}$ stocks and short in the lowest-$\beta^{\Delta NInfections}$ stocks is -0.29% per day with a Newey & West (1987) t-statistic of -2.88. Furthermore, the four-factor alphas decrease monotonically from 0.39% for the lowest $\beta^{\Delta NInfections}$ quintile to 0.03% for the highest $\beta^{\Delta NInfections}$ quintile. The daily four-factor alpha on the High-Low portfolio is -0.36% with a corresponding Newey & West (1987) t-statistic of -3.07. Also, the six-factor alpha of Fama & French (2018) model exhibit a monotonically decreasing pattern across the quintile portfolios of $\beta^{\Delta NInfections}$. The difference in six-factor alphas between the high-$\beta^{\Delta NInfections}$ and low-$\beta^{\Delta NInfections}$ portfolios is -0.36% with a t-statistic of -3.12. Panel B shows that for the equal-weighted portfolios, the average return decreases monotonically from 0.13% to -0.12% per day, as we move from the lowest to the highest $\beta^{\Delta NInfections}$ quintile. The average return on the High-Low portfolio is -0.25% per day (t-statistic = -1.96). The corresponding four-factor and six-factor alphas on the spread portfolio are equal to -0.36% with the t-statistics of -2.09 and -2.12, respectively.

**[Insert Table 7]**

Similar to the previous findings obtained in Section 3.1, the results indicate that the negative relation between $\beta^{\Delta NInfections}$ and future stock returns remain statistically significant.

## 5.2 Fama and MacBeth cross-sectional regressions

We demonstrated the importance of COVID-19 beta as a predictor of future stock returns at the portfolio level using both univariate and bivariate sorts analyses. In this section, we supplement our analysis by investigating the cross-sectional relation between $\beta^{\Delta NInfections}$ and future equity returns at the firm-level using Fama and MacBeth (FMB) regressions as in Fama & MacBeth (1973). To this end, we estimate the time-series regressions using a rolling window of 22 observations to capture the time variation in betas. We first obtain time-varying factor loadings ($\beta_{i,t}^{\Delta NInfections}$) using our rolling regressions over windows of 22 daily observation. We then estimate the prices of risk (λ) via a cross-sectional regression of average excess returns of the stocks on these factor loadings. Thus, we use the estimated factor loadings to estimate the prices of COVID-19 risk, $\lambda_{1,t}$, from the following cross-sectional regression:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{\Delta NInfections} + \lambda_{2,t}\beta_{i,t}^{F} + \varepsilon_{i,t+1} \tag{5}$$

where $R_{i,t+1}$ is the excess return of stock $i$ on day $t$+*1*, $\beta_{i,t}^{\Delta NInfections}$ is the changes in new infections beta (COVID-19 beta) of stock $i$ on day $t$ , and $\beta_{i,t}^{F}$ is the beta of a collection of control variables which include standard risk factors (the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), investment (CMA), and profitability (RMW) factors). We run FMB regressions using different specifications. Specifically, we consider the Fama & French (1993) three-factor model exposures (FF3) and the Fama & French (2015) five-factor model exposures (FF5), and the Fama-French models augmented by the momentum factor (FF4 and FF6) as control factors.

After the second stage, a daily time series of the price of risk is estimated and the final estimate is obtained by averaging the series. Panel A of Table 8 reports the time-series averages of the slope coefficients from FMB regressions. The first column controls for the market (MKT), size (SMB), book-to-market (HML) risk factors corresponding to the Fama & French (1993) three-factor model. The results show a negative and statistically significant relation between the $\beta^{\Delta NInfections}$ and the cross-section of future equity returns, with an estimated price of risk of -0.32 and a Newey & West (1987) t-statistic of -2.05. In the second column, we add the momentum factor corresponding to the Carhart (1997) four-factor model. Columns 3 and 4 present the slope coefficient of a cross-sectional specification corresponding to the Fama & French (2015) five-factor and the Fama & French (2018) six-factor models, respectively.

For all specifications, the slope coefficient of $\beta^{\Delta NInfections}$ remains negative, in the range of -0.31 and -0.36, and statistically significant with t-statistics ranging from -2.03 to -2.51 (Columns 2-4).

**[Insert Table** 8**]**

To summarize, similar to our findings of the univariate portfolio sorts, the cross-sectional regressions provide compelling evidence of an economically and statistically significant negative relation between $\beta^{\Delta NInfections}$ and future stock returns.

Figure 4 also displays the time series of the risk prices estimated from eq. 5 after controlling for the market, size, book-to-market, momentum, investment, and profitability factors. As we can see, the prices of risk are so volatile over the sample period, with the mean and median values of -0.34% and -0.14%, respectively. The prices of risk are mostly negative (62.92%), indicating that investors are willing to pay higher prices and get lower returns to reduce their risk exposure during the COVID-19 outbreak.

**[Insert Figure** 4**]**

**-Fama and MacBeth regressions on equity portfolios**. Next, we check the robustness of the previous section estimates running the same Fama & MacBeth (1973) cross-sectional regressions on three different equity portfolios, namely, 100 and 25 Fama and French portfolios sorted on size and book-to-market ratio and 48 industry portfolios. Panel B of Table 8 reports the time-series averages of the estimated prices of risk ($\lambda$) from FMB regressions on the three equity portfolios using four different specifications described in the previous section. For the 100 portfolios sorted on size and book-to-market, the results show the price of COVID-19 risk is in the range of -0.55 to -1.50 with t-statistics from -0.85 to -2.33, and it is statistically significant in two specifications. For the 25 portfolios sorted on size and book-to-market, the price of COVID-19 risk is statistically significant in the first three specifications. Finally, for the 48 industry portfolios, the estimated price of COVID-19 risk ranges from -0.65 (t-statistic=-1.38) to -1.08 (t-statistic = -2.57), and it is statistically significant in two specifications. Overall, the results show that COVID-19 is fairly priced in the cross-section of portfolio returns.

### 5.3 Performance of pandemic risk after the first wave of the COVID-19 outbreak in the United States

The COVID-19 outbreak caused an economic panic in early 2020. Following sharp drops in stock prices, the Federal Reserve Board (Fed) responded to the panic by designing policies to mitigate the economic fallout of the COVID crisis. Specifically, the Fed expanded its balance sheet assets by 66 percent from US$4,241,507 million in March 2020 to US$7,037,258 million in May, 2020, allowing the US stock market to recoup the majority of its losses in June 2020 (Sunder (2021)).[19]

Therefore, we examine the impact of the COVID-19 pandemic on the U.S. stock market from July 01, 2020 to December 31, 2021 to see whether exposure to pandemic risk is still priced during this period. To do so, we replicate the univariate portfolio sorts exercise during the period from July 01, 2020 thorough December 31, 2021. The results

[19] Moreover, good news about the progress in the development of effective vaccines started to spread in May 2020.

of this exercise are reported in Table 9. For both equal-weighted and value-weighted portfolios, the difference in average daily return between deciles 10 and 1 is not statistically significant. Also, for the equal-weighted and value-weighted portfolios, both the four-factor and the six-factor alphas of the spread portfolio are not statistically different from zero.

These findings implies that investors updated their beliefs and expectations about the economic consequences of the outbreak and became less responsive to new infections as the trajectory of the pandemic became less severe than initially expected. Thus, investors gradually priced less exposure to pandemic risk after June 30, 2020.

**[Insert Table 9]**

## 5.4 Further robustness analysis

In addition to the main robustness checks, we also run a set of tests to further examine the robustness of our benchmark results. The corresponding results are reported in the Supplementary Appendix and we present the main conclusions in this section.

**Portfolio sorts on $\beta^{\Delta NInfections}$ in the subsamples of big and liquid stocks**. Hou et al. (2020) examine 452 anomalies and document that 65% of these anomalies fail to pass the standard cutoff t-statistic of 1.96 after excluding microcap stocks based on NYSE breakpoints and employing value-weighted portfolios. In addition, according to the authors, anomalies in microcap stocks are difficult for marginal investors to exploit because microcap stocks are costly to trade and lack sufficient liquidity. To address this concern, we follow Arısoy et al. (forthcoming) and divide our sample into two subsamples of big and liquid stocks. In particular, the subsample of big stocks contain stocks with above-median market capitalization and the subsample of liquid stocks include stocks with below-median Amihud (2002) illiquidity measure. To check the predictive power of our COVID-19 measure, we replicate the decile portfolio sorts exercise using the two subsamples of big and liquid stocks.

Table A6, in the Supplementary Appendix, reports the results of decile portfolios sorted on $\beta^{\triangle NInfections}$ for the subsample of big (Panel A) and liquid (Panel B) stocks. The results indicate that the negative relation between $\beta^{\Delta NInfections}$ and future equity returns remains statistically significant in both subsamples. Specifically, the average return on the spread portfolio is -0.30% per day with a t-statistic of -2.20 for the big stocks and -0.30% per day with a t-statistic of -2.05 for the liquid stock. Furthermore, for the big stocks, the four-factor and six-factor alphas of the High-Low portfolio are equal to -0.44% with the corresponding t-statistics = -2.32 and -2.30, respectively. For the subset of liquid stocks, the four-factor and six-factor alphas of the High-Low portfolio are equal to -0.47% with the corresponding t-statistics of -2.21 and -2.20, respectively.

**Portfolio sorts by alternative measures of $\Delta NInfections$ exposure**. To check the predictive power of alternative measures of the $\Delta NInfections$ beta, we employ two alternative specifications to estimate the $\Delta NInfections$ beta.[20] In Section 3.1, we estimate the COVID-19 beta after simultaneously controlling for the market, size, book-to-market, momentum, investment, and profitability factors. Now, we estimate the $\Delta NInfections$ beta using two alternative models:

Specification (1):

$$\begin{aligned} R_{i,t} - R_{f,t} = \beta_0^{i,t} + \beta_{\Delta NInfections}^{i,t} \Delta NInfections_t + \beta_{MKT}^{i,t} MKT_t \\ + \beta_{SMB}^{i,t} SMB_t + \beta_{HML}^{i,t} HML_t + \beta_{UMD}^{i,t} UMD_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

Specification (2):

$$\begin{aligned} R_{i,t} - R_{f,t} = \beta_0^{i,t} + \beta_{\Delta NInfections}^{i,t} \Delta NInfections_t + \beta_{MKT}^{i,t} MKT_t + \beta_{SMB}^{i,t} SMB_t \\ + \beta_{HML}^{i,t} HML_t + \beta_{RMW}^{i,t} RMW_t + \beta_{CMA}^{i,t} CMA_t + \varepsilon_{i,t} \end{aligned} \tag{7}$$

The first specification controls for the factors corresponding to the Carhart (1997) four-factor model, and the second specification controls for the factors corresponding to the Fama & French (2015) five-factor model.

The results of this exercise are shown in Table A7 in the Supplementary Appendix.

[20] We adopt a similar approach as in Bali et al. (2017).

Table A7 presents the results of the decile portfolio sorts analysis using the two alternative measures of $\beta^{\Delta NInfections}$ for the equal-weighted (Panel A) and value-weighted (Panel B) portfolios. When $\beta^{\Delta NInfections}$ is measured using Specification (1), for the equal-weighted portfolios, four-factor and six-factor alphas on the spread portfolio are equal to -0.54% with the corresponding t-statistic of -3.27 and -3.28, respectively. Also, for the value-weighted portfolios, four-factor and six-factor alphas on the spread portfolio are equal to -0.66% with the corresponding t-statistic of -2.62 and -2.61, respectively. When $\beta^{\Delta NInfections}$ is measured using Specification (2), for the equal-weighted portfolios, four-factor and six-factor alphas on the High-Low portfolio are equal to -0.72% with the corresponding t-statistic of -2.93 and -2.96, respectively. In addition, for the value-weighted portfolios, four-factor and six-factor alphas on the High-Low portfolio are -0.66% and -0.65% with the corresponding t-statistic of -2.08 and -2.09, respectively.

Our findings confirm the predictive power of alternative measures of the $\beta^{\Delta NInfections}$ over future stock returns.

**Controlling for Economic Policy Uncertainty (EPU).** To address a further concern that the performance of our COVID-19 measure may be driven by the exposure to overall economic policy uncertainty (EPU), we conduct bivariate portfolio sorts analysis to control for the effect of economic policy uncertainty (EPU). We utilize a daily news-based measure of EPU developed by Baker et al. (2016) to estimate firm exposure to the economic policy uncertainty index.[21]

To perform bivariate portfolio sorts, we first sort all the stocks into quintile portfolios based on their economic policy uncertainty beta ($\beta^{EPU}$ ) and then, within each $\beta^{EPU}$ quintile, we further sort stocks into five quintile portfolios based on their $\beta^{\Delta NInfections}$. We also form High-Low portfolios buying (selling) stocks with the highest (lowest) $\beta^{\Delta NInfections}$. Finally, we calculate the average of each of the $\beta^{\Delta NInfections}$-sorted quintile portfolios across the five $\beta^{EPU}$quintile portfolios to create portfolios with dispersion in $\beta^{\Delta NInfections}$ but similar levels of $\beta^{EPU}$.

Table A8 presents the average returns on $\beta^{\Delta NInfections}$portfolios averaged across dif-

[21]The data can be downloaded from www.policyuncertainty.com

ferent quintiles of $\beta^{EPU}$ for both equal-weighted and value-weighted portfolios, as well as average return differentials between high- and low-$\beta^{\Delta NInfections}$-sorted portfolios and the corresponding four-factor and six-factor alphas. The results show that after controlling for $\beta^{EPU}$, the daily average return on the equal-weighted High-Low portfolio is -0.18% with a Newey & West (1987) t-statistic of -2.20. Also, the four-factor alpha and six-factor on the spread portfolio are equal to -0.23% with the corresponding t-statistics of -3.02. For the value-weighted portfolios, after controlling for $\beta^{EPU}$, the daily average return on the spread portfolio is -0.30% with a Newey & West (1987) t-statistic of -2.67. Also, the four-factor alpha and six-factor on the spread portfolio are equal to -0.34% with the t-statistics of -2.81 and -2.84, respectively.

Overall, our findings confirm that after controlling for economic policy uncertainty, the negative relation between the COVID-19 beta and future equity returns remains statistically significant.

## 5.5 Portfolio sorts in International Markets

So far we have examined the significance of the COVID-19 beta as a predictor of the cross-section of future returns in the US equity market. However, we are curious to know that whether the same pattern exists in other equity markets. Therefore, we now investigate the cross-sectional relation between the COVID-19 beta and future returns in European stock markets. We obtain daily stock prices for all common stocks (the issue type code (tpci) of 0) reported in the Compustat Capital IQ Global Daily database via Wharton Research Data Services (WRDS). We also adjust prices for the daily total return factor (TRFD) and daily adjustment factors (AJEXDI) found in Compustat and compute stock returns denominated in US dollars to control for the effect of exchange rate risk on stock returns. The sample contains 16 European markets: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. We follow Chaieb et al. (2021) to apply different filters and handle data errors in the Compustat data set. The first European COVID-19 infection was reported in France on 24 January 2020, so the sample period runs from 24 January 2020 to 30 June 2020.[22]

We examine the predictive ability of the $\Delta NInfections$ beta across 16 European markets by replicating the univariate portfolios sorts analysis as for Table 2. Within each country, we sort individual stocks into decile portfolios based on their $\Delta NInfections$ beta. Subsequently, we form equal-weighted and equal-weighted portfolios, as well as long-short portfolios buying (selling) the decile of stocks with the highest (lowest) $\Delta NInfections$ beta. Due to the fact that many international stock markets are significantly smaller than the US equity market, we compute aggregate average returns and alphas across all the European markets.

Table 10 presents the aggregate daily average return as well as the aggregate Carhart (1997) four-factor and Fama & French (2018) six-factor alphas of each decile portfolio across all the European markets for the equal- and value-weighted portfolios. As shown in Table 10, for the value-weighted portfolio, the daily average return spread between the high-$\beta^{\Delta NInfections}$ and low-$\beta^{\Delta NInfections}$ decile portfolios is -0.25% with a t-statistic of -2.01. The four factor and six-factor alpha spreads between the high-$\beta^{\Delta NInfections}$ and low-$\beta^{\Delta NInfections}$ deciles are -0.30% and -0.33% and statistically significant with the corresponding t-statistics of -2.35 and -2.49, respectively.

**[Insert Table** 10**]**

Consistent with our results from the univariate portfolio sorts analysis for the U.S. stock market, our findings provide evidence of a negative and significant cross-sectional relation between the $\Delta NInfections$ beta and future stock returns across all European markets.

[22]There are many issues with Worldometers' COVID-19 figures for Spain and France, so we obtain the COVID-19 data for Spain from https://www.nytimes.com/interactive/2020/world/europe/spain-coronavirus-cases.html and for France from dashboard.covid19.data.gouv.fr.

# 6 Conclusion

In this paper, we use COVID-19-related data to investigate the predicting abilities of the COVID-19 pandemic beta in the cross-section of equities and equity portfolios. To quantify the pandemic risk, we utilize the daily change in the number of new infections and deaths. We estimate stock exposure to these two measures of COVID-19 and find that only the daily change in the number of new infections is negatively priced in the cross-section of U.S. equity returns.

We first construct decile portfolios depending on the exposure of stocks returns to any given COVID-19 measure, and the risk premium of these portfolios is estimated by computing their average return and alphas. By doing this exercise, we find a statistically negative relation between the changes in the number of new infections beta and future equity returns. Also, this relation is not driven by any single industry. Moreover, the performance of the COVID-19 risk factor is not explained by the market (MKT), size (SMB), value (HML), momentum (UMD), profitability (RMW), and investment (CMA) risk factors.

We find that market participants expected the COVID shock to be amplified through financial channels. Specifically, we document that U.S. firms with stronger pre-pandemic financial condition–high cash, high profitability, and low leverage–experienced smaller declines in stock prices in response to the pandemic than other firms.

Consistent with the decile portfolio sorts exercise, the quintile portfolio sorts analysis provides compelling evidence of a significantly negative relation between the COVID-19 beta and future equity returns. Furthermore, the Fama and MacBeth cross-sectional regressions at the firm level and by using equity portfolios as test assets confirms the predictive power of the COVID-19 beta. Further analyses indicate that the negative relation between the COVID-19 beta and future stock returns remains robust in the subsamples of big and liquid stocks, using alternative measures of the COVID-19 exposure, and controlling for economic policy uncertainty. Our main findings also hold for European stock markets.

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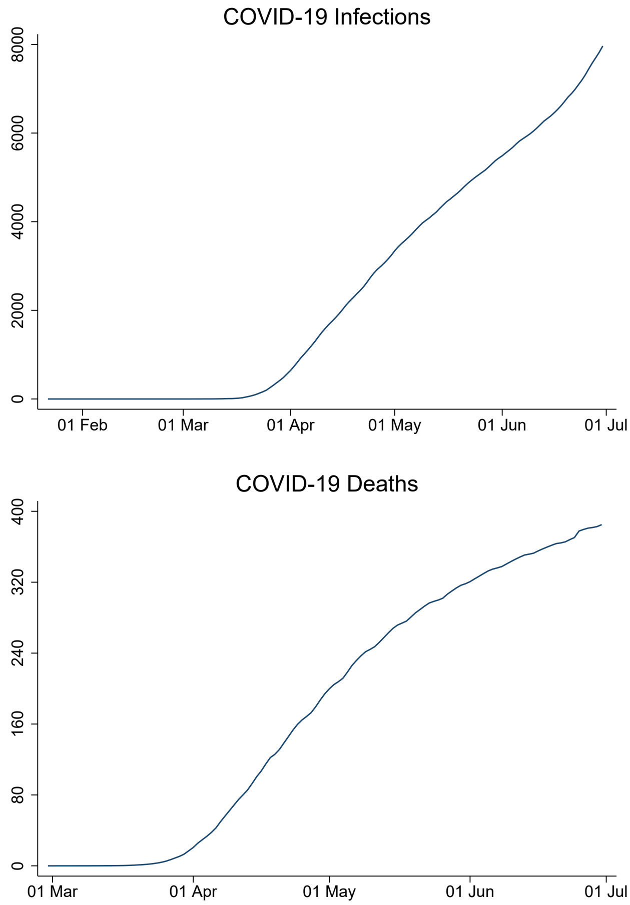


Figure 1: Daily cumulative number of COVID-19 infections and deaths per capita (per million of the US population) in the US. The sample period for COVID-19 infections is January 22 to June 30, 2020, and for COVID-19 deaths is February 29 to June 30, 2020.

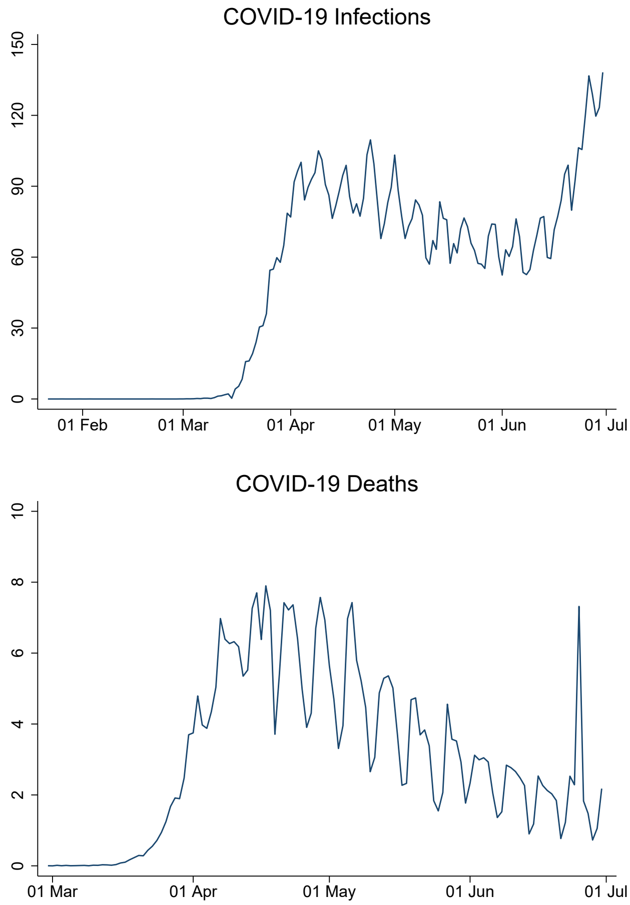


Figure 2: Daily number of new COVID-19 infections and deaths per capita (per million of the US population) in the US. The sample period for COVID-19 infections is January 22 to June 30, 2020, and for COVID-19 deaths is February 29 to June 30, 2020.

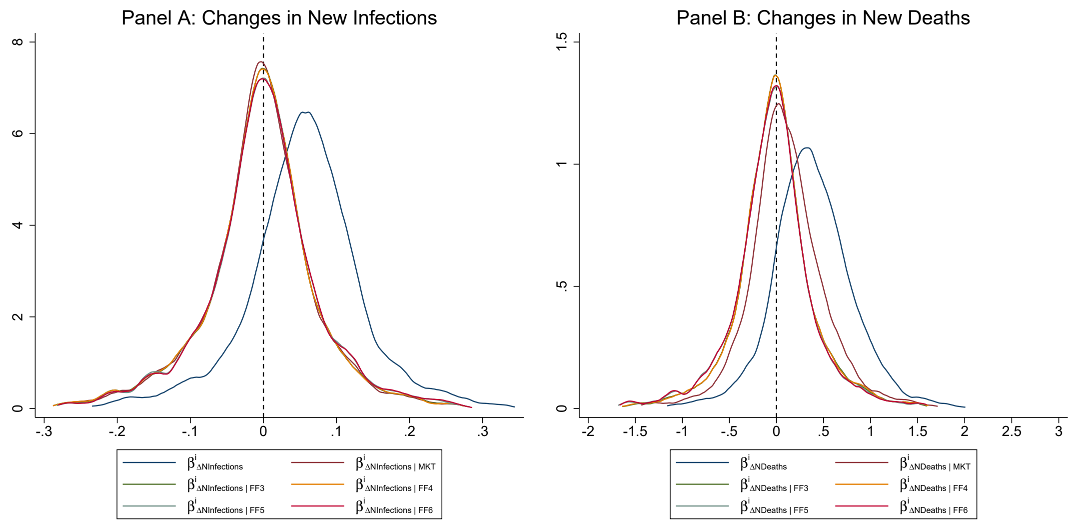


Figure 3: This figure shows the distribution of firm sensitivities to the daily change in the number of COVID-19 new infections and deaths, $\Delta NInfections$ and $\Delta NDeaths$, estimated using equation 1. The sample period for $\Delta NInfections$ is January 22 to June 30, 2020, and for $\Delta NDeaths$ is February 29 to June 30, 2020.

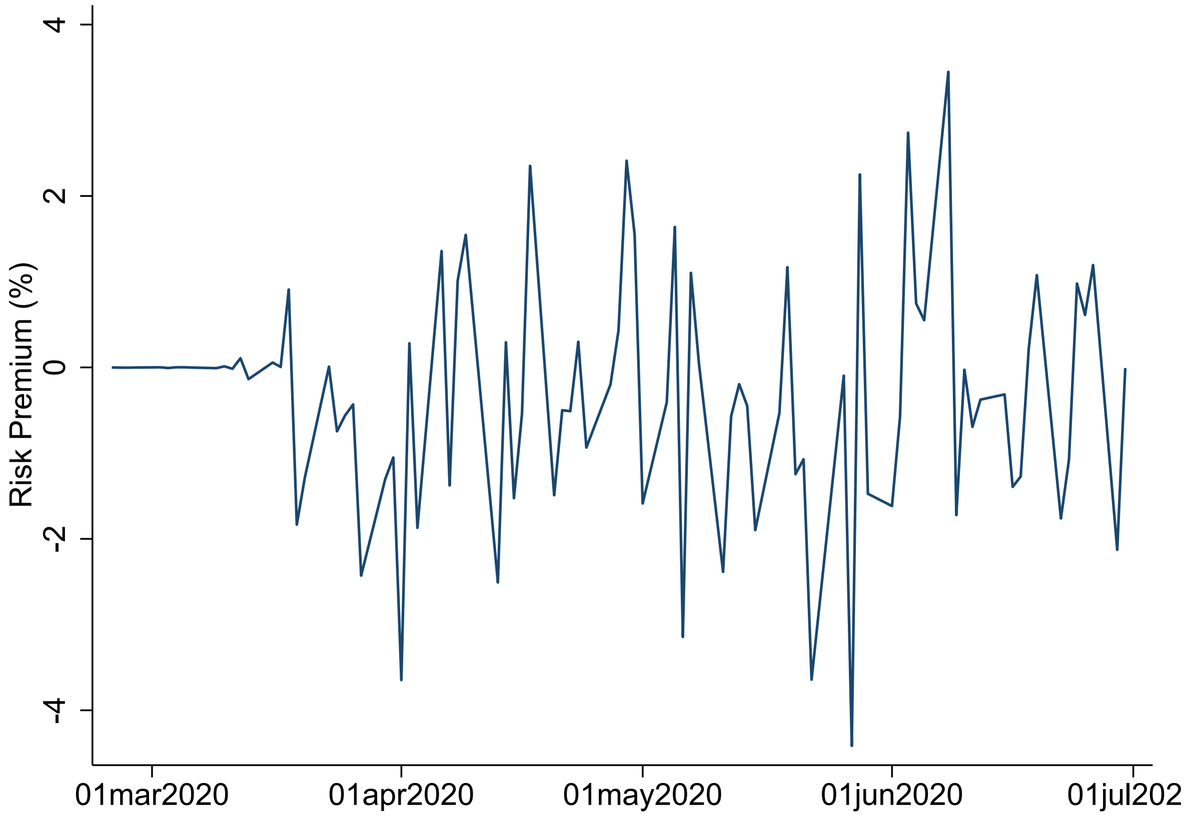


Figure 4: The Risk premium time series.
The figure plots the daily time-series for the risk prices estimated from eq. 5 after controlling for the six factors from Fama & French (2018). The sample period is from January 22 to June 30, 2020, and the sample estimated spans February 25 to June 30, 2020.

Table 1: Descriptive statistics and correlation matrix of the employed variables over the sample period.

This table reports summary statistics and the correlations between daily cumulative infections (*CInfections*), cumulative deaths (*CDeaths*), new infections (*NInfections*), new deaths (*NDeaths*), change in new infections ($\Delta$*NInfections*), and change in new deaths ($\Delta$*NDeaths*), and the standard pricing factors, $R_m - R_f$, SMB, HML, UMD, RMW, and CMA. $R_m - R_f$, SMB, HML, UMD, RMW, and CMA are market, size, book-to-market, momentum, profitability, and investment factors. The sample period for $CNInfections$, $NInfections$, and $\Delta NInfections$ is January 22 to June 30, 2020, and for $CDeaths$, $NDeaths$, and $\Delta NDeaths$ is February 29 to June 30, 2020.

| Risk factor | Obs. | Mean | Std. Dev. | Correlation | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | *CInfections* | *CDeaths* | *NInfections* | *NDeaths* | $\Delta$*NInfections* | $\Delta$*NDeaths* |
| *CInfections* | 112 | 2453.29 | 2606.30 | | | | | | |
| *CDeaths* | 85 | 180.51 | 142.18 | | | | | | |
| *NInfections* | 112 | 49.53 | 41.20 | | | | | | |
| *NDeaths* | 85 | 3.42 | 2.47 | | | | | | |
| $\Delta$*NInfections* | 111 | 3.37 | 6.24 | | | | | | |
| $\Delta$*NDeaths* | 84 | 0.31 | 1.19 | | | | | | |
| $R_m - R_f$ | 112 | 0.00 | 3.06 | 0.08 | 0.05 | 0.16 | 0.12 | 0.12 | 0.10 |
| SMB | 112 | -0.04 | 1.26 | 0.14 | 0.16 | 0.16 | 0.14 | 0.03 | 0.12 |
| HML | 112 | -0.25 | 1.83 | 0.09 | 0.11 | 0.08 | 0.06 | 0.02 | 0.12 |
| UMD | 112 | -0.02 | 2.17 | -0.06 | -0.06 | -0.08 | -0.09 | -0.00 | -0.09 |
| RMW | 112 | -0.01 | 0.62 | 0.10 | 0.08 | 0.09 | 0.09 | 0.06 | 0.02 |
| CMA | 112 | -0.05 | 0.45 | 0.01 | -0.06 | 0.01 | -0.19 | 0.02 | -0.10 |

Table 2: Decile portfolios of stocks sorted by $\Delta NInfections$ and $\Delta NDeaths$ loadings. We run regression (2) on the daily returns of each stock, using a window of 22 daily observations. We then form decile portfolios by sorting stocks based on their regression coefficients, $\beta^{\Delta NInfections}$ ($\beta^{\Delta NDeaths}$), where Decile 1 contains stocks with the lowest $\beta^{\Delta NInfections}$ ($\beta^{\Delta NDeaths}$) and Decile 10 contains stocks with the highest $\beta^{\Delta NInfections}$ ($\beta^{\Delta NDeaths}$) during the estimation period. After portfolio formation, we record one-day post ranking returns of each decile portfolio. We repeat the process by moving the beta estimation window forward by one day. Panel (A) and Panel (B) reports the results of portfolio sorts by daily changes in new infection ($\Delta NInfections$) and daily changes in new deaths ($\Delta NDeaths$) loadings, respectively. In each panel, the first row presents the daily average post-ranking return, and the remaining rows report the Carhart (1997) four-factor alpha, and the Fama & French (2018) six-factor alpha of each decile portfolio for the equal-weighted and value-weighted portfolios separately. All values are expressed in percent. The last column presents the average return and alphas of the spread portfolio (High-Low). Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | Decile portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sorting statistic | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | High-Low |
| *Panel A: Change in New Infections* | | | | | | | | | | | |
| *Equal-weighted* | | | | | | | | | | | |
| Average Return | 0.45 | 0.25 | 0.18 | 0.11 | 0.04 | 0.10 | 0.01 | 0.02 | 0.10 | -0.01 | -0.46*** |
| | (0.97) | (0.55) | (0.45) | (0.27) | (0.11) | (0.29) | (0.03) | (0.05) | (0.25) | (-0.01) | (-2.91) |
| Four-factor alpha | 0.51*** | 0.27** | 0.23** | 0.16** | 0.08 | 0.15** | 0.06 | 0.05 | 0.12 | -0.06 | -0.57*** |
| | (3.00) | (2.10) | (2.59) | (2.04) | (1.08) | (2.13) | (1.39) | (0.64) | (1.35) | (-0.38) | (-3.04) |
| Six-factor alpha | 0.52*** | 0.28** | 0.24*** | 0.17** | 0.08 | 0.16** | 0.06* | 0.05 | 0.13 | -0.05 | -0.57*** |
| | (3.49) | (2.48) | (3.12) | (2.62) | (1.33) | (2.51) | (1.72) | (0.79) | (1.56) | (-0.34) | (-3.02) |
| *Value-weighted* | | | | | | | | | | | |
| Average Return | 0.33 | 0.06 | 0.13 | 0.03 | 0.02 | 0.05 | 0.01 | -0.04 | -0.11 | -0.16 | -0.49** |
| | (0.68) | (0.15) | (0.41) | (0.08) | (0.06) | (0.18) | (0.03) | (-0.13) | (-0.32) | (-0.36) | (-2.27) |
| Four-factor alpha | 0.39* | 0.11 | 0.18* | 0.04 | -0.04 | 0.03 | -0.03 | -0.14** | -0.15 | -0.22* | -0.61** |
| | (1.88) | (1.03) | (1.80) | (0.72) | (-0.79) | (0.71) | (-0.65) | (-2.42) | (-1.66) | (-1.73) | (-2.62) |
| Six-factor alpha | 0.40* | 0.11 | 0.18* | 0.04 | -0.04 | 0.04 | -0.03 | -0.14** | -0.16 | -0.21* | -0.61*** |
| | (2.10) | (1.05) | (1.81) | (0.68) | (-0.76) | (0.75) | (-0.73) | (-2.40) | (-1.64) | (-1.75) | (-2.66) |
| *Panel B: Change in New Deaths* | | | | | | | | | | | |
| *Equal-weighted* | | | | | | | | | | | |
| Average Return | 0.45 | 0.33 | 0.24 | 0.12 | 0.14 | 0.11 | 0.09 | 0.13 | 0.16 | 0.28 | -0.17 |
| | (0.88) | (0.71) | (0.57) | (0.30) | (0.38) | (0.29) | (0.22) | (0.29) | (0.38) | (0.61) | (-0.92) |
| Four-factor alpha | 0.37* | 0.30** | 0.22** | 0.11 | 0.13** | 0.09 | 0.06 | 0.09 | 0.11 | 0.16 | -0.21 |
| | (1.92) | (2.45) | (2.40) | (1.59) | (2.35) | (1.32) | (0.85) | (0.93) | (1.06) | (1.09) | (-1.23) |
| Six-factor alpha | 0.40** | 0.31*** | 0.23*** | 0.12* | 0.13*** | 0.09 | 0.07 | 0.09 | 0.12 | 0.18 | -0.22 |
| | (2.39) | (2.91) | (2.82) | (1.99) | (2.98) | (1.47) | (0.97) | (1.09) | (1.22) | (1.25) | (-1.30) |
| *Value-weighted* | | | | | | | | | | | |
| Average Return | 0.08 | 0.10 | 0.12 | 0.09 | 0.13 | -0.01 | 0.16 | 0.07 | 0.02 | 0.27 | 0.19 |
| | (0.18) | (0.24) | (0.33) | (0.30) | (0.47) | (-0.02) | (0.54) | (0.22) | (0.06) | (0.61) | (0.70) |
| Four-factor alpha | 0.05 | 0.03 | 0.05 | 0.04 | 0.05 | -0.06* | 0.05 | -0.02 | -0.07 | 0.14 | 0.09 |
| | (0.22) | (0.28) | (0.52) | (0.66) | (0.79) | (-1.81) | (0.92) | (-0.35) | (-0.55) | (0.73) | (0.33) |
| Six-factor alpha | 0.07 | 0.03 | 0.06 | 0.04 | 0.05 | -0.06* | 0.05 | -0.03 | -0.07 | 0.15 | 0.08 |
| | (0.38) | (0.32) | (0.54) | (0.59) | (0.82) | (-1.99) | (0.86) | (-0.38) | (-0.53) | (0.81) | (0.26) |

Table 3: Average stock characteristics of $\beta^{\Delta NInfections}$-sorted portfolios.
The table presents the average stock characteristics of $\beta^{\Delta NInfections}$-sorted portfolios for the sample period from January to June 2020. The characteristics are the share price, the size or market capitalization (in millions of dollars), book-to-market ratio, market beta, idiosyncratic volatility, and illiquidity, respectively. The value average illiquidity is multiplied by 1000.

| Decile portfolio | Average stock characteristics of $\beta^{\Delta NInfections}$-sorted portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Price ($) | Size ($m) | Book to Market | Market Beta | Idiosyncratic Volatility | Illiquidity |
| Low | 13.04 | 1127.46 | 1.24 | 1.01 | 0.06 | 0.45 |
| 2 | 26.89 | 3188.03 | 0.88 | 1.01 | 0.04 | 0.33 |
| 3 | 39.15 | 6828.11 | 0.80 | 1.01 | 0.04 | 0.26 |
| 4 | 45.97 | 10913.97 | 0.74 | 1.00 | 0.03 | 0.23 |
| 5 | 47.38 | 14175.32 | 0.74 | 0.96 | 0.03 | 0.25 |
| 6 | 47.34 | 14781.90 | 0.73 | 0.95 | 0.03 | 0.33 |
| 7 | 47.19 | 12630.82 | 0.76 | 0.99 | 0.03 | 0.28 |
| 8 | 42.02 | 9230.59 | 0.80 | 1.01 | 0.03 | 0.23 |
| 9 | 32.92 | 4307.40 | 0.88 | 1.02 | 0.04 | 0.37 |
| High | 16.48 | 1263.97 | 1.33 | 1.00 | 0.05 | 0.62 |

Table 4: Industry-level portfolio sorts by $\beta^{\Delta NInfections}$.

The table reports the Fama & French (2018) six-factor alpha for the equal- and value-weighted portfolios (Panels A and B). Stocks are divided into seven industries, based on the Industry Classification Benchmark (ICB). Then, we form quintile portfolios by sorting stocks in each of the seven industry groups based on their $\beta^{\Delta NInfections}$, where Quantile 1 contains stocks with the lowest $\beta^{\Delta NInfections}$ and Quantile 5 contains stocks with the highest $\beta^{\Delta NInfections}$ during the estimation period. The last row of each panel presents the differences in the six-factor alpha between Quintile 1 (Low) and Quintile 5 (High). All numbers are in percentage. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | *Panel A: Equal-weighted portfolios* | | | | | | |
|---|---|---|---|---|---|---|---|
| Quintile | Basic Materials | Consumer Staples & Discretionary | Energy | Financials and Real Estate | Health Care | Industrials and Utilities | Technology and Telecommunicatio ns |
| Low | 0.20 | 0.14 | -0.05 | -0.01 | 0.16 | 0.03 | 0.05 |
| 2 | 0.16 | 0.09 | -0.01 | -0.01 | 0.03 | 0.05 | 0.07 |
| 3 | 0.16 | 0.07 | -0.29 | 0.04 | 0.06 | 0.03 | 0.05 |
| 4 | 0.00 | 0.04 | -0.25 | 0.02 | -0.04 | -0.01 | 0.01 |
| High | -0.13 | -0.07 | -0.46 | -0.05 | -0.21 | -0.08 | -0.07 |
| High-Low | -0.33*** | -0.21** | -0.41** | -0.04 | -0.37*** | -0.11 | -0.12 |
| | (-2.81) | (-2.08) | (-2.54) | (-0.35) | (-4.12) | (-1.03) | (-1.59) |
| | *Panel B: Value-weighted portfolios* | | | | | | |
| Low | 0.32 | 0.22 | 0.51 | 0.08 | 0.32 | -0.23 | 0.28 |
| 2 | 0.16 | 0.20 | 0.01 | -0.08 | 0.15 | -0.03 | 0.02 |
| 3 | 0.10 | 0.08 | -0.21 | 0.00 | -0.03 | 0.01 | 0.05 |
| 4 | 0.02 | -0.11 | -0.01 | 0.11 | -0.11 | 0.02 | -0.01 |
| High | -0.13 | -0.31 | -0.27 | 0.33 | -0.16 | -0.08 | 0.05 |
| High-Low | -0.45** | -0.53** | -0.78** | 0.25 | -0.48** | 0.15 | -0.23 |
| | (-2.18) | (-2.04) | (-2.42) | (1.40) | (-2.38) | (0.85) | (-1.17) |

Table 5: COVID-19 risk factor.

The table reports the results for the COVID-19 risk factor portfolio. We form an Covid-19 risk factor by sorting all stocks into two groups based on market capitalization (one group includes the stocks that account for 90% of the total stock market capitalization and the other group consists of the stocks that comprise 10% of the total market capitalization) and three $\beta^{\Delta NInfections}$ groups using the 30th and 70th percentile values of $\beta^{\Delta NInfections}$ as breakpoints. Then, the intersections of the two size groups and the three $\beta^{\Delta NInfections}$ groups produce six portfolios. The $\beta^{\Delta NInfections}$ factor return is measured by taking the difference between the average return of the two high-$\beta^{\Delta NInfections}$ portfolios and the average return of the two low-$\beta^{\Delta NInfections}$ portfolios. Panel A and Panel B report the average daily returns of the $\beta^{\Delta NInfections}$ factor (the first column of each panel) and the alphas obtained using three different factor models for equal-weighted portfolios and value-weighted portfolios, respectively. The table also presents the slope coefficients of exposure to different risk factors, namely the market, size, book-to-market, momentum, profitability, and investment factors. All values are in percentage. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | *Panel A: Equal-weighted portfolios* | | | | *Panel B: Value-weighted portfolios* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| $R_m - R_f$ | | -0.06 | -0.02 | -0.01 | | -0.05 | -0.00 | -0.00 |
| | | (-1.06) | (-0.43) | (-0.37) | | (-1.26) | (-0.11) | (-0.07) |
| SMB | | | -0.50* | -0.55** | | | -0.27 | -0.27 |
| | | | (-1.95) | (-2.58) | | | (-1.35) | (-1.52) |
| HML | | | -0.32 | -0.18 | | | -0.33 | -0.27 |
| | | | (-1.68) | (-0.90) | | | (-1.68) | (-1.24) |
| UMD | | | -0.38** | -0.37*** | | | -0.30** | -0.28** |
| | | | (-2.51) | (-2.83) | | | (-2.08) | (-2.20) |
| RMW | | | | 0.16 | | | | 0.17 |
| | | | | (0.61) | | | | (0.71) |
| CMA | | | | -0.17 | | | | -0.01 |
| | | | | (-0.52) | | | | (-0.04) |
| Average | -0.34** | -0.33** | -0.43** | -0.43** | -0.25** | -0.25** | -0.35** | -0.35** |
| Return/Alpha | (-2.44) | (-2.38) | (-2.47) | (-2.44) | (-2.36) | (-2.32) | (-2.48) | (-2.46) |

Table 6: Pre-pandemic financial conditions and stock returns in response to COVID-19. The table presents regression results of stock price reactions to COVID-19 as functions of these pre-pandemic firm conditions. The dependent variable is the daily stock return of each firm. *Covid* is the daily change in the number of new COVID-19 infections. Firm Size is the natural logarithm of the book value of total assets. Leverage is defined as book debt divided by total assets. Cash ratio, which is defined as the total amount of cash and short-term investments divided by total assets. ROA is the ratio of net income to total assets. For all quantities we use the latest data available at the end of 2019. The sample period runs from January to June, 2020. All models control for industry (two-digit SIC) fixed effects. Standard errors, in parentheses, are clustered at the firm level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | *Dependent variable: Daily stock return* | |
|---|---|---|
| | (1) | (2) |
| Covid19 | -2.25*** | -2.18*** |
| | (0.05) | (0.24) |
| Firm size* Covid19 | | 0.02 |
| | | (0.03) |
| Leverage* Covid19 | | -0.74*** |
| | | (0.27) |
| Cash ratio* Covid19 | | 0.59** |
| | | (0.25) |
| Roa* Covid19 | | 1.10*** |
| | | (0.20) |
| Industry FE | YES | YES |
| Adjusted $R^2$ | 0.01 | 0.01 |
| Observations | 319,684 | 319,684 |

Table 7: Quintile portfolios of stocks sorted by $\Delta NInfections$ loading.
We run regression (2) on the daily returns of each stock, using a window of 22 daily observations. We then form quintile portfolios by sorting stocks based on their regression coefficients, $\beta^{\Delta NInfections}$, where Quintile 1 contains stocks with the lowest $\beta^{\Delta NInfections}$ and Quintile 5 contains stocks with the highest $\beta^{\Delta NInfections}$ during the estimation period. After portfolio formation, we record one-day post ranking returns of each quintile portfolio. We repeat the process by moving the beta estimation window forward by one day. This table reports the results on value-weighted (Panel A) and equal-weighted (Panel B) portfolios. The first row of the table presents the average pre-ranking beta. In each panel, the first row presents the daily average post-ranking return, and remaining rows report the Carhart (1997) four-factor alpha, and the Fama & French (2018) six-factor alpha of each quintile portfolio separately. The last column presents the average return and alphas of the spread portfolio (High-Low). All values are expressed in percent. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | Quintile portfolio | | | | | |
|---|---|---|---|---|---|---|
| Sorting statistic | Low | 2 | 3 | 4 | High | High-Low |
| *Panel A: Equal-weighted Portfolios* | | | | | | |
| Average Return | 0.35 | 0.15 | 0.08 | 0.02 | 0.05 | -0.30*** |
| | (0.77) | (0.37) | (0.20) | (0.05) | (0.12) | (-2.88) |
| Four-factor alpha | 0.39*** | 0.20** | 0.12* | 0.05 | 0.03 | -0.36*** |
| | (2.96) | (2.43) | (1.73) | (0.96) | (0.26) | (-3.07) |
| Six-factor alpha | 0.40*** | 0.20*** | 0.12** | 0.06 | 0.04 | -0.36*** |
| | (3.66) | (3.02) | (2.11) | (1.20) | (0.35) | (-3.12) |
| *Panel B: Value-weighted Portfolios* | | | | | | |
| Average Return | 0.13 | 0.07 | 0.05 | -0.08 | -0.12 | -0.25* |
| | (0.34) | (0.22) | (0.17) | (-0.03) | (-0.34) | (-1.96) |
| Four-factor alpha | 0.19 | 0.09 | 0.01 | -0.07* | -0.17* | -0.36** |
| | (1.58) | (1.49) | (0.56) | (-1.70) | (-1.92) | (-2.09) |
| Six-factor alpha | 0.19* | 0.09 | 0.01 | -0.07* | -0.17* | -0.36** |
| | (1.70) | (1.47) | (0.58) | (-1.75) | (-1.89) | (-2.12) |

Table 8: Fama-MacBeth cross-sectional regressions.
This table reports the results of Fama & MacBeth (1973) cross-sectional regressions relation between $\beta^{\Delta NInfections}$ and future equity returns at the firm and equity portfolios-level, separately. Panel A presents the time-series averages of the daily cross-sectional regression intercepts and slope coefficients at the stock-level. The results for each cross-sectional regression specification are shown in each column. In Panel B, the prices of risk are calculated using the Fama & MacBeth (1973) cross-sectional regressions to the 100 and 25 Fama and French portfolios sorted on size and book-to-market, and 48 industry portfolios. This panel presents the time-series averages of the estimated prices of COVID-19 risk on the three equity portfolios using four different specifications. The results for each cross-sectional regression specification are shown in each row. The control variables are the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), investment (CMA), and profitability (RMW) factors. Newey & West (1987) adjusted t-statistics are also reported in parenthesis. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

*Panel A: Fama and MacBeth regressions on individual stocks*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Constant | 0.16 | 0.14 | 0.15 | 0.13 |
| | (0.54) | (0.49) | (0.50) | (0.46) |
| $\Delta NInfections$ | -0.32** | -0.36** | -0.31** | -0.34** |
| | (-2.05) | (-2.51) | (-2.03) | (-2.43) |
| $R_m - R_f$ | -0.08 | -0.06 | -0.07 | -0.06 |
| | (-0.51) | (-0.41) | (-0.45) | (-0.39) |
| SMB | 0.04 | 0.04 | 0.04 | 0.04 |
| | (1.22) | (1.14) | (0.69) | (0.66) |
| HML | -0.02 | -0.01 | -0.01 | -0.01 |
| | (-0.14) | (-0.08) | (-0.11) | (-0.09) |
| UMD | | 0.03 | | 0.03 |
| | | (0.22) | | (0.18) |
| RMW | | | -0.03 | -0.04 |
| | | | (-1.08) | (-1.24) |
| CMA | | | -0.03 | -0.02 |
| | | | (-1.51) | (-1.33) |

*Panel B: Fama and MacBeth regressions on equity portfolios*

| Price of risk | Test portfolio | | |
|---|---|---|---|
| | 100 size and book-to-market portfolios | 25 size and book-to-market portfolios | 48 industry portfolios |
| $\lambda_{\Delta NInfections\|FF3}$ | -0.55 | -2.16*** | -0.65 |
| | (-0.85) | (-3.03) | (-1.38) |
| $\lambda_{\Delta NInfections\|FF4}$ | -1.36** | -2.30*** | -0.96** |
| | (-2.05) | (-3.37) | (-2.32) |
| $\lambda_{\Delta NInfections\|FF5}$ | -0.73 | -1.80** | -0.90* |
| | (-1.04) | (-2.06) | (-1.87) |
| $\lambda_{\Delta NInfections\|FF6}$ | -1.50** | -1.46 | -1.08** |
| | (-2.33) | (-1.66) | (-2.57) |

Table 9: Univariate portfolio sorts during the period from July 01, 2020 thorough December 30, 2021.
We run regression (2) on the daily returns of each stock, using a window of 22 daily observations. We then form decile portfolios by sorting stocks based on their regression coefficients, $\beta^{\Delta NInfections}$, where Decile 1 contains stocks with the lowest $\beta^{\Delta NInfections}$ and Decile 10 contains stocks with the highest $\beta^{\Delta NInfections}$ during the estimation period. After portfolio formation, we record one-day post ranking returns of each decile portfolio. We repeat the process by moving the beta estimation window forward by one day. The table reports the results of portfolio sorts by the daily changes in new infection ($\Delta NInfections$) loading. In each panel, the first row presents the daily average post-ranking return and the remaining rows report the Carhart (1997) four-factor alpha, and the Fama & French (2018) six-factor alpha of each decile portfolio for the equal-weighted and value-weighted portfolios separately. All values are expressed in percent. The last column presents the average return and alphas of the spread portfolio (High-Low). Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is July 2020 to December 2021.

| | Decile portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sorting statistic | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | High-Low |
| *Equal-weighted* | | | | | | | | | | | |
| Average | 0.14 | 0.14* | 0.15** | 0.17*** | 0.14** | 0.14** | 0.17*** | 0.18** | 0.16* | 0.12 | -0.02 |
| Return | (1.28) | (1.79) | (2.31) | (2.79) | (2.52) | (2.44) | (2.60) | (2.54) | (1.93) | (1.02) | (-0.62) |
| Four-factor | -0.00 | 0.00 | 0.01 | 0.04** | 0.02 | 0.01 | 0.03 | 0.04* | 0.01 | -0.01 | -0.01 |
| alpha | (-0.08) | (0.06) | (0.62) | (2.25) | (1.14) | (0.88) | (1.61) | (1.85) | (0.48) | (0.33) | (-0.47) |
| Six-factor | 0.04 | 0.03 | 0.03* | 0.05*** | 0.02* | 0.02* | 0.05*** | 0.05*** | 0.04* | 0.04 | -0.00 |
| alpha | (0.94) | (1.30) | (1.83) | (3.32) | (1.83) | (1.66) | (2.82) | (3.33) | (1.86) | (0.78) | (-0.13) |
| *Value-weighted* | | | | | | | | | | | |
| Average | 0.13 | 0.12 | 0.12 | 0.12* | 0.10 | 0.11 | 0.09 | 0.09 | 0.10 | 0.05 | -0.07 |
| Return | (1.07) | (1.30) | (1.61) | (1.72) | (1.52) | (1.64) | (1.44) | (1.19) | (1.14) | (0.47) | (-1.03) |
| Four-factor | -0.03 | -0.00 | 0.02 | 0.02 | 0.00 | 0.01 | -0.09 | -0.02 | -0.02 | -0.09 | -0.06 |
| alpha | (-0.54) | (-0.12) | (0.59) | (0.84) | (0.10) | (0.55) | (-0.49) | (-0.94) | (-0.67) | (-1.61) | (-0.77) |
| Six-factor | 0.01 | 0.01 | 0.02 | 0.02 | -0.01 | 0.00 | -0.01 | -0.02 | -0.01 | -0.05 | -0.06 |
| alpha | (0.16) | (0.25) | (0.73) | (0.86) | (-0.28) | (0.08) | (-0.69) | (-0.70) | (-0.20) | (-1.06) | (-0.87) |

Table 10: Portfolio sorts in International Markets

We run regression (2) on the daily returns of each stock, using a window of 22 daily observations. We then form decile portfolios by sorting stocks based on their regression coefficients, $\beta^{NInfections}$ , where Decile 1 contains stocks with the lowest $\beta^{NInfections}$ and Decile 10 contains stocks with the highest $\beta^{NInfections}$ during the estimation period. After portfolio formation, we record one-day post ranking returns of each decile portfolio. We repeat the process by moving the beta estimation window forward by one day. The table reports the aggregate daily average post-ranking return, the aggregate Carhart (1997) four-factor alpha, and the aggregate Fama & French (2018) six-factor alpha of each decile portfolio across all 15 European markets for the equal- and value-weighted portfolios. All values are expressed in percent. The last row presents the aggregate average return and alphas of the spread portfolio (High-Low) across all 15 European markets. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 24, 2020 to June 30, 2020.

| Decile Portfolio | Equal-weighted portfolio | | | Value-weighted portfolio | | |
|---|---|---|---|---|---|---|
| | Average Return | Four-factor alpha | Six-factor alpha | Average Return | Four-factor alpha | Six-factor alpha |
| Low | 0.25 | 0.30 | 0.34 | 0.09 | 0.15 | 0.17 |
| 2 | -0.01 | 0.09 | 0.13 | -0.04 | 0.04 | 0.07 |
| 3 | 0.03 | 0.09 | 0.11 | 0.06 | 0.09 | 0.13 |
| 4 | -0.01 | 0.03 | 0.04 | -0.06 | -0.05 | 0.01 |
| 5 | -0.03 | 0.03 | 0.05 | -0.09 | -0.02 | 0.00 |
| 6 | 0.03 | 0.09 | 0.11 | 0.03 | 0.04 | 0.06 |
| 7 | -0.05 | 0.01 | 0.03 | -0.01 | 0.01 | 0.04 |
| 8 | -0.03 | -0.00 | 0.04 | -0.09 | -0.12 | -0.08 |
| 9 | 0.04 | 0.11 | 0.12 | 0.03 | 0.02 | 0.04 |
| High | 0.03 | 0.09 | 0.05 | -0.17 | -0.15 | -0.16 |
| High-Low | -0.22* | -0.21* | -0.29** | -0.25** | -0.30** | -0.33** |
| | (-1.72) | (-1.80) | (-2.43) | (-2.01) | (-2.35) | (-2.49) |

# COVID-19 Pandemic Risk and the Cross-Section of Stock Returns

# Supplementary Appendix

## A.1 Autocorrelation plots of the COVID-19 risk factors

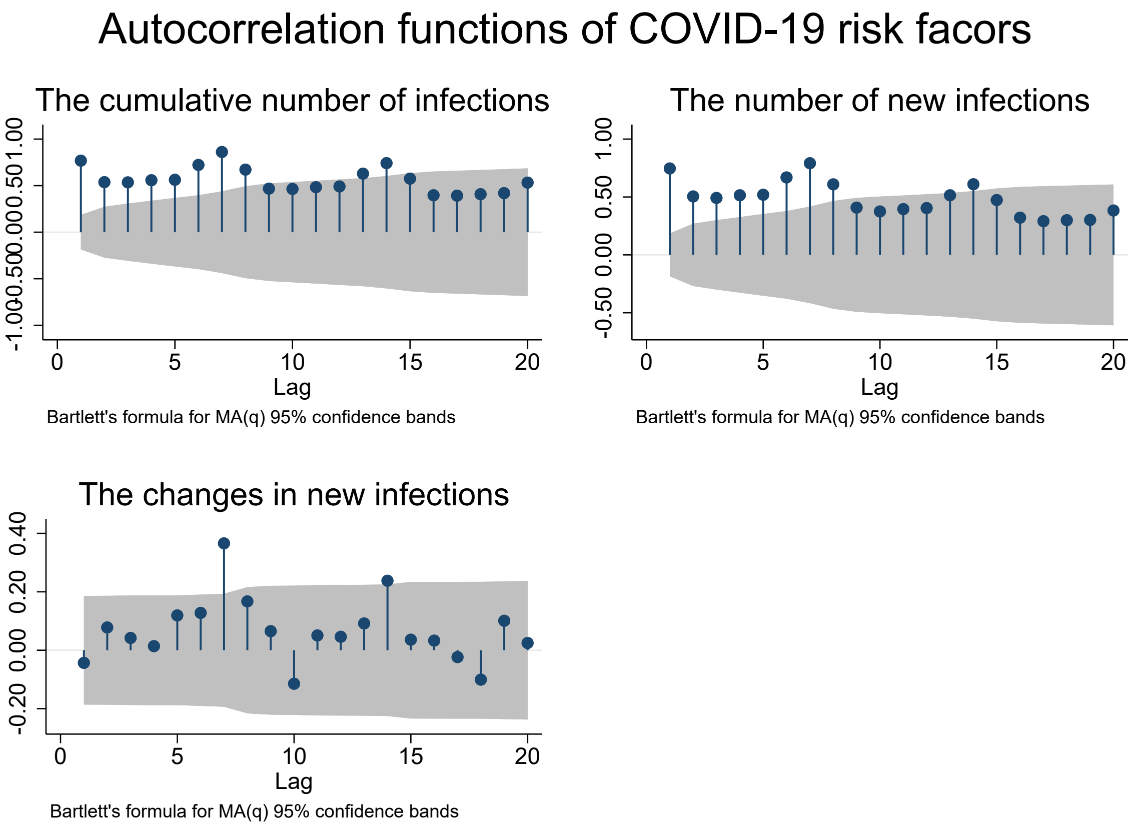


Figure A1: Autocorrelation plots of the COVID-19 risk factors. The figure plots the autocorrelation functions of the cumulative number of infections, the number of new infections, and the daily change in new infections. The shaded area of the graphs represent 95% confidence intervals.

## A.2 Bivariate Sorts

In this section, we conduct bivariate portfolio sorts to ensure that the predictive power of our COVID-19 measure after controlling for two well-known stock characteristics, market beta and size. There is concern that these stock characteristics may explain the predictive ability of $\beta^{\Delta NInfections}$ on future returns. We first examine the effect of market beta ($\beta^{MKT}$) to asses whether the predictive power of $\beta^{\Delta NInfections}$ also exists after controlling for the stocks' market beta. To do so, we first sort all the stocks into quintile portfolios by their market beta. Then, within each $\beta^{MKT}$ quintile, we further sort stocks into five quintiles according to their $\beta^{\Delta NInfections}$, where Quinitle 1 (Quinitle 5) contains stocks with the lowest (highest) $\beta^{\Delta NInfections}$. We also construct High-Low portfolios buying (selling) stocks with the highest (lowest) $\beta^{\Delta NInfections}$. Finally, we compute the average of each of the $\beta^{\Delta NInfections}$-sorted quintile portfolios across the five $\beta^{MKT}$ quintile portfolios to construct portfolios with dispersion in $\beta^{\Delta NInfections}$ ("Average" row). This way, we form five $\beta^{\Delta NInfections}$ portfolios with nearly identical levels of $\beta^{MKT}$, and therefore these $\beta^{\Delta NInfections}$ portfolios control for variations in $\beta^{MKT}$.

Table A1 presents the equal-weighted (Panel A) and value-weighted (Panel B) average returns for each of the 25 portfolios, as well as return differentials between high- and low-$\beta^{\Delta NInfections}$-sorted portfolios and the corresponding four-factor and six-factor alphas. The results show that after controlling for the market beta, the average return on the equal-weighted High-Low portfolio is -0.32% per day with a Newey & West (1987) t-statistic of -2.88. Furthermore, the four-factor alpha and six-factor on the spread portfolio are about -0.39% with the t-statistics of -2.95 and -2.98, respectively. For the value-weighted portfolios, the results indicate that the average return on the High-Low portfolio is -0.23% per day with a Newey & West (1987) t-statistic of -2.07. Also, the four-factor alpha and six-factor on the spread portfolio are about -0.36% with the the t-statistics of -2.51 and -2.56, respectively. Therefore, the predictive ability of $\beta^{\Delta NInfections}$ on future returns cannot be explained by market beta.

Table A1: Returns on Equity Portfolios from Bivariate Sorts on Market Beta ($\beta^{MKT}$) and $\beta^{\Delta NInfections}$.

This table reports the average returns on the equal-weighted (Panel A) and value-weighted (Panel B) portfolios from bivariate sorts on market beta and $\beta^{\Delta NInfections}$. We first sort stocks into market beta ($\beta^{MKT}$) quintile portfolios and then, within each market beta quintile, into $\beta^{\Delta NInfections}$ quintiles to form 25 portfolios. Average row denotes to the average return across all the market beta quintiles. High-Low indicates the average return on the spread portfolio. The table also presents the Carhart (1997) four-factor alpha and the Fama & French (2018) six-factor alpha on the spread portfolio. All values are in percentage. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

*Panel A: Equal-weighted portfolios*

| | $\beta^{\Delta NInfections}$ quintile | | | | | High-Low Portfolio | | Four-factor alpha | | Six-factor alpha | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta^{MKT}$ quintile | Low | 2 | 3 | 4 | High | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat |
| 1 (small) | 0.50 | 0.16 | 0.19 | 0.10 | 0.02 | -0.48*** | (-3.57) | -0.55*** | (-3.60) | -0.55*** | (-3.52) |
| 2 | 0.33 | 0.10 | 0.10 | -0.08 | 0.11 | -0.22 | (-1.46) | -0.35* | (-1.94) | -0.35** | (-2.00) |
| 3 | 0.33 | 0.11 | 0.06 | -0.01 | -0.00 | -0.33** | (-2.35) | -0.42*** | (-2.89) | -0.42*** | (-2.91) |
| 4 | 0.25 | 0.13 | -0.02 | 0.07 | 0.07 | -0.18 | (-1.51) | -0.25* | (-1.68) | -0.25* | (-1.67) |
| 5 (big) | 0.32 | 0.21 | 0.06 | 0.08 | -0.05 | -0.37 | (-1.51) | -0.39 | (-1.63) | -0.40 | (-1.66) |
| Average | 0.35 | 0.14 | 0.08 | 0.03 | 0.03 | -0.32*** | (-2.88) | -0.39*** | (-2.95) | -0.39*** | (-2.98) |

*Panel B: Value-weighted portfolios*

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 (small) | 0.27 | 0.31 | 0.01 | -0.04 | -0.08 | -0.35 | (-1.66) | -0.45* | (-1.88) | -0.45* | (-1.92) |
| 2 | 0.23 | -0.07 | -0.02 | -0.10 | -0.21 | -0.44** | (-2.57) | -0.66*** | (-3.31) | -0.65*** | (-3.34) |
| 3 | 0.25 | 0.15 | 0.08 | 0.05 | -0.02 | -0.27* | (-1.71) | -0.38** | (-2.16) | -0.38** | (-2.28) |
| 4 | 0.08 | 0.08 | 0.08 | -0.01 | 0.01 | -0.07 | (-0.53) | -0.21 | (-1.04) | -0.21 | (-1.01) |
| 5 (big) | 0.01 | 0.32 | 0.20 | 0.09 | -0.02 | -0.03 | (-0.12) | -0.12 | (-0.54) | -0.13 | (-0.55) |
| Average | 0.17 | 0.16 | 0.07 | -0.00 | -0.06 | -0.23** | (-2.07) | -0.36** | (-2.51) | -0.36** | (-2.56) |

Similar to the analysis presented in Table A1, we examine the predictive power of $\beta^{\Delta NInfections}$ after controlling market capitalization (size). To do so, stocks are first sorted into quintile portfolios by size, and then into $\beta^{\Delta NInfections}$ quintile portfolios within each size quintile. Table A2 reports the average returns on the resulting 25 portfolios, as well as return differentials between high- and low-$\beta^{\Delta NInfections}$-sorted portfolios and the corresponding four-factor and six-factor alphas for both the equal-weighted (Panel A) and value-weighted (Panel B) portfolios. The results indicate that after controlling for the market capitalization (size), the average return on the equal-weighted High-Low portfolio is -0.28% per day with a Newey & West (1987) t-statistic of -2.72. Also, the four-factor alpha and six-factor on the spread portfolio are equal -0.35% with the t-statistics of -2.80 and -2.82, respectively. For the value-weighted portfolios, the results show that the average return on the High-Low portfolio is -0.27% per day with a Newey & West (1987) t-statistic of -2.97. In addition, the four-factor alpha and six-factor on the spread portfolio are about -0.36% with the t-statistics of -3.07 and -3.05, respectively.

Table A2: Returns on Equity Portfolios from Bivariate Sorts on Size and $\beta^{\Delta NInfections}$. This table reports the average returns on the equal-weighted (Panel A) and value-weighted (Panel B) portfolios from bivariate sorts on size and $\beta^{\Delta NInfections}$. We first sort stocks into size quintiles and then, within each size quintile, into $\beta^{\Delta NInfections}$ quintiles to form 25 portfolios. Average row denotes to the average return across all the market beta quintiles. High-Low indicates the average return on the spread portfolio. The table also presents the Carhart (1997) four-factor alpha and the Fama & French (2018) six-factor alpha on the spread portfolio. All values are in percentage. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Equal-weighted portfolios* | | | | | | | | | | | |
| | $\beta^{\Delta NInfections}$ quintile | | | | | High-Low Portfolio | | Four-factor alpha | | Six-factor alpha | |
| Size quintile | Low | 2 | 3 | 4 | High | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat |
| 1 (small) | 0.86 | 0.62 | 0.47 | 0.44 | 0.13 | -0.73*** | (-3.32) | -0.83*** | (-3.42) | -0.83*** | (-3.30) |
| 2 | 0.10 | 0.19 | 0.10 | 0.06 | 0.02 | -0.08 | (-1.76) | -0.13 | (-1.01) | -0.14 | (-1.09) |
| 3 | 0.20 | 0.02 | -0.01 | -0.04 | -0.08 | -0.28* | (-1.98) | -0.30** | (-2.25) | -0.31** | (-2.33) |
| 4 | 0.12 | 0.07 | -0.04 | 0.04 | -0.06 | -0.18 | (-1.43) | -0.30* | (-1.91) | -0.30* | (-1.94) |
| 5 (big) | 0.07 | -0.03 | -0.02 | -0.02 | -0.04 | -0.11 | (-1.18) | -0.18 | (-1.58) | -0.18 | (-1.59) |
| Average | 0.27 | 0.17 | 0.10 | 0.10 | -0.01 | -0.28*** | (-2.72) | -0.35*** | (-2.80) | -0.35*** | (-2.82) |
| *Panel B: Value-weighted portfolios* | | | | | | | | | | | |
| 1 (small) | 0.51 | 0.37 | 0.23 | 0.26 | -0.01 | -0.52*** | (-2.69) | -0.63*** | (-2.98) | -0.63*** | (-2.95) |
| 2 | 0.13 | 0.15 | 0.09 | 0.01 | -0.00 | -0.13 | (-1.04) | -0.19 | (-1.39) | -0.20 | (-1.45) |
| 3 | 0.19 | 0.03 | -0.03 | -0.05 | -0.10 | -0.29** | (-2.29) | -0.34** | (-2.59) | -0.34** | (-2.62) |
| 4 | 0.11 | 0.04 | -0.04 | 0.04 | -0.08 | -0.19 | (-1.46) | -0.29** | (-2.00) | -0.30** | (-2.03) |
| 5 (big) | 0.14 | 0.02 | 0.03 | 0.06 | -0.08 | -0.22* | (-1.85) | -0.35** | (-2.23) | -0.35** | (-2.23) |
| Average | 0.22 | 0.12 | 0.06 | 0.06 | -0.05 | -0.27*** | (-2.97) | -0.36*** | (-3.07) | -0.36*** | (-3.05) |

To conclude, the results confirm that the negative relation between $\beta^{\Delta NInfections}$ and future stock returns remains statistically significant even after controlling for market beta and size, as two well-known stock characteristics.

Second, we perform bivariate portfolio sorts to control for the effect of two well-known stock characteristics, market beta and size. After we control for these stock return predicting variables, our results indicate that the negative relation between the variations in the daily number of new infections beta and future returns is not captured by market beta and size as two standard stock returns predictors.

## A.3 Predicting stock market volatility

Table A3: This table reports the estimation results for the following single long-horizon predictive regression:

$$svar_{t+1,t+q} = \alpha_q + \beta_q NInfections_t + u_{t+1,t+q}$$

where $svar_{t+1,t+q} \equiv svar_{t+1} + ... + svar_{t+q}$ and $svar_t$ is the log of market realized volatility. $NInfections_t$ represents the daily changes in the number of new infections. We use forecasting horizons of 5, 10, 15, 20, 30, and 45 days ahead, such that $q$ observations are lost in each of the respective q-horizon regressions. Newey & West (1987) adjusted t-statistics are computed with $q$ lags and reported in parenthesis. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | q=5 | q=10 | q=15 | q=20 | q=30 | q=45 |
|---|---|---|---|---|---|---|
| $\beta_q$ | 0.09*** | 0.15*** | 0.20*** | 0.23** | 0.25** | 0.24** |
| t-ratio | (4.83) | (3.54) | (2.91) | (2.61) | (2.51) | (2.61) |
| $R^2$ | 0.57 | 0.54 | 0.51 | 0.46 | 0.40 | 0.30 |

## A.4 Firm characteristics and stock returns in response to COVID-19

Table A4: Pre-pandemic CSR activities and stock returns in response to COVID-19. The table presents regression results of stock price reactions to COVID-19 as functions of these pre-pandemic firm CSR activities. The dependent variable is the daily stock return of each firm. We use the overall ESG score and Environmental, Social, and Governance scores to measure a firm's CSR performance. *Covid* is the daily growth rate of the number of new COVID-19 infections. Firm controls * COVID includes the interactions of *Covid* and standard firm characteristics (i.e., Firm Size, Leverage, Cash ratio, and ROA). For all quantities we use the latest data available at the end of 2019. The sample period runs from January to June, 2020. All models control for industry (two-digit SIC) fixed effects. Standard errors, in parentheses, are clustered at the firm level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | *Dependent variable: Daily stock return* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Covid | -1.34*** | -1.42*** | -1.27*** | -1.40*** |
| | (0.32) | (0.32) | (0.32) | (0.36) |
| ESG score * Covid | -0.21 | | | |
| | (0.39) | | | |
| Environmental * Covid | | -0.22 | | |
| | | (0.24) | | |
| Social * Covid | | | 0.11 | |
| | | | (0.26) | |
| Governmental * Covid | | | | 0.17 |
| | | | | (0.31) |
| Firm controls* Covid | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES |
| Adjusted $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| Observations | 236119 | 233979 | 236012 | 236012 |

Table A5: Pre-pandemic corporate governance structure and stock returns in response to COVID-19.

The table presents regression results of stock price reactions to COVID-19 as functions of these pre-pandemic firm governance structure. The dependent variable is the daily stock return of each firm. Antitakeover Devices is the number of anti-takeover devices in place. Board Size is the number of board members. Independent Board Members is the proportion of independent members sitting on the board. Performance-based Compensation equals one if the company has a performance-based compensation policy for the senior executives and board members and Executive Compensation LT Objectives equals one if managers and board remuneration is partly linked to long-term objectives and targets. *Covid* is the daily growth rate of the number of new COVID-19 infections. Firm controls * COVID includes the interactions of *Covid* and standard firm characteristics (i.e., Firm Size, Leverage, Cash ratio, and ROA). For all quantities we use the latest data available at the end of 2019. The sample period runs from January to June, 2020. All models control for industry (two-digit SIC) fixed effects. Standard errors, in parentheses, are clustered at the firm level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | *Dependent variable: Daily stock return* | | |
|---|---|---|---|
| | Anti-takeover provisions | Board structure | Executive compensation |
| | (1) | (2) | (3) |
| Covid | -1.29*** | -1.16*** | -2.26 |
| | (0.38) | (0.33) | (1.37) |
| Antitakeover Devices * Covid | 0.00 | | |
| | (0.03) | | |
| Board Size* Covid | | -0.05 | |
| | | (0.03) | |
| Performance-based Compensation* Covid | | | 1.00 |
| | | | (1.35) |
| Executive Compensation LT Objectives * Covid | | | -0.01 |
| | | | (0.15) |
| Firm controls * Covid | YES | YES | YES |
| Industry FE | YES | YES | YES |
| Adjusted $R^2$ | 0.01 | 0.01 | 0.01 |
| Observations | 231738 | 231738 | 231738 |

## A.5 Additional robustness tests

Table A6: Sorting on $\beta^{\Delta NInfections}$ in the subsamples of big and liquid stocks.
The table presents the results from univariate portfolios of stocks sorted by $\beta^{\Delta NInfections}$ using two different subsamples of big and liquid stocks. Each panel reports the daily average post-ranking return and the Carhart (1997) four-factor and Fama & French (2018) six-factor alphas of each decile portfolio for the value-weighted portfolios. Panel A includes the subsample of stocks with above-median market capitalization, and Panel B consists of the subset of stocks with below-median Amihud (2002) illiquidity measure. The last row presents the average return and alphas of the spread portfolio (High-Low). All numbers are in percentage. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | Panel A: Big Stocks | | | Panel B: Liquid stocks | | |
|---|---|---|---|---|---|---|
| Decile | Average Return | Four-factor alpha | Six-factor alpha | Average Return | Four-factor alpha | Six-factor alpha |
| 1 (Low) | 0.22 | 0.32** | 0.32** | 0.22 | 0.34** | 0.34** |
| | (0.51) | (2.01) | (2.18) | (0.51) | (2.00) | (2.17) |
| 2 | 0.13 | 0.17 | 0.17 | 0.14 | 0.18 | 0.18 |
| | (0.39) | (1.57) | (1.56) | (0.42) | (1.62) | (1.61) |
| 3 | 0.12 | 0.17** | 0.17** | 0.12 | 0.17** | 0.17** |
| | (0.34) | (2.12) | (2.15) | (0.37) | (2.20) | (2.21) |
| 4 | -0.06 | -0.06 | -0.06 | -0.03 | -0.03 | -0.03 |
| | (-0.21) | (-0.85) | (-0.87) | (-0.10) | (-0.39) | (-0.42) |
| 5 | 0.04 | -0.02 | -0.02 | 0.02 | -0.06 | -0.06 |
| | (0.13) | (-0.51) | (-0.47) | (0.06) | (-1.43) | (-1.32) |
| 6 | 0.07 | 0.05 | 0.04 | 0.08 | 0.07 | 0.07 |
| | (0.23) | (0.87) | (0.89) | (0.28) | (1.44) | (1.45) |
| 7 | 0.03 | -0.02 | -0.03 | 0.05 | 0.00 | -0.00 |
| | (0.11) | (-0.51) | (-0.55) | (0.18) | (0.01) | (-0.02) |
| 8 | -0.07 | -0.15*** | -0.16*** | -0.09 | -0.17*** | -0.17*** |
| | (-0.25) | (-2.92) | (-2.90) | (-0.31) | (-3.26) | (-3.22) |
| 9 | -0.04 | -0.10 | -0.10 | -0.06 | -0.13 | -0.13 |
| | (-0.12) | (-1.09) | (-1.09) | (-0.19) | (-1.39) | (-1.37) |
| 10 (High) | -0.08 | -0.12 | -0.12 | -0.08 | -0.13 | -0.13 |
| | (-0.20) | (-1.04) | (-1.03) | (-0.20) | (-0.98) | (-0.97) |
| High-Low | -0.30** | -0.44** | -0.44** | -0.30** | -0.47** | -0.47** |
| | (-2.20) | (-2.32) | (-2.30) | (-2.05) | (-2.21) | (-2.20) |

Table A7: Decile portfolios of stocks sorted by alternative measures of $\beta^{\Delta NInfections}$.

The table reports the results of sorting stocks into decile portfolios according to $\beta^{\Delta NInfections}$, which is estimated for each stock using two alternative specifications:

Specification (1): $R_{i,t} - R_{f,t} = \beta_0^{i,t} + \beta_{\Delta NInfections}^{i,t} \Delta NInfections_t + \beta_{MKT}^{i,t} MKT_t + \beta_{SMB}^{i,t} SMB_t + \beta_{HML}^{i,t} HML_t + \beta_{UMD}^{i,t} UMD_t + \varepsilon_{i,t}$

Specification (2): $R_{i,t} - R_{f,t} = \beta_0^{i,t} + \beta_{\Delta NInfections}^{i,t} \Delta NInfections_t + \beta_{MKT}^{i,t} MKT_t + \beta_{SMB}^{i,t} SMB_t + \beta_{HML}^{i,t} HML_t + \beta_{RMW}^{i,t} RMW_t + \beta_{CMA}^{i,t} CMA_t + \varepsilon_{i,t}$

where MKT, SMB, HML, UMD, RMW, and CMA are the market, size, book-to-market, momentum, profitability, and investment factors. The table presents the four-factor alphas from Carhart (1997) and the six-factor alphas from Fama & French (2018) for the equal-weighted (Panel A) and value-weighted (Panel B) portfolios separately. The last row displays the alphas for the spread portfolio. All values are reported in percentage. The adjusted t-statistics from Newey & West (1987) are given in parentheses. Significance levels are denoted by *, **, and *** for 10%, 5%, and 1% levels, respectively. The sample period covers January 22, 2020, to June 30, 2020.

| | *Panel A: Equal-weighted portfolios* | | | | *Panel B: Value-weighted portfolios* | | | |
|---|---|---|---|---|---|---|---|---|
| | Model (1) | | Model (2) | | Model (1) | | Model (2) | |
| Decile | Four-Factor alpha | Six-Factor alpha | Four-Factor alpha | Six-Factor alpha | Four-Factor alpha | Six-Factor alpha | Four-Factor alpha | Six-Factor alpha |
| 1 (Low) | 0.51*** | 0.52*** | 0.64*** | 0.65*** | 0.34* | 0.35** | 0.45* | 0.46* |
| | (3.09) | (3.70) | (2.73) | (3.20) | (1.78) | (2.10) | (1.75) | (1.94) |
| 2 | 0.30** | 0.31*** | 0.36** | 0.37*** | 0.17 | 0.18 | 0.26 | 0.26* |
| | (2.35) | (2.92) | (2.42) | (2.84) | (1.42) | (1.47) | (1.61) | (1.68) |
| 3 | 0.18** | 0.19*** | 0.20** | 0.21** | 0.08 | 0.08 | 0.09 | 0.09 |
| | (2.45) | (3.08) | (2.26) | (2.64) | (0.92) | (0.93) | (1.09) | (1.10) |
| 4 | 0.13 | 0.14* | 0.12 | 0.12** | 0.05 | 0.05 | 0.07 | 0.07 |
| | (1.51) | (1.82) | (1.61) | (2.01) | (1.01) | (1.01) | (0.99) | (0.97) |
| 5 | 0.09 | 0.10 | 0.10* | 0.10** | -0.01 | -0.00 | -0.02 | -0.02 |
| | (1.24) | (1.62) | (1.91) | (2.42) | (-0.11) | (-0.07) | (-0.61) | (-0.70) |
| 6 | 0.16*** | 0.16*** | 0.11** | 0.11** | -0.02 | -0.02 | 0.02 | 0.02 |
| | (2.77) | (3.13) | (2.06) | (2.46) | (-0.35) | (-0.36) | (0.37) | (0.38) |
| 7 | 0.10 | 0.11* | 0.07 | 0.07 | 0.04 | 0.04 | -0.00 | -0.00 |
| | (1.49) | (1.74) | (1.26) | (1.49) | (0.95) | (0.93) | (-0.05) | (-0.06) |
| 8 | 0.07 | 0.07 | 0.01 | 0.02 | -0.14** | -0.15** | -0.19** | -0.19** |
| | (0.96) | (1.07) | (0.19) | (0.26) | (-2.33) | (-2.40) | (-2.49) | (-2.46) |
| 9 | 0.05 | 0.06 | 0.04 | 0.04 | -0.13 | -0.13 | -0.22* | -0.22* |
| | (0.59) | (0.66) | (0.40) | (0.43) | (-1.15) | (-1.18) | (-1.98) | (-1.97) |
| 10 | -0.03 | -0.02 | -0.08 | -0.07 | -0.32* | -0.31* | -0.21 | -0.21 |
| (High) | (-0.16) | (-0.13) | (-0.53) | (-0.50) | (-1.73) | (-1.75) | (-1.64) | (-1.62) |
| High- | -0.54*** | -0.54*** | -0.72*** | -0.72*** | -0.66** | -0.66** | -0.66** | -0.65** |
| Low | (-3.27) | (-3.28) | (-2.93) | (-2.96) | (-2.62) | (-2.61) | (-2.08) | (-2.09) |

Table A8: Bivariate sorts of equity portfolios by controlling for Economic Policy Uncertainty (EPU).
We first sort stocks into $\beta^{\Delta NInfections}$quintiles and then, within each size quintile, into $\beta^{\Delta NInfections}$ quintiles to form 25 portfolios. This table reports the average returns on $\beta^{\Delta NInfections}$portfolios averaged across different quintiles of $\beta^{EPU}$ for both equal-weighted (the first row) and value-weighted (the second row) portfolios. High-Low indicates the average return on the spread portfolio. The table also presents the Carhart (1997) four-factor alpha and the Fama & French (2018) six-factor alpha on the spread portfolio. All values are in percentage. Newey & West (1987) adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. The sample period is January 22, 2020 to June 30, 2020.

| | Quintile | | | | | High-Low Portfolio | | Four-factor alpha | | Six-factor alpha | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat |
| EW $\beta^{EPU}$ | 0.26 | 0.15 | 0.07 | 0.07 | 0.08 | -0.18** | (-2.20) | -0.23*** | (-3.02) | -0.23*** | (-3.02) |
| VW $\beta^{EPU}$ | 0.21 | 0.01 | -0.03 | -0.00 | -0.09 | -0.30*** | (-2.67) | -0.34*** | (-2.81) | -0.34*** | (-2.84) |