The risk transmission of COVID-19 in the US stock market

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\textbf{ABSTRACT}

This paper studies volatility transmission effects between the US stock market and the COVID-19. Using BEKK-multivariate GARCH model, we find the US stock market volatility depends both its own past shocks and past COVID-19 shocks. Further, we find the US stock market volatility is positively affected by the death rate (bad news) while the recovered rate (good news) has a negative impact on the US stock market volatility. In addition, we find there is an asymmetric volatility impact of COVID-19 on the US stock market: the bad news affects the current US stock market much more than the good news. Our fixed effect panel regression results support the volatility spillover effects.

\textbf{I. Introduction}

There is a burgeoning literature that studies the link between the recent COVID-19 crisis and the stock market. Given that the stock market has experienced several infectious disease outbreaks such as MERS, Ebola epidemic, SARS, and avian flu over the past decades, why then the recent COVID-19 pandemic has drawn attention to the stock market? Unlike other outbreaks that had virtually no impact on the stock market, the unprecedented COVID-19 pandemic has a sizable impact on the US stock market (see Baker et al. 2020). This paper sheds light on the link between the COVID-19 pandemic and the US stock market by exploring volatility transmission effects between the US stock market and the COVID-19 risk.

To this end, we use BEKK-multivariate GARCH (MGARCH) model and conduct the fixed effect panel analysis exploiting sectoral and time series variations. Using daily data on the sector-level US stock market, macroeconomic variables and COVID-19 news (i.e., growth rate of death and recovered case) from January to April 2020, we find COVID-19 shocks have been transmitted to the US stock market. More specifically, the BEKK-MGARCH model results suggest that the US stock market volatility is dependent on both its own past shocks and past COVID-19 news. Further, we find the volatility of COVID-19 mortality rate (i.e. bad news) significantly and positively affects the US stock market volatility while the volatility of COVID-19 recovered rate (i.e. good news) has an opposite effect on the US stock market volatility. Moreover, we find there is an asymmetric volatility impact of COVID-19 on the US stock market: the bad news affects the current US stock market volatility much more than the good news.

Our fixed effect panel regression analysis supports the volatility transmission effects between COVID-19 and the US stock market. We find the growth rate of death has a positive effect on the US stock market risk whereas the recovered rate growth has a negative impact on the risk. These results indicate that investors interpret a rise in the daily death toll as a negative signal. In contrast, an increase in the growth rate of the recovered rate positively signals to investors. Finally, we confirm our results are invariant to the sample sectors.

Our study contributes to the literature that studies the effect of COVID-19 on the financial market. One branch of the literature complies with evidence of the negative impacts of COVID-19 on firm-level stock returns within a country. Al-Awadhi et al. (2020) use Chinese firms, and several studies (Alfaro et al. 2020; Albuquerque et al. 2020; Baker...
The other branch expands the scope of analysis using cross-country data and provides evidence supporting the negative effect of the COVID-19 pandemic on stock markets across the world (Ashraf 2020; Ding et al. 2020; Liu et al. 2020; Ru, Yang, and Zou 2020; Zhang, Hu, and Ji 2020). These studies focus on confirmed and death cases of COVID-19 separately while we further include recovered cases. Therefore, we provide evidence showing both the negative effects of death cases and the positive effects of recovered cases of COVID-19 on the US stock market volatility and hence complement the aforementioned studies. In addition to this, unlike the above studies, we provide a structural model showing whether the COVID-19 volatility shock has been transmitted to the volatility of the US stock market. Further, we explore how the US stock market risk is associated with COVID-19 mortality and recovered rate while controlling for systemic risk and fear sentiment factor extracted from principal component analysis.

The paper is organized as follows: Section 2 develops the research framework for Markov switching regime, principle component analysis, the impact of COVID-19 risk on the volatility transmission in the US stock market and time series and panel regressions. Section 3 describes the data, classification of the US stock market into pre- and COVID-19 period and construction of the systemic risk factor and the fear sentiment factor. Section 4 reports results linking the COVID-19 risk to the US stock market, along with the panel regression results. We conclude in section 5.

II. Research framework

Markov switching regime

To examine whether the COVID-19 pandemic results in a regime shift, we employ the Markov switching model (also known as the regime-switching model). We let $s_t$ denote an unobservable state variable whose value is zero or one, and $R_t$ be daily stock index return that follows two-state AR(1):

$$R_t - \mu_{s_t} = \varphi (R_{t-1} - \mu_{s_{t-1}}) + \varepsilon_t, \varepsilon_t \sim (0, \sigma^2)$$  \hspace{1cm} (1)

where $\mu_{s_t}$ is the time-varying mean for the given value of $s_t$, and $\varepsilon_t$ is an i.i.d. error term which follows a normal distribution with mean zero and standard deviation of $\sigma^2$. The transition matrix of $s_t$ is specified as follows:

$$P = \begin{bmatrix} p(s_t=0|s_{t-1}=0) = p_{00} & p(s_t=1|s_{t-1}=0) = p_{10} \\ p(s_t=0|s_{t-1}=1) = p_{01} & p(s_t=1|s_{t-1}=1) = p_{11} \end{bmatrix}$$  \hspace{1cm} (2)

where $p_{lk}$ ($l, k = 0, 1$) represent the transition probabilities of $s_t = l$ given that $s_{t-1} = k$. Estimating $p_{lk}$ allows us to examine whether the stochastic process of $R_t$ over the sample period has been differentiated by the respective states.

Principal component analysis

We use principal component analysis (PCA), a statistical dimension reduction method, to find parsimonious principal factors explaining the overall variability of macroeconomic variables. To this end, we perform the eigenvalue decomposition on the covariance matrix. More specifically, let $\mathbf{Z}$ denote a random vector of standardized macroeconomic indicators, $PC_i$ as $i^{th}$ principal component of $\mathbf{Z}$, and $e_{ij}$ as factor loadings. The principal components are as follows:

$$\mathbf{PC} = \begin{pmatrix} PC_1 \\ \vdots \\ PC_p \end{pmatrix} = \begin{pmatrix} e_{11} & \cdots & e_{1p} \\ \vdots & \ddots & \vdots \\ e_{p1} & \cdots & e_{pp} \end{pmatrix} \begin{pmatrix} Z_1 \\ \vdots \\ Z_p \end{pmatrix} = \mathbf{e} \cdot \mathbf{Z} \hspace{1cm} (3)$$

Then, the random vector $\mathbf{Z}$ is written as in equation (2).

$$\mathbf{Z} = \begin{pmatrix} e_{11} & \cdots & e_{p1} \\ \vdots & \ddots & \vdots \\ e_{1p} & \cdots & e_{pp} \end{pmatrix} \begin{pmatrix} PC_1 \\ \vdots \\ PC_p \end{pmatrix} = \mathbf{e}^T \cdot \mathbf{PC} \hspace{1cm} (4)$$
Using the parsimonious principal factors, we can estimate the original normalized values, $\tilde{Z}$, which is specified as:

$$\tilde{Z} = e^T_R \cdot PC_R$$  \hspace{1cm} (5)

Based on the above reduced form, we find two most influential principal factors and name the two factors as systemic risk (SR) factor and fear sentiment factor (FS), respectively. We use them as proxies for financial market fundamentals (see section 3 for more details).

**Volatility transmissions: BEKK-multivariate GARCH**

To examine the impact of COVID-19 risk on the volatility transmission in the US stock market, we use a BEKK-multivariate GARCH (MGARCH) framework, which extended Engle and Kroner (1995). Since the BEKK model allows the interaction between the time varying conditional variances and covariances, it captures spillovers between variances (Clements, Hurn, and Volkov 2015 and Katsiampa, Corbet, and Lucey 2019). The BEKK model, $H_t$, is the conditional covariance matrix of the $k$-dimensional random vector $\varepsilon_t$:

$$H_t = C' + A'\varepsilon_{t-1}^2 C + G'H_{t-1}G$$  \hspace{1cm} (6)

where $A$ and $G$ are $k \times k$ parameter matrices and $C$ is an upper triangular matrix. The diagonal elements of $H_t$, i.e. $h_{ii,t}$, are conditional variance terms whereas the off-diagonal elements of $H_t$, i.e. $h_{ij,t}$, are conditional covariances. The diagonal elements of $A$ and $G$ ($a_{ii,t}$ and $g_{ii,t}$, respectively) capture the impact of each element’s own past shocks and past volatility while the off-diagonal elements of $A$ and $G$ ($a_{ij,t}$ and $g_{ij,t}$ where $i \neq j$) explain the cross-element effects, shock transmission and volatility spillover effects, respectively.

The unrestricted BEKK model in multivariate form is given by:

$$
\begin{pmatrix}
    \varepsilon^2_{11,t-1} & \varepsilon^2_{12,t-1} & \varepsilon^2_{13,t-1} \\
    \varepsilon^2_{21,t-1} & \varepsilon^2_{22,t-1} & \varepsilon^2_{23,t-1} \\
    \varepsilon^2_{31,t-1} & \varepsilon^2_{32,t-1} & \varepsilon^2_{33,t-1}
\end{pmatrix}
= C' + A'
\begin{pmatrix}
    \varepsilon^2_{11,t-1} & \varepsilon^2_{12,t-1} & \varepsilon^2_{13,t-1} \\
    \varepsilon^2_{21,t-1} & \varepsilon^2_{22,t-1} & \varepsilon^2_{23,t-1} \\
    \varepsilon^2_{31,t-1} & \varepsilon^2_{32,t-1} & \varepsilon^2_{33,t-1}
\end{pmatrix} + G'H_{t-1}G 
$$

Since we are interested in how changes in COVID-19 death and recovered rate affect the US stock return volatility, we use the following GARCH (1,1) form:

$$h_{11,t} = c^2_{11} + a^2_{11}\varepsilon^2_{11,t-1} + a^2_{21}\varepsilon^2_{22,t-1} + a^2_{31}\varepsilon^2_{33,t-1} + g^2_{11}h_{11,t-1} + g^2_{21}h_{22,t-1} + g^2_{31}h_{33,t-1} + 2a_{11}a_{21}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + 2a_{11}a_{31}\varepsilon_{11,t-1}\varepsilon_{33,t-1} + 2g_{11}g_{21}h_{23,t-1}$$

(8)

In equation (8), $a_{11}$, $a_{21}$ and $a_{31}$ capture the effects of past squared shocks in the US stock market, COVID-19 death rate and recovered rate, respectively, on the US stock market shock while $g_{11}$, $g_{21}$ and $g_{31}$, respectively, capture the effects of past volatility in the US stock market and that of the two COVID-19 rates on the US stock market volatility. Estimating these parameters allows us to examine the volatility transmission.

**Time series and panel regressions**

We estimate equation (9) for the time series regression:

$$Risk_t = \alpha_0 + \alpha_1 SR_t + \alpha_2 FS_t + \alpha_3 dDeath_t + \alpha_4 dRecovered_t + e_t$$

(9)

where $Risk_t$ is an aggregate risk or a daily standard deviation of CRSP value weighted (VW) index return. More specifically, we compute the standard deviation basing on a two-year rolling basis (i.e. $Risk_t$ is calculated using a standard deviation of the returns between day $t$ and $t - 503$). $SR_t$ represents systemic risk factor. $FS_t$ is fear sentiment factor. $dDeath_t$ and $dRecovered_t$ are standardized growth rate of death and recovered case, respectively, obtained by first demeaning death and recovered
case growth rate and normalizing each to have a standard deviation of one.

In addition, to exploit panel variations across sectors and time, we estimate equation (10):

\[
Risk_{st} = \beta_0 + \beta_1 SR_t + \beta_2 FS_t + \beta_3 dDeath_t + \beta_4 dRecovered_t + \delta_s + \epsilon_{st}
\]  

(10)

where \( Risk_{st} \) is a daily standard deviation in stock index returns in sector \( s \) at a given date \( t \). Similar to the aggregate risk, we compute the standard deviation basing on a two-year rolling basis within sectors. \( \delta_s \) denotes sector-fixed effects and \( \epsilon_{st} \) is an error term. All other variables are defined as above. It is challenging to observe sectoral variables that daily change and affect the volatility of returns. Alternatively, we include sector fixed effects to absorb time-invariant sectoral characteristics that may affect the volatility.\(^1\) In all estimates, we cluster standard errors on sectors to account for possible serial correlation within sectors.

III. Data, regime change, and economic risk indicators

To empirically examine the impact of COVID-19 on the US stock market volatility, we collect daily data on the US stock index value, return, macro-economic variables, and COVID-19 variables from January 2nd, 2020 to April 30th, 2020.\(^2\) The macro-economic variables are from FRED, 49 industry stock returns from Kenneth French data library,\(^3\) stock index values from Bloomberg terminal and CRSP database, death and recovered statistics of COVID-19 from Johns Hopkins Coronavirus Resource Centre.\(^4\)

We use the growth rate of recoveries and mortality to examine the impact of the COVID-19 on US stock market based on daily interval data. More specifically, stock price and most of other economic variables are updated during weekdays, while the COVID-19 data is daily updated at noon based on data confirmed at 4:00 pm ET the day before.\(^5\) Centres for Disease Control and Prevention (CDC) updates the number of recovery and death on Saturday and Sunday as well. Thus, if we calculate the growth rate in recovery and mortality on Monday based on the number of recovery and death on Friday, the growth rates on Monday are relatively higher than any other days. To address this issue, we first calculate the daily growth rates of recovery and mortality on Monday based on the number of recovery and mortality on Sunday. Next, we combine our COVID-19 variables with other variables by calendar dates. Thus, our sample includes 49 industries over 83 days from Jan. 02 to 30 April 2020. The number of observation used in our panel analysis is 4,067.

We first examine whether the variation of CRSP VW stock returns in the US has been shifted to another regime by the COVID-19 crisis using the Markov switching regime AR (1) model (Hamilton and Susmel 1994). To be clear, we choose the lag length of one based on AIC, SIC, and HQC. Figure 1 reports the results. As shown in Figure 1, regime 1 is a low volatility state while regime 2 is a high volatility state. This result demonstrates that the US stock market has been switched to a high volatility regime due to the COVID-19 pandemic since February 24th, 2020. As per the Markov switching AR(1) model, we divided the full sample into two sub-periods: Pre-COVID-19 regime period (2 January 2020 to 23 February 2020) and COVID-19 regime period (24 February 2020–30 April 2020).

Table 1 presents the respective averages and standard deviations for 11 economic indicators for the pre-COVID-19 regime and the COVID-19 regime. The economic indicators have been commonly used as proxies for expected economic fundamentals in finance and economics. For example, Levanon et al. (2015) and Andreou, Ghysels, and Kourtellos (2013) use the indicators to detect the

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1. A simple variance decomposition of the standard deviation of returns shows that about 50% of the total variation in the standard deviation is due to variation in time-invariant sectoral characteristics.
2. Our data sample is restricted from 2 January 2020 to 30 April 2020 because of the data availability. The daily COVID-19 data has been released daily by Johns Hopkins Coronavirus resource centre since 22 January 2020 when one person was first confirmed in the US. In addition, we employ daily industry level US stock market data from the Kenneth French library. This data is based on CRSP data and has been updated on a quarterly basis. The most up-to-date available data was up to April 30 2020.
3. Kenneth R. French data library: https://www-personal.umich.edu/~yfrench/data_library.html
4. Johns Hopkins University of Medicine Coronavirus Resource Centre: https://coronavirus.jhu.edu/data
5. CDC website, https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/previous-testing-in-us.html
economic cycle (e.g., trough and peak) in the US. Following the literature, in this paper, we use the publicly available indicators from the Federal Reserve Bank of St. Louis.

Interestingly, there are notable differences between the pre-COVID-19 period and the COVID-19 period. During the COVID-19 period, the average values of the S&P500 index, overnight LIBOR, effective federal fund rate, and West Texas intermediate oil prices decreased, compared to the pre-COVID-19 periods. On the other hand, the other seven indicators substantially increased. These changes might allude that all the indicators are highly associated with the recent economic regime change triggered by the pandemic.

To examine whether these notable differences are statistically meaningful, for each indicator we conduct the mean equivalence test between the pre- and the COVID-19 period. The absolute values of all the t-statistics greater than 2.00, and hence we reject the null hypothesis that there is no mean difference between two periods.

In addition, Table 1 shows that the volatility of all the indicators, measured by the standard deviation, is higher during the COVID-19 period than the pre-COVID-19 period. Since all the F-statistics reject the null hypothesis of an equal variance at the 1% significant level, this provides supporting evidence that the distinctly different variations in all the economic indicators between the two periods are associated with the COVID-19 virus spread.

Figure 2 displays time series movements of 11 economic indicators, and changes in the number of death, confirmed, and recovered cases over the sample period. All the variables are standardized in order to compare all at once. Specifically, the panel (a) of Figure 2 shows daily movements of the economic indicators, including S&P500 index (SP500), Cboe Volatility Index (VIX), Economic Policy Uncertainty Index (EPUI), Overnight
LIBOR (LIBOR), TED spread (TED), Term Spread (TERM), Effective Federal Fund Rate (EFF. Fed Rate), West Texas Intermediate Crude Oil Price (WTI), Bank of America CCC and Lower Yield Bond Index (CCC B-Yield), Bank of America High Yield Bond Index (High B-Yield), and Traded Weighted Dollar Index (TW Dollar). Panel (b) reports the changes in the number of death, confirmed, and recovered cases of COVID-19. After the death case soared, we see that most of the macroeconomic indicators started to sharply fluctuate. In contrast, a substantial increase in the recovered case made the indicators move in the opposite direction. These may imply that the mortality rate of COVID-19 is interpreted as a bad investment signal while the recovered rate of COVID-19 as a proxy for good news to the US market.

As shown in Figure 2, it is apparent the economic indicators are correlated with each other. In our auxiliary analysis, we find that the average values of the absolute correlation coefficients are 0.86 for SP500 index, 0.76 for VIX, 0.89 for EPUI, 0.90 for overnight LIBOR, 0.87 for TED, 0.78 for TERM, 0.90 for effective Federal fund rate, 0.82 for WTI, 0.91 for CCC below high yield bond index, 0.87 for high yield bond index, and 0.86 for TWD index.

To overcome the high correlations, we extract common latent factors using the principal component analysis and use the common factors as proxies for the eleven indicators. More specifically, we select two principal components in that the two components account for around 92% of total variance of all the economic indicators. The scree plot in Figure 3 shows the first principal component is the most influential factor: it explains 87% of the total variance. The second component explains 5% of the total variation. Since the contribution of other remaining components to the total variance is negligible, compared to the first and second components, we include the first two components in a pool of our control variables.

As shown in Table 2, for the first factor, the absolute value of all factor loadings is about 0.3. This means the economic indicators are almost equally influenced by the first component and hence we name the first principal component as systemic risk (SR) factor as in Billio et al. (2010) and Baek, Cursio, and Cha (2015). For the second factor, we call it as fear sentiment (FS) factor for the US stock market because it has the most significant impact on the factor loading of SP500 and VIX and the two indexes reflect the level of fear in the stock market. For example, if the fear level in the stock market rises, we expect SP500 to fall whereas VIX to rise, consistent with their factor loading sign.

Figure 4 displays the validity of the two factors. We find that the first principal factor (i.e., SR) classifies observations into two groups: the first group of observations is on the left side of the vertical line (SR) while the second group of observations is on the right side of the line. Note that most of the observations in the first group are from the pre-COVID19 periods whereas all observations of the second group are from the COVID-19 periods. More specifically, the first 35 observations are concentrated and form a cloud on the left side of the first principal factor, and then the observation gradually moves to the rightward starting from observation 36 (corresponding to February 24th, 2020). Since our Markov switching model in Figure

Table 1. Means and standard deviations of economic risk indicators during pre- and Covid-19 regime.

| Economic Risk Indicators                  | Mean Pre-Covid | Covid | t-stat | Mean Pre-Covid | Covid | Std. Deviation | F-test |
|-----------------------------------------|----------------|-------|--------|----------------|-------|----------------|--------|
| S&P500 Index                            | 3.305.94       | 2.744.95 | -15.96 | 48.29 | 236.9 | 24.06 |
| Cboe Volatility Index (VIX)             | 14.46          | 47.93  | 15.97*** | 1.82 | 14.37 | 62.24*** |
| Economic Policy Uncertainty Index       | 96.11          | 414.29 | 11.83*** | 28.7 | 183.36 | 40.83*** |
| Overnight LIBOR                         | 1.55           | 0.49   | -12.04*** | 0.02 | 0.58 | 874.13 |
| TED Spread                              | 0.24           | 0.81   | 9.35*** | 0.08 | 0.41 | 27.62*** |
| Term Spread (10 YR T-bond – 3 Month T-bill) | 0.13       | 0.47   | -6.96*** | 0.14 | 0.31 | 5.17*** |
| Effective Federal Fund Rate             | 1.57           | 0.47   | -12.67*** | 0.02 | 0.60 | 861.03*** |
| West Texas Intermediate Oil Prices      | 55.04          | 25.66  | -12.88*** | 4.21 | 15.02 | 12.74*** |
| Bank of America CCC & Lower Bond Index  | 11.49          | 16.50  | 13.86*** | 0.24 | 2.49 | 111.50*** |
| Bank of America High Yield Bond Index   | 5.19           | 8.24   | 12.88*** | 0.13 | 1.63 | 167.61*** |
| Traded Weighted Dollar Index            | 110.34         | 112.97 | 8.05*** | 0.88 | 2.01 | 5.22*** |
suggests that the US stock return has relatively low volatilities during the pre-COVID19 periods while it has high volatilities during the COVID-19 periods, it is evident that the first factor is associated with the systemic shock.

In addition to the first component, the second component (i.e., FS) provides additional information. When looking into the area below the second component (the horizontal line) and the right side of the first component, all the observations are from March 11th, 2020 (observation 48) to April 3rd, 2020 (observation 65). During this period, the COVID-19 spread was intensified, the market fear index substantially increased and the SP500 index decreased. For example, about 1 month after the regime change (March 25th, 2020), the number of death case increased from zero to 1,320, the number of the confirmed case increased from 51 to 65,844, the market fear index (VIX) dramatically increased from 25.03 to 63.95,

Figure 2. Daily Economic Indicators and Change in the Number of COVID-19 Cases.
and the SP500 index substantially decreased from 3225.89 to 2475.56. This implies that the second index is associated with the sentiment of fear in the market.

To examine how these two factors are associated with the US market movements, in Figure 5 we plot changes in the CRSP VW index return, the systemic risk factor, and the fear sentiment factor over the sample period. As shown in the top panel of Figure 5, CRSP VW returns started to fluctuate after February 24th, 2020 when the systemic risk factor simultaneously started to increase. Similarly, the bottom panel shows that both the CRSP VW index return and the fear sentiment factor move closely together. In particular, the two series increase after the COVID-19 pandemic shock hit the US stock market. These comovements are consistent with our principal component analysis result that the two factors capture the variation in the stock market.

IV. Empirical results
Volatility spillover results

We are interested in the conditional variance between COVID-19 and US stock market and whether COVID-19 risk can spread over the US stock market. To this end, as mentioned above, we use the BEKK-MGARCH approach.

In Table 3 we report the estimates of the BEKK-MGARCH model. \(a_{11}, a_{21}, \) and \(a_{31}\) correspond to ARCH parameters and capture the effect of past-squared shocks in the US market, COVID-19 death rate, and COVID-19 recovered rate, respectively, on the US stock market shock. All t-statistics for \(a_{11}, a_{21}, a_{31}\) are statistically significant. We interpret these results as evidence showing associations between the volatility in the US stock market, the past-squared standardized innovation in the US stock market (i.e. own ARCH effect), COVID-19 death and recovered rate (i.e. COVID-19 shock transmission effect).

Next \(g_{11}, g_{21},\) and \(g_{31}\) are GARCH parameters and show the effect of past volatility in the US stock market, COVID-19 death and recovered rates, respectively, on the US stock market volatility. Interestingly, \(g_{21}\) and \(g_{31}\) are statistically meaningful while \(g_{11}\) is statistically insignificant. These results indicate that the volatility of the US stock

\*We use squared CRSP VW index return because the squared index return approximates the variation of the daily CRSP VW index returns: \(E(R^2) = V(R) - [E(R)]^2\) where \(R\) denotes VW index returns, \(V(R)\) is the variance of \(R\) and \(E(R)\) is mean of \(R\). Since \(E(R) \approx 0\), we can simplify \(E(R^2) = V(R)\). To make the change comparable, the systemic risk factor and the fear sentiment are also squared.
market is affected by the volatilities of COVID-19 death rate and recovered rate rather than the past volatility of the US stock market. Furthermore, from the positive sign of \( g_{21} \) and the negative sign of \( g_{31} \), we see that the volatility in the stock market is significantly and positively influenced by the volatility of COVID-19 mortality rate while negatively associated with the volatility of COVID-19 recovered rate. These results imply there is a volatility spillover effect between the US stock market and COVID-19 death and recovered rate. Note \( |g_{21}| > |g_{31}| \), implying the COVID-19 death rate volatility affects the current US stock market volatility more than the COVID-19 recovered rate volatility. Put another way, the bad news has a much larger impact on the US stock market the good news during the pandemic crisis. This finding is consistent with Koutmos and Booth (1995). They find that there is an asymmetric impact of good news and bad news on volatility spillovers, and further show that the bad news has increased the volatility more than the good news.

**Time series regressions**

In Table 4 we report estimates of equation (9). As shown in Column (1), we find that over the full sample period the variation in the US stock market is positively associated with \( SR_t \), \( FS_t \) and \( dDeath_t \), while the risk of US market has a negative association with \( dRecovered_t \). Since the point estimate of \( dDeath_t \) (3.722) is higher than estimates of any other variables \( (SR_t = 0.085; \ FS_t = 0.131; dRecovered_t = -0.950) \), the risk in US stock market is significantly affected by the changes in the number of death due to the COVID-19 pandemic.

Further, we split the sample into the pre-COVID19 period (i.e. Jan.02 to 23 February 2020) and the COVID19 period (i.e. Feb.24 to 30 April 2020) to examine whether our result in column (1) is driven by the pre-COVID19 variations. As shown in column (2), during the pre-COVID19 period, except for \( SR_t \) and \( dRecovered_t \), the estimates of \( FS_t \) and \( dDeath_t \) are not statistically meaningful. This may be because the number of death due to the COVID-19 in US during the pre-COVID19 period is zero: the estimated coefficient on in column (2) is zero. However, during the COVID-19 period, as reported in column (3), all the coefficients are similar to those from the full sample period. Thus, we conclude that the variation in the US stock market over the full sample period arises mainly from the COVID-19.

To examine whether our regression results capture a spurious relationship, we use the Phillips-Perron test for the unit root test, and the Augment Dicky Fuller and Phillips-Ouliaris test for the cointegration test.\(^7\)

For the stationarity test, we experiment with an AR(1) model with a constant but no trend: \( \Delta y_t = \alpha + \gamma y_{t-1} + \nu_t \) where \( y_t \) is a time series variable, \( \gamma \) is a coefficient, and \( \nu_t \) represents an error. Our auxiliary analysis shows that all the variables in our regression model are not stationary. However, as in panel A of Table 5, all \( \tau \)-statistics indicate that the difference of a nonstationary process is stationary.

\(^7\)We use the Phillips-Ouliaris cointegration test because the distribution of the Phillips-Ouliaris statistic is asymptotically same as that of Engle-Granger test statistic.
Table 3. Volatility transmission.

|        | Coefficient | s.e  | t-statistic |
|--------|-------------|------|-------------|
| $\epsilon_{11}$ | 0.000 | 0.001 | 0.45 |
| $\delta_{11}$ | -0.566 | 0.247 | -2.3** |
| $\delta_{21}$ | -0.089 | 0.045 | -1.99* |
| $\sigma_{11}$ | 0.297 | 0.089 | 3.34*** |
| $g_{11}$ | -0.122 | 0.165 | -0.74 |
| $g_{21}$ | 0.147 | 0.057 | 2.59** |
| $g_{31}$ | -0.086 | 0.021 | -4.16*** |

This table reports the results of volatility transmission from COVID volatility (i.e. volatilities of the daily growth rate of the number of death and recovered cases due to the COVID pandemic in U.S.) to market return volatility during the sample period. $\epsilon_{11}$, $\delta_{11}$ and $\delta_{21}$ represent ARCH effect for past shocks from the US stock market and COVID-19 spread in the US (i.e., the growth rates in the number of death and recovered). $g_{11}$, $g_{21}$ and $g_{31}$ are GARCH parameters for the response of volatility in the US market to the past volatility of S&P500 and the growth rates in the number of death and recovered.

*** p < 0.01, ** p < 0.05, * p < 0.1.

Figure 5. CRSP Value Weighted Index Returns, Systemic Factor, and Fear Sentiment Factors.
Table 4. Regressions of aggregate risk on principal factors and COVID-19 information.

| Variables       | (1) All Sample | (2) Pre-COVID-19 | (3) COVID-19 |
|-----------------|----------------|-----------------|--------------|
| Dep Var: Risk   | Dep Var: Risk  | Dep Var: Risk   |              |
| SR   | 0.085***        | 0.032***        | 0.078***     |
|      | (0.003)         | (0.008)         | (0.006)      |
| FS   | 0.131***        | 0.003           | 0.138***     |
|      | (0.006)         | (0.005)         | (0.015)      |
| dDeath | 3.722*          | 0.000           | 2.426*       |
|      | (2.259)         | (0.00)          | (1.336)      |
| dRecovered | -0.950**        | -0.473***       | -1.866*      |
|      | (0.529)         | (0.100)         | (1.104)      |
| Constant     | 1.503***        | 1.352***        | 1.565***     |
|      | (0.011)         | (0.025)         | (0.065)      |
| Observations | 83             | 35              | 48           |
| Adj. R²      | 0.966           | 0.754           | 0.938        |

This table summarizes the results of the linear regression model. Column (1), (2) and (3) report the estimates of the linear model over the full sample period (Jan 02 to 30 April 2020), the Pre-COVID-19 period (Jan 02 to 23 February 2020), and the COVID-19 period (Feb 24 to 30 April 2020), respectively. Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5. Unit root and cointegration test.

| Variables       | r-statistics |
|-----------------|--------------|
| Panel A: Unit Root Test |
| ΔRisk   | -0.507***     |
| ΔPC₁   | -6.596***     |
| ΔPC₂   | -13.833***    |
| ΔDeath | -8.703***     |
| ΔRecovered | -8.999***     |
| Panel B: Cointegration Test |
| Engle-Granger statistic | -3.130*** |
| Phillips-Ouliaris statistic | -3.937*** |

This table reports test results for unit root and cointegration. Panel A exhibits a unit root test result for stationary for each series using the Phillips-Perron statistic. Panel B presents test results for cointegration with the Engle-Granger test statistic and the Phillips-Ouliaris test statistic. *** p < 0.01, ** p < 0.05, * p < 0.1. In all regressions sector fixed effects are included.

Next, we test for stationarity in the residual error of equation (9). In order to correct autocorrelation, we run the augmented Dicky Fuller regression with one lagged term: Δ̂zₜ = 0 + Δ̂zₜ₋₁ + vₜ. All the r-statistics in Panel B reject the null hypothesis that the residuals are nonstationary and thus series are not cointegrated. Thus, we conclude that our risk variable is cointegrated with our control variables.

**Panel regression results**

Table 6 reports estimates of equation (10). In all estimates, we include sector-fixed effects and cluster standard errors on sectors to account for possible serial correlation within sectors. For completeness, we report estimates of the two principle factors and the COVID-19 indicators separately and together. We find both SR and FS coefficients are precisely estimated and positively affect the standard deviation of the US stock market returns in all estimates. We interpret these results as evidence showing the systemic risk factor and the fear sentiment factor can be proxies for the risk of the US stock market. More precisely, one unit increase in SR (FS) results in about 0.09 (0.12) increase in the standard deviation of the US stock market returns.

Further, Table 6 shows that the COVID-19 indicators play a role in the increase in the stock market volatility. More specifically, the US stock market risk is significantly and positively related to the growth rate of death while it is negatively but still significantly affected by the growth rate of recovered cases rises. These imply investors interpret a rise in the daily death toll as a negative signal while an increase in the growth rate of recovered cases positively signals to investors. Note the results are in line with the above volatility transmission results. Quantitatively, one standard deviation increase in the death rate leads to 0.001 standard deviation increase in the volatility, and one standard deviation increase in the recovered rate decreases the standard deviation of the volatility by 0.005.

Our estimation of the US stock market risk equation (9) uses all sectors, and this may be particularly inappropriate in the case of finance sectors (i.e., banks, insurance, real estate, finance sector), accommodations (i.e. restaurants, hotels and motels), transportation (especially airline industry) and oil sector because the finance sectors have the largest leverage ratio and the accommodations, transportation and oil sector have the greatest exposure to COVID-19 due to negative shocks to demand. To address this, in
Table 7. Sensitivity to Sample Sectors.

| Variables       | (1)     | (2)     | (3)     | (4)     | (5)     |
|-----------------|---------|---------|---------|---------|---------|
| SR_i            | 0.089***| 0.086***| 0.089***| 0.088***| 0.089***|
| (0.003)         | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| FS_i            | 0.121***| 0.118***| 0.121***| 0.121***| 0.122***|
| (0.006)         | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| dDeath_i        | 0.001*  | 0.001*  | 0.001*  | 0.001*  | 0.001*  |
| (0.000)         | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| dRecovered_i    | −0.005***| −0.005***| −0.005***| −0.005***| −0.005***|
| (0.000)         | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant        | 1.510***| 1.516***| 1.518***| 1.505***| 1.527***|
| (0.000)         | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations    | 4,067   | 3,735   | 3,901   | 3,984   | 3,901   |
| Adj. R²         | 0.901   | 0.902   | 0.899   | 0.902   | 0.899   |
| Number of sector | 49      | 45      | 47      | 48      | 47      |
| Sector Excluded | None    | Finance | Accommodations | Transportation | Oil | Food Beverage |

Clustered robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1. In all regressions sector fixed effects are included.

Table 7 we experiment with the sample sectors. In column (1) we repeat the last column of Table 6 for a comparison purpose. In columns (2) – (4), we experiment with excluding the finance sectors and the sectors that have the greatest exposure to COVID-19. In column (5), we exclude food and beverage sector since these two sectors would be least impacted by COVID-19 because of their necessity. As shown in Table 7, we find the invariance of the results to the sectors. These results imply our results in Table 6 are robust to the sample sectors and more importantly indicate the COVID-19 shock affects the entire US stock market in a similar fashion.

In addition, we re-estimate equation (10) by dropping one sector at a time. As reported in the appendix (Table A2), we find the results do not quantitatively and qualitatively change, implying that our panel regression results are not driven by a specific single sector.

V. Conclusion

This paper systematically explains the risk transmission of COVID-19 to the US stock market. Specifically, we examine how much daily COVID-19 news, proxied by daily death rate and recovered rate of COVID-19 in US, contribute to the daily volatility in the US stock market. Using the BEKK-MGARCH (1,1) model, we find the US stock market return volatility depends on both its own past shocks and past COVID-19 shocks. In addition, we provide evidence showing the volatility spillover effect between the US stock market and the COVID-19 news. More specifically, we find that the volatility in the stock market is significantly and positively influenced by the volatility of the COVID-19 mortality rate (i.e., bad news) while negatively associated with the volatility of the COVID-19 recovered rate (i.e., good news). Moreover, we find there is an asymmetric volatility impact of COVID-19 on the US stock market: the bad news affects the current US stock market volatility much more than the good news.

To examine the link between the COVID-19 the US stock market risk, we conduct fixed effect panel regressions, controlling for the systemic risk factor and the fear sentiment factor extracted from the PCA method. We find that the US stock market risk rises as the growth rate of death rises, whereas it falls as the growth rate of recovered cases rises. These empirical findings are in line with the volatility spillover effects, and more importantly indicate that investors interpret a rise in the daily death toll as a negative signal while an increase in the growth rate of the recovered rate positively signals to investors. Further, we find both the systemic risk factor and the fear risk factor are statistically significantly explains the variation of risk of the US stock market returns. Finally, we confirm that our findings are robust to sample industries.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1. Description of Economic Risk Indicators.

| Economic Risk Indicators               | Description                                                                                                                                 |
|----------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| S&P500 Index                           | The observations for the S&P 500 represent the daily index value at market close. The market typically closes at 4 PM ET, except for holidays when it sometimes closes early. |
| VIX                                     | VIX measures market expectation of near term volatility conveyed by stock index option prices.                                               |
| Economic Policy Uncertainty Index       | The daily news-based Economic Policy Uncertainty Index is based on newspapers in the United States. For additional details, including an analysis of the performance of the model, see Baker, Bloom, and Davis (2016) |
| Overnight LIBOR                         | It is the loan reference rate for short term interest rates. Overnight LIBOR is the average interest rate at which leading banks borrow a sizable amount from other banks in the London market |
| TED Spread                             | The TED spread is the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. The series is lagged by one week because the LIBOR series is lagged by one week due to an agreement with the source. |
| Term Spread (30 YR T-bond – 3 Month T-bill) | The TED spread is calculated as the spread between a 10-year treasury bond and a 3-month treasury bill. The widespread indicates economic growth condition, whereas the negative spread indicates recession. |
| Effective Federal Fund Rate             | The interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight. |
| West Texas Intermediate Oil Prices     | The effective yield of the intercontinental exchange (ICE) Bank of America US Corporate C Index (a subset of the ICE Bank of America US High Yield Master II Index) tracks the performance of US dollar denominated low investment grade rated corporate debt publicly issued in the US domestic market. This subset includes all securities with a given investment grade rating CCC or below. |
| Bank of America CCC&Lower Bond Yield Index | The effective yield of the ICE Bank of America US High Yield Index tracks the performance of US dollar-denominated below investment grade rated corporate debt publicly issued in the US domestic market. All securities included in the index must have a below investment grade rating (based on an average of Moody’s, S&P, and Fitch) and an investment grade rated country of risk (based on an average of Moody’s, S&P, and Fitch foreign currency long term sovereign debt ratings). |
| Traded Weighted Dollar Index            | Trade share weighted US dollar index (Jan 2006 = 100).                                                                                     |

Variable description is from the Federal Reserve Bank of St. Louis website.

Table A2. Sensitivity to Sample Sectors

| Sector Excluded | $S_t$  | $F_S$  | $dDeath_t$ | $dRecovered_t$ | Constant | Observations | Adj. $R^2$ |
|-----------------|--------|--------|------------|----------------|----------|--------------|------------|
| None            | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.510*** | 4,067        | 0.901      |
| Agric           | 0.089*** | 0.122*** | 0.001      | −0.005***      | 1.507*** | 3,984        | 0.899      |
| Food            | 0.090*** | 0.123*** | 0.001*     | −0.005***      | 1.519*** | 3,984        | 0.902      |
| Soda            | 0.090*** | 0.122*** | 0.001      | −0.005***      | 1.517*** | 3,984        | 0.901      |
| Beer            | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.517*** | 3,984        | 0.899      |
| Smoke           | 0.090*** | 0.123*** | 0.001*     | −0.005***      | 1.509*** | 3,984        | 0.902      |
| Toys            | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.501*** | 3,984        | 0.901      |
| Fun             | 0.090*** | 0.123*** | 0.001*     | −0.005***      | 1.503*** | 3,984        | 0.902      |
| Books           | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.514*** | 3,984        | 0.900      |
| Hshld           | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.518*** | 3,984        | 0.900      |
| Chths           | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.510*** | 3,984        | 0.900      |
| Hth             | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.511*** | 3,984        | 0.899      |
| MedEq           | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.514*** | 3,984        | 0.901      |
| Drugs           | 0.090*** | 0.123*** | 0.001*     | −0.005***      | 1.517*** | 3,984        | 0.903      |
| Chems           | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.511*** | 3,984        | 0.899      |
| Rubbr           | 0.090*** | 0.122*** | 0.001*     | −0.005***      | 1.517*** | 3,984        | 0.901      |
| Txl              | 0.089*** | 0.119*** | 0.001*     | −0.005***      | 1.496*** | 3,984        | 0.901      |
| BdMt            | 0.089*** | 0.120*** | 0.001*     | −0.005***      | 1.510*** | 3,984        | 0.900      |
| Cnstr           | 0.088*** | 0.120*** | 0.001*     | −0.005***      | 1.508*** | 3,984        | 0.901      |
| Steel           | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.502*** | 3,984        | 0.899      |
| FabPr           | 0.088*** | 0.120*** | 0.001*     | −0.005***      | 1.500*** | 3,984        | 0.902      |
| Mach            | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.508*** | 3,984        | 0.900      |
| EqEq            | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.503*** | 3,984        | 0.900      |
| Autos           | 0.089*** | 0.121*** | 0.000      | −0.005***      | 1.505*** | 3,984        | 0.900      |
| Aero            | 0.088*** | 0.119*** | 0.001*     | −0.005***      | 1.506*** | 3,984        | 0.905      |
| Ships           | 0.090*** | 0.122*** | 0.001*     | −0.005***      | 1.507*** | 3,984        | 0.901      |
| Guns            | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.511*** | 3,984        | 0.899      |
| Gold            | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.504*** | 3,984        | 0.901      |
| Mines           | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.504*** | 3,984        | 0.899      |
| Coal            | 0.089*** | 0.121*** | 0.001*     | −0.005***      | 1.492*** | 3,984        | 0.900      |
| Oil             | 0.088*** | 0.121*** | 0.001*     | −0.005***      | 1.505*** | 3,984        | 0.902      |
| Util            | 0.088*** | 0.120*** | 0.001*     | −0.005***      | 1.519*** | 3,984        | 0.901      |
| Telcm           | 0.089*** | 0.122*** | 0.001*     | −0.005***      | 1.519*** | 3,984        | 0.901      |

(Continued)
Table A2. (Continued).

| Sector Excluded | $SR_t$ | $FS_t$ | $dDeath_t$ | $dRecovered_t$ | Constant | Observations | Adj. R$^2$ |
|-----------------|-------|-------|------------|----------------|----------|--------------|------------|
| PerSv           | 0.089*** | 0.121*** | 0.001* | −0.005*** | 1.516*** | 3,984 | 0.899 |
| BusSv           | 0.089*** | 0.121*** | 0.001* | −0.005*** | 1.513*** | 3,984 | 0.899 |
| Hardw           | 0.089*** | 0.122*** | 0.001* | −0.005*** | 1.508*** | 3,984 | 0.901 |
| Softw           | 0.089*** | 0.122*** | 0.001* | −0.005*** | 1.511*** | 3,984 | 0.901 |
| Chips           | 0.089*** | 0.122*** | 0.001* | −0.005*** | 1.508*** | 3,984 | 0.900 |
| LabEq           | 0.090*** | 0.122*** | 0.001* | −0.005*** | 1.512*** | 3,984 | 0.902 |
| Paper           | 0.090*** | 0.122*** | 0.001* | −0.005*** | 1.515*** | 3,984 | 0.902 |
| Boxes           | 0.089*** | 0.122*** | 0.001* | −0.005*** | 1.513*** | 3,984 | 0.900 |
| Trans           | 0.089*** | 0.122*** | 0.001* | −0.005*** | 1.512*** | 3,984 | 0.900 |
| Whisl           | 0.089*** | 0.121*** | 0.001* | −0.005*** | 1.516*** | 3,984 | 0.899 |
| Rail            | 0.090*** | 0.123*** | 0.001* | −0.005*** | 1.515*** | 3,984 | 0.904 |
| Meals           | 0.089*** | 0.120*** | 0.001* | −0.005*** | 1.517*** | 3,984 | 0.900 |
| Banks           | 0.088*** | 0.121*** | 0.001* | −0.005*** | 1.511*** | 3,984 | 0.901 |
| Insur           | 0.088*** | 0.121*** | 0.001  | −0.005*** | 1.515*** | 3,984 | 0.900 |
| REst            | 0.088*** | 0.120*** | 0.001* | −0.005*** | 1.509*** | 3,984 | 0.902 |
| Fin             | 0.089*** | 0.121*** | 0.001* | −0.005*** | 1.512*** | 3,984 | 0.899 |
| Other           | 0.089*** | 0.122*** | 0.001** | −0.005*** | 1.516*** | 3,984 | 0.900 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In all regressions sector-fixed effects are included.