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The impact of COVID-19 pandemic on the volatility connectedness network of global stock market

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Abstract

This paper investigates how the COVID-19 pandemic affects the connectedness network of stock market volatility in 19 economies around the world. Our method builds on the Diebold-Yilmaz volatility network model to construct the volatility spillover index, and uses lag sparse group LASSO to accommodate the high-dimensional system. We find that the outbreak of the COVID-19 pandemic strengthens the overall volatility connectedness, and the global connectedness level remains high throughout 2020. In particular, connections across different continents have become stronger during this period. However, China is shown to be disconnected from the global volatility connectedness network until late November 2020. We find evidence that China is not the main source of volatility spillover during the COVID-19 pandemic.

1. Introduction

The global stock market fluctuated wildly as the Novel Coronavirus (COVID-19) pandemic broke out from China and spread to the rest of the world in early 2020. The volatility caused by this shock is comparable to that of the “Great Depression” in 1929 and the “Black Monday” of 1987, and even surpasses the volatility of the stock market during the 2008 global financial crisis (Baker et al., 2020). At the same time, various macroeconomic uncertainty indicators surged in reaction to the COVID-19 pandemic (Altig et al., 2020). This health crisis has created a huge challenge to the continued development of the global economy.

How the COVID-19 pandemic affects the economy has attracted an increasing amount of interest in the academic literature. Related empirical studies, which assess COVID-19’s impact on output, company value and portfolio pricing (see, for example, Caggiano et al., 2020; Ramelli and Wagner, 2020; Sun et al., 2021), has begun to appear. In the financial market literature, O’Hara and Zhou (2021) examine the impact of COVID-19 on corporate bonds and shows that COVID-19 has caused higher uncertainty and increased corporate credit risk. Corbet et al. (2020) investigate the relationship between cryptocurrency and media sentiment during COVID-19 and shows that cryptocurrency has a hedging property similar to precious metals during the crisis. There have also been studies investigating how COVID-19 affects the stock market, while most of the debates focus on stock market returns. For example, Alfaro et al. (2020) study the relationship between the number of people infected with COVID-19 and stock market returns during COVID-19, and found that the unexpected increase in the number of infections will reduce the total market value of U.S. stocks by 4%–11%. There are also

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discussions on the risk transmission between stock markets in various countries around the world. Contessi and De Pace (2021) examine the spread of risks among 18 stock markets and found that the instability of the Chinese stock market during COVID-19 was transmitted to the global market.

This paper takes a different angle and examines how COVID-19 pandemic affects the volatility connectedness network of the global stock market. To the best of our knowledge, this is the first detailed analysis on how the strength of connectedness among different stock markets evolves in 2020, and whether the development of COVID-19 pandemic plays a role in these changes. Specifically, we use high-frequency intra-day data of stock market indices from 19 economies from January 4, 2016 to December 1, 2020, with an emphasis on the Asia-Pacific region. Realized volatilities calculated from intra-day data are used to estimate a classic Diebold-Yilmaz volatility network model (DY-framework hereafter) pioneered by Diebold and Yilmaz (2009, 2012, 2014) in order to detect the transmission of risks. The DY-framework constructs a vector autoregressive (VAR) model for the vector of volatilities, and use generalized variance decomposition to measure the strength of transmission. In order to address the high dimensionality, we use the lag sparse group LASSO proposed by Simon et al. (2013) to estimate the VAR system.

We provide in-depth empirical investigations of the transmission of instability among the 19 stock markets during the COVID-19 pandemic. First, comparing the COVID-19 period from 2020 to the pre-COVID subsample, we find that the aggregate connectedness index among the 19 stock markets began to rise sharply in late February 2020, reached its historical peak on March 13, 2020, and then remained at a high level until December 2020. Second, the European, American, and Australian stock markets are more closely connected during COVID-19 than other markets, while China is disconnected from the global stock market volatility spillover network. Third, in contrast to the conclusion drawn by Contessi and De Pace (2021) that during the worst time of the pandemic, instability of stock market spread from China to European countries, we find evidence that global stock market volatility is not transmitted from the Chinese market.

The remainder of the paper proceeds as follows. Section 2 outlines the empirical methodology based on the generalised variance decomposition of a high-dimensional VAR model. Section 3 describes the data used in the analyses. Section 4 presents the empirical analysis using the full sample from 2016 to 2020, and Section 5 zooms in onto the subsample since 2020 to investigate the influence of the COVID-19 pandemic on the volatility spillover globally. Section 6 concludes the paper.

2. Methodology

This section introduces different measures of volatility spillover index based on generalized variance decomposition. The modelling framework follows Diebold and Yilmaz (2009, 2012, 2014). Section 2.1 outlines the construction of the volatility spillover indices from a VAR model, and Section 2.2 introduces the LASSO estimation of the VAR model which is more suitable for high-dimensional systems.

2.1. Volatility spillover index

Consider a covariance stationary $N$-dimensional vector autoregressive model with $p$ lags $\text{VAR}(p)$,

$$
y_t = \delta + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \epsilon_t = \delta + \sum_{i=1}^{p} \Gamma_i y_{t-i} + \epsilon_t,
$$

where $y_t$ is an $N$-dimensional vector, which represents the realized volatility (RV) of $N$ stock markets, $\delta$ is an $N$-dimensional vector of intercept term, $\Gamma_1, \ldots, \Gamma_p$ are $N \times N$ matrices of coefficients. The $N$-dimensional error vector $\epsilon_t \sim \text{(0, } \Sigma \text{)}$ is an independent and identically distributed (i.i.d.) process. The variance-covariance matrix $\Sigma$ is not necessarily a diagonal matrix, in other words, the shocks in $\epsilon_t$ are allowed to be contemporaneously correlated. We transform the $\text{VAR}(p)$ in (1) into an infinite-lag vector moving average model $\text{VMA}(\infty)$, which is expressed as $y_t = \alpha + \sum_{i=0}^{\infty} \Psi_i \epsilon_{t-i}$, where $\Psi_0 \equiv I_N$, $\Psi_i$ are $N \times N$ matrices such that $\Psi_i = \sum_{j=1}^{i} \Gamma_i \Gamma_j$ for $i = 1, 2, \ldots$, and $\alpha \equiv \Gamma(L)^{-1} \delta$, where $\Gamma(L)^{-1} \equiv \Psi(L) = \Psi_0 + \Psi_1 L + \Psi_2 L^2 + \cdots$, and $L$ represents the lag operator.

Koop et al. (1996) and Pesaran and Shin (1998) proposed a generalized variance decomposition (GVD) to evaluate the influence of each disturbance in $\epsilon_t$ on each of the dependent variable in $y_t$. Compared with the variance decomposition based on Cholesky factorization, GVD has the advantage that it is invariant to the ordering of variables in $y_t$. Let $\theta^i_j$ denote the generalized $H$-step-ahead forecast error variance decomposition from shock $j$ to variable $i$, then we have

$$
\theta^i_j = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_{h} \Sigma_h e_{h})^2}{\sum_{h=0}^{H-1} (e_{h} \Sigma_h e_{h})},
$$

where $\Sigma$ is the covariance matrix of $\epsilon_t$, $\sigma_{ij}$ is the standard deviation of the $i$-th disturbance term, and $e_t$ denotes the selection vector, whose $l$-th element is 1 and all other elements are 0. $\theta^i_j$ represents the share of $H$-step-ahead forecast error variance of forecasting $y_t$ due
to the shock to \( y_j \) for \( i, j = 1, 2, \ldots, N \).

Since the elements in \( \epsilon_i \) are not necessarily orthogonal shocks, for a given forecast error variance decomposition of variable \( y_i \), the sum of the shares in (2) across all shocks \( j \), is not necessarily equal to 1. In other words, \( \sum_{j=1}^{N} \theta_{ij}^H \neq 1 \), for \( i = 1, 2, \ldots, N \). Therefore we standardize each row, i.e., each \( i \), of the generalized \( H \)-step-ahead forecast error variance decomposition matrix, so that the shares in each row sum up to 1. Let \( S_{i\to j}^H \) denote pairwise volatility spillover from market \( j \) to market \( i \), defined as the standardized share \( \bar{\theta}_{ij}^H \),

\[
S_{i\to j}^H = \frac{\bar{\theta}_{ij}^H}{\left( \sum_{j=1}^{N} \bar{\theta}_{ij}^H \right)}
\]

We can construct a few indices on more aggregate levels using the directional volatility spillover index (3), which are introduced below.\(^2\)

(i) “from volatility spillover index (FIX)”, denoted by \( S_{i\to j}^H \), represents the volatility spillover from all other markets \( j, j \neq i \), to market \( i \),

\[
S_{i\to j}^H = \sum_{j=1, j \neq i}^{N} \bar{\theta}_{ij}^H.
\]

(ii) “to volatility spillover index (TIX)”, denoted by \( S_{i\to j}^H \), represents the volatility spillover from market \( i \) to all other markets \( j, j \neq i \),

\[
S_{i\to j}^H = \sum_{j=1, j \neq i}^{N} \bar{\theta}_{ij}^H.
\]

(iii) “net volatility spillover index (NIX)”, denoted by \( S_{i\to j}^H \), represents the net volatility spillover from market \( i \) to all other markets \( j, j \neq i \), which subtracts FIX from TIX for market \( i \),

\[
S_{i\to j}^H = S_{i\to j}^H - S_{i\to j}^H.
\]

(iv) “aggregate volatility spillover index (AIX)”, denoted by \( S^H \), measures the system-wide volatility spillover index. It is calculated as the sum of all market volatility spillover indices in the entire system for \( i \neq j \), rescaled by \( N \),

\[
S^H = \frac{1}{N} \sum_{i,j=1, j \neq i}^{N} \bar{\theta}_{ij}^H.
\]

Existing literature has widely documented the cluster effect that financial institutions in the same sector, industry, and region are more closely connected (see, for example, Kenett et al., 2010; Wang et al., 2017). We use the same reasoning to examine the volatility spillover for markets across different geographical areas, or within the same area. Following Wang et al. (2017), we define the area volatility spillover index. Suppose that the \( N \) markets belong to \( M \) areas, and \( A_{m\to n}^H \) denotes a measure of volatility spillover from area \( n \) to area \( m, m, n = 1, \ldots, M \). Then the index \( A_{m\to n}^H \) can be expressed as follows:

\[
A_{m\to n}^H = \sum_{i=1}^{N_m} \sum_{j=1}^{N_n} S_{i\to j}^H = \sum_{i=1}^{N_m} \sum_{j=1}^{N_n} \bar{\theta}_{ij}^H,
\]

where \( N_m \) and \( N_n \) denote the number of markets in areas \( m \) and \( n \), respectively. We further define within-area volatility spillover index (\( W^H \)) and cross-area volatility spillover index (\( C^H \)), which can be expressed as:

\[
W^H = \frac{1}{N} \sum_{m=1}^{M} A_{m\to m}^H, \quad C^H = \frac{1}{N} \sum_{m \neq n} A_{m\to n}^H.
\]

It is easy to show that the relationship \( W^H + C^H = S^H \) holds. That is to say, AIX can be decomposed as the sum of the cross and within-area indices.

\(^2\) Appendix A.2 gives more details on the how each of the indices above are calculated.
2.2. Estimation of high-dimensional VARs

The first step to calculate the volatility spillover index is to estimate a VAR model (1) using the volatility measure for $N$ markets. The number of parameters in the VAR model will increase dramatically as the number of markets under consideration increases, which may render the estimation infeasible when the sample size is small. For example, if the VAR system includes $N = 20$ markets and $p = 3$ lags, there are $20^2 \times 3 + 20 = 1220$ parameters to be estimated. Even with daily observations, this requires a minimum sample of 5-year’s data. To address this “curse of dimensionality” issue, following Demirer et al. (2018), we use the Least Absolute Shrinkage and Selection Operator (LASSO) to reduce the number of parameters to be estimated in the VAR model.

The ordinary least squares estimator for the VAR($p$) model in Equation (1) is obtained by solving the minimization problem

$$\min_{\Gamma} \| y_t - \delta - \sum_{i=1}^{p} \Gamma_{i} y_{t-i} \|_2^2,$$  \hfill (6)

where $\Gamma$ denotes the entire set of parameters $\{ \delta, \Gamma_1, \ldots, \Gamma_p \}$, $\| X \|_2 = \sqrt{\sum X_i^2}$ is the $\ell_2$ norm of a vector $X$, and $\| X \|_2^2$ denotes the square of $\| X \|_2$. We impose constraints on Equation (6) using a group penalty function on the coefficients $\Gamma$,

$$\min_{\Gamma} \| y_t - \delta - \sum_{i=1}^{p} \Gamma_{i} y_{t-i} \|_2^2 + \lambda P(\Gamma),$$  \hfill (7)

where $\lambda \geq 0$ denotes a tuning parameter that controls the strength of the penalty, typically estimated by cross-validation. Considering the serial dependence structure of time series data (Bergmeir et al., 2018), rather than estimate $\lambda$ by k-fold cross-validation, we follow Nicholson et al. (2017) and estimate $\lambda$ in a rolling-window manner.

The basic LASSO estimator proposed by Tibshirani (1996) uses $\ell_1$ penalty, $P(\Gamma) = \| \Gamma \|_1 = \| \delta \| + \sum_{i=1}^{p} | \Gamma_i |$, where $\| \cdot \|_1$ denotes the $\ell_1$ norm. Yuan and Lin (2006) proposed a group LASSO with the penalty function $P(\Gamma) = N(\| \delta \|_2 + \sum_{i=1}^{p} | \Gamma_i |_2 )$. The basic LASSO shrinks any parameter that is less than a certain threshold value to 0, while the group LASSO shrinks certain groups of parameters to 0. We use the lag sparse group LASSO developed by Simon et al. (2013), which has the penalty function of the form,

$$P(\Gamma) = (1 - \alpha) \left[ N \left( \| \delta \|_2 + \sum_{i=1}^{p} | \Gamma_i |_2 \right) \right] + \alpha \| \Gamma \|_1,$$  \hfill (8)

where $0 < \alpha < 1$ is the parameter that controls the weights of the two penalties. When $\alpha = 1$, we obtain penalty function of basic LASSO, which is equivalent to putting all parameters into one group and sparse the parameters in the group equally. That is to say, the basic LASSO allows for “within-group” sparsity. When $\alpha = 0$, we get penalty function of the group LASSO, which divides the parameter space into different groups and allows the degree of sparsity to differ between groups. Therefore, the lag sparse group LASSO achieves sparsity by considering the effects at both levels. Following Nicholson et al. (2017), we set $\alpha$ according to the relative group number of the two penalties, i.e., $\alpha = 1/(N + 1)$.

By estimating the high-dimensional VAR model using LASSO, we effectively impose zero restrictions on some of the VAR parameters $\Gamma$. However, it does not translate into zero restrictions on coefficients in the VMA($\infty$) representation, $\Psi_l$, $l = 1, 2, \ldots$, or zero

| Market | Code | Market Index | Trading Hour | Continent |
|--------|------|--------------|--------------|-----------|
| Australia | AU | ASX All Ordinaries Index | 10:00AM to 4:00PM | Oceania |
| Brazil | BR | Bovespa Index | 10:00AM to 5:00PM | S.America |
| Canada | CA | S&P/TSX Composite Index | 9:30AM to 4:00PM | N.America |
| China | CN | Shanghai SE Composite Index | 9:30AM to 11:30AM & 1:00PM to 3:00PM | Asia |
| France | FR | CAC 40 Index | 8:00AM to 8:00PM | Europe |
| Germany | DE | DAX Index | 9:00AM to 5:30PM | Europe |
| Hong Kong | HK | Hang Seng Index | 9:30AM to 12:00AM & 1:00PM to 4:00PM | Asia |
| India | IN | S&P BSESENSEX Index | 9:00AM to 11:30AM & 1:30PM to 3:00PM | Asia |
| Indonesia | ID | Jakarta SE Composite Index | 9:15AM to 3:30PM | Asia |
| Japan | JP | Nikkei 225 Index | 9:00AM to 11:30AM & 12:30PM to 3:00PM | Asia |
| Korea | KR | Korea SE KOPSI Index | 9:00AM to 3:30PM | Asia |
| Malaysia | MY | FTSE Bursa Malaysia KLCI | 8:30AM to 3:00PM | Asia |
| Mexico | MX | IPC Index | 9:00AM to 12:30PM & 2:30PM to 4:50PM | N.America |
| Netherlands | NL | Amsterdam Exchange Index | 9:00AM to 5:40PM | Europe |
| Philippines | PH | The PSE Composite Index | 9:30AM to 12:00AM | Asia |
| Singapore | SG | Strait Times Index | 9:00AM to 12:00AM & 1:00PM to 5:00PM | Asia |
| Thailand | TH | SET Index | 10:00AM to 12:30PM & 2:30PM to 4:30PM | Asia |
| UK | UK | FTSE 100 Index | 8:00AM to 4:30PM | Europe |
| U.S. | US | S&P 500 Index | 9:30AM to 4:00PM | N.America |

Note: This table reports the country names, country codes, their respective market indices and the trading hour, and the continents where the markets are located. Trading hour is in local time.
restrictions on the spillover indices.

3. Data

We download tick-by-tick data of 19 major stock market indices around the globe from Refinitiv DataScope Select provided by Thomson Reuters Tick History. The sample covers the period from January 4, 2016, to December 1, 2020, with a total of 1219 common trading days. The list of markets and indices are presented in Table 1. We place particular emphasis on the Asian stock markets by incorporating 11 major indices in the Asia-Pacific region. Several other markets are included based on their systematic importance in the world economy, such as US, UK, France and Germany. As intra-day level analysis is infeasible because of the differences in the trading hours of these stock markets, we turn our attention to daily realized volatility (RV), which is calculated by sampling transaction price series at 5-minute frequency. Therefore, we calculate daily realized volatility (RV) using 5-minute price observations. Liu et al. (2015) have shown that the choice of 5-minute sampling frequency can largely circumvent the impact of market microstructure noise.

For each market index, let \( p_{i,t} \) denote its price at the end of the \( i \)-th 5-minute interval on day \( t \), and the realized volatility is calculated as

\[
RV_t = \sum_{i=1}^{n_t} (\log p_{i,t} - \log p_{i-1,t})^2, \quad i = 1, 2, ..., n_t, \quad t = 1, 2, ..., 1219,
\]

where \( n_t \) represents the number of 5-minute intervals on each trading day for a given market. Fig. 1 depicts the RV for five major stock markets: China, U.S., Japan, U.K. and Germany. Each of these markets has experienced abrupt increase in volatility since 2020. It is worth noting that the highest volatility occurred in the Chinese stock market occurred earlier than the other markets, in late January and early February. On the other hand, other markets have stayed relatively calm until March 2020.

Table 2 reports the descriptive statistics of the RV for the 19 stock markets before COVID-19 (January 4, 2016 to December 31, 2019) and during COVID-19 (January 1, 2020 to December 1, 2020). Both the mean and median of the RV have increased for all market indices since the COVID-19 pandemic, which shows that the uncertainty in the stock market has increased globally. The increased variance of RV indicates that the uncertainty about the volatility of the stock market have also increased during COVID-19. As expected, the RV is always positively skewed for any index both before and during COVID-19. It is worth noting that the skewness and the kurtosis in most markets have become smaller during COVID-19. One possible explanation is that there are more days with high values of volatility during COVID-19, increasing the mean of RV, and hence the skewness and the kurtosis have become smaller.

4. Full-sample analysis

We estimate the VAR model using the lag sparse group LASSO outlined in Section 2.2 with a rolling window of 200 days. The model parameters are chosen according to Diebold and Yilmaz (2012). The lag length of the VAR is \( p = 3 \), and forecast horizon for GVD is set as \( H = 10 \). The first 200-day estimation window ends on October 24, 2016, and hence the first set of volatility spillover indices are estimated for this date. We also explore estimation window length of 150, 200 and 250 days, VAR lag order of 1, \ldots, 6, and predictive horizon of 10, 15 and 20 days for robustness checks. The results are qualitatively similar, and are summarized in Appendix A.1.

4.1. Aggregate volatility spillover index

We first examine the evolution of the “aggregate volatility spillover index” during the full sample period. Fig. 2 depicts the
Table 2
Summary statistics of RV, before and during COVID-19.

|         | Mean Before | Mean During | Median Before | Median During | Std. Dev. Before | Std. Dev. During | Skewness Before | Skewness During | Kurtosis Before | Kurtosis During |
|---------|-------------|-------------|---------------|---------------|------------------|------------------|-----------------|----------------|----------------|----------------|
| AU      | 0.27        | 1.84        | 0.18          | 0.56          | 0.38             | 4.42             | 9.71            | 5.32           | 143.76         | 36.53          |
| BR      | 1.43        | 6.04        | 0.96          | 1.68          | 3.03             | 18.11            | 21.09           | 6.97           | 560.13         | 57.82          |
| CA      | 0.22        | 1.34        | 0.14          | 0.41          | 0.35             | 2.99             | 10.36           | 4.19           | 170.95         | 22.69          |
| CN      | 1.02        | 1.65        | 0.51          | 0.68          | 1.80             | 5.91             | 6.29            | 12.57          | 60.12          | 174.87         |
| DE      | 0.60        | 2.20        | 0.44          | 1.03          | 0.63             | 4.00             | 4.94            | 4.49           | 46.19          | 26.52          |
| FR      | 0.55        | 2.26        | 0.38          | 1.11          | 0.71             | 4.12             | 9.23            | 4.36           | 142.38         | 24.33          |
| HK      | 0.53        | 1.04        | 0.41          | 0.71          | 0.53             | 1.86             | 8.99            | 10.60          | 138.90         | 135.75         |
| ID      | 0.25        | 0.91        | 0.17          | 0.33          | 0.23             | 2.15             | 4.40            | 6.31           | 34.21          | 53.05          |
| IN      | 0.47        | 2.43        | 0.34          | 0.83          | 0.57             | 7.20             | 8.20            | 8.95           | 99.53          | 102.63         |
| JP      | 0.61        | 1.20        | 0.28          | 0.39          | 1.65             | 3.05             | 10.11           | 7.22           | 124.91         | 70.11          |
| KR      | 0.55        | 2.19        | 0.29          | 1.18          | 0.71             | 3.58             | 4.51            | 5.26           | 33.53          | 38.41          |
| MX      | 0.44        | 1.04        | 0.34          | 0.61          | 0.45             | 1.57             | 9.47            | 5.00           | 161.48         | 34.48          |
| MY      | 0.18        | 0.66        | 0.13          | 0.40          | 0.23             | 0.87             | 14.46           | 4.61           | 316.25         | 30.96          |
| NL      | 0.47        | 1.97        | 0.30          | 0.79          | 0.73             | 4.10             | 12.57           | 4.32           | 250.11         | 22.50          |
| PH      | 0.42        | 2.09        | 0.31          | 0.59          | 0.42             | 12.23            | 4.68            | 13.97          | 42.41          | 204.74         |
| SG      | 0.56        | 1.75        | 0.35          | 0.70          | 0.70             | 3.69             | 6.64            | 6.45           | 78.50          | 59.84          |
| TH      | 0.33        | 1.52        | 0.25          | 0.61          | 0.76             | 6.83             | 25.55           | 13.93          | 732.90         | 204.43         |
| UK      | 0.51        | 1.76        | 0.31          | 0.72          | 2.09             | 3.42             | 27.83           | 4.36           | 835.94         | 23.50          |
| US      | 0.38        | 2.29        | 0.17          | 0.67          | 0.62             | 5.20             | 4.68            | 4.43           | 33.49          | 25.27          |

Note: This table reports the mean, median, standard deviation, skewness and kurtosis of the realized volatility of the 16 stock market indices in our sample, before and during COVID-19 respectively. Mean, median and standard deviation are rescaled by 10^4. ‘Before’ and ‘During’ represent sub-sample periods of January 4, 2016 to December 31, 2019 and January 1, 2020 to December 1, 2020, respectively.

“aggregate volatility spillover index” (AIX) for all the 19 stock market indices (right-axis) together with the CBOE Volatility Index (VIX) (left-axis) from October 24, 2016 to December 1, 2020. The black vertical line marks January 1, 2020 when COVID-19 was first reported.

2017 is the year with the smallest volatility in most of stock markets in our sample, and the VIX remains at a low level throughout the year. On the contrary, the AIX has experienced a large drop in late August, 2017. A few events occurred in August 2017 have impacted certain local areas, for example, the dispute between the U.S. and North Korea escalated in August 2017, which affected the East Asian (especially Japan and South Korea) and U.S. stock markets, and the terrorist attack in Barcelona, Spain occurred on August 17, 2017, which affected the European stock markets. These changes in volatility in a small subset of stock markets led to a decrease in the global network, and hence a substantial drop in the AIX on the global level. There is a large increase in AIX in early February, 2018. The U.S. stock market experienced a “Black Monday” on February 5, 2018, which was one of the largest declines in recent years. The plunge in the U.S. market spread to the world. The Japanese Nikkei 225 Index plunged 4% in early trading on the next trading day, while the Australian ASX 200 index fell by 3%. The Shanghai Composite Index opened down 1.99%, the UK FTSE 100 Index opened 2% lower, and the French CAC40 Index opened 3.2% lower. This event caused heightened volatility in many stock markets. As the global stock markets were more closely connected, the aggregate spillover index rose.

On January 1, 2020, COVID-19 was reported for the first time. On January 23, Wuhan started a lockdown, as a response to the outbreak of COVID-19 in China. The COVID-19 outbreak in Europe began in northern Italy in late February. At the same time, the AIX started to rise sharply, reaching its peak on March 13. The outbreak of COVID-19 in Europe and America caused a violent shock to global stock markets, and the connections among these stock markets increased dramatically. As a result, the spillover index rose sharply, surpassing its highest value in early 2017, and maintained at elevated level of over 80 throughout 2020.

The VIX on the right-axis measures the volatility expectations of the U.S. stock market based on S&P 500 index options. It is evident that VIX and the “aggregate volatility spillover index” (AIX) have many commonalities. First, they both rose sharply when the U.S. stock market triggered a global stock market crash in February 2018. Second, the outbreak of COVID-19 in Europe and America made both of them reach their respective historical highs. However, there are also visible differences between the two indices as the AIX measures the strength of connectedness among the stock market volatility for the 19 markets in the model, while the VIX is an indicator of the implied volatility of US stock market alone. Even when the level of volatility drops, the connectedness across markets may still remain high.

4.2. Directional volatility spillover

We further examine the three more detailed volatility spillover indicators, separating the sources and the recipients of volatility between markets, and calculate the net spillover. Figs. 3–5 depict the to, from, and net volatility spillover index, respectively. We have only shown five most important markets: China, U.S., Japan, Germany and UK for the ease of exposition, other results are available upon request.

The general trends of TIX and FIX shown in Figs. 3 and 4 in these markets are similar to the AIX shown in Fig. 2, except for China. Fig. 3 shows that after experiencing a volatility spike in February 2020, the Chinese market had an extremely low TIX for most of 2020 at about 10. On the other hand, the TIX of the other four markets remain at high levels in 2020 at over 100, with U.S. being the lowest.
Fig. 2. Aggregate volatility spillover index (AIX) and the VIX, October 24, 2016 to December 1, 2020. Note: This figure shows the dynamic evolution of aggregate volatility spillover index (AIX), together with the CBOE Volatility Index (VIX) for the comparison. The black vertical line represents January 01, 2020 when COVID-19 was first reported. In the construction of AIX, window length $w = 200$, predictive horizon $H = 1$, and lag order $p = 3$.

Fig. 3. To volatility spillover index (TIX), October 24, 2016 to December 1, 2020. Note: This figure shows the to volatility spillover index (TIX) of the five major countries: China, U.S., Japan, U.K. and Germany.

Fig. 4. From volatility spillover index (FIX), October 24, 2016 to December 1, 2020. Note: This figure shows the from volatility spillover index (FIX) of the five major countries: China, U.S., Japan, U.K. and Germany.
A closer examination of Fig. 3 reveals that the volatility spillover from the Chinese market to all other markets began to fall in late January, after the lockdown in Wuhan. At the same time, the AIX rose sharply as the COVID-19 outbreaks took place in Europe and the U.S. Therefore, there is strong evidence that the global stock market volatility is not propagated from the Chinese market, and the Chinese market is rather insulated from the rest of the system. We arrive at a different conclusion from Contessi and De Pace (2021) who found that the instability of stock market spreads from China to European countries during the worst of the COVID-19 pandemic.

Fig. 4 shows the “from volatility spillover index” (FIX) of the five countries. Starting from March 2020, the FIX of all five countries began to rise to higher levels, with China rising slightly to around 40. This implies that after the outbreak of COVID-19, for each individual market the spillover effect from external markets contributed more to the rise of individual volatility. The global network of volatility spillovers is more closely linked since the start of COVID-19 pandemic. By subtracting the FIX from the TIX, we obtain the “net volatility spillover index” (NIX) of each market, and plot them in Fig. 5. The black horizontal line represents NIX=0. NIX>0 indicates a net risk spillover market, and NIX<0 indicates a net risk receiver market. We find that China is a risk receiver during almost the entire sample period, while the other four markets are net risk spillovers most of the time. In particular, after the shock of COVID-19, China’s net risk acceptance reached the maximum. This empirical evidence suggests that Chinese stock market acted as a receiver of volatility spillover among the 19 markets considered in our network.

4.3. Intercontinental spillover

Financial markets in the same region tend to have closer connections (see, for example, Demirer et al., 2018). In this section, we investigate whether there is clustering effect in the connectedness between stock markets due to their geographic location. We divide the 19 countries into continental groups shown in Table 1. We then decompose the AIX into cross-area (Cross) and within-area (Within) volatility spillover indices. The Cross index is the sum of all pairwise connections of stock markets located in different continents, while
the within index is the sum of all pairwise connections located in the same continent. The decomposition helps us investigate the stock market clustering effect at the continental level and identify the source of variations in AIX.

Fig. 6 plots the Cross and Within indices at the continental level. During the sample period, the average Cross is about 40, while the average Within is around 20. This shows that on average, the connectedness level between markets from different continents is twice as high as the connectedness between markets from the same continent. The Cross index is higher than the Within index throughout most of the sample period, suggesting a stronger cross-continent connection than the within-continent volatility transmissions. Therefore, we do not find the geographical clustering effect in the volatility of the global stock market. In addition, the Within index has smaller fluctuations than the Cross index, which shows that the effect of geographical connections is less strong than the influences of the world event. One possible explanation is that the economic ties between geographically neighboring countries are stable, while the pandemic is an outside shock whose impact is ex ante unpredictable. Last but not least, both the Cross and the Within indices have risen since the COVID-19 outbreak in early 2020, indicating that COVID-19 has increased the overall level of connectedness both intra- and inter-continental.

5. The influence of COVID-19

The analyses above identifies, at a large scale of time, the pandemic’s impact on the rise of global connectedness in stock market volatility. This section zooms in on the year of 2020 to further investigate the influence of the COVID-19 pandemic. We first compare the changes in the volatility connectedness between various markets before and during the outbreak. We examine data in two adjacent subsample periods: (1) January 1, 2019 to December 31, 2019, a total of 246 trading days, as the pre-COVID-19 period; and (2) January 1, 2020 to December 1, 2020, a total of 229 trading days, as the during-COVID-19 period. The last 10 days of each subsample are used to perform the forecast error variance decomposition, and the estimation sample consists of all other observations in each year. In other words, the estimation window length is 236 and 219 days for the two subsamples, respectively, and the prediction horizon is \( H = 10 \) for both subsamples. The pairwise spillover indices among the 19 countries are shown in Fig. 7. The countries are ordered according to the following order of continents: Europe, North America, South America, Oceania and Asia. Each block represents the level of volatility spillover from the market on the x-axis to the market on the y-axis. Darker color indicates weaker volatility spillover, and lighter color indicates stronger spillover.

Fig. 7a presents the pairwise spillover index for the subsample before COVID-19. It is evident that the connection was mainly concentrated among the developed economies in Europe and North America. Another group of strong connection occurs among the developed economies in the Asia-Pacific region, namely, Japan, Hong Kong, Singapore and Australia. Fig. 7b depicts the pairwise volatility spillover for the subsample during COVID-19. The connection among the global stock markets has strengthened considerably, spreading across different continents in a much larger scale. The only exception is China, whose pairwise RV spillover effect dropped during the pandemic. In general, the outbreak of COVID-19 has extended the existing connections between European and North American stock markets to markets worldwide.

The development of the pandemic can be split into three stages. The first stage is its initial outbreak in China. COVID-19 was first reported on January 1, 2020 in the city of Wuhan, and quickly spread within China. On January 23, Wuhan implemented a city-wide lockdown. On February 14, the 7-day rolling average of daily confirmed cases of China peaked at over 4,600. This figure quickly fell below 500 towards the end of February.

The beginning of the second stage is marked by the COVID-19 outbreak in northern Italy in late February. Italy became the first western country to impose lockdown on some cities on February 24. By the end of February, all four European countries in our study have reported clusters of COVID-19 cases that are linked to the outbreak of northern Italy. On March 8, lockdown measures were imposed on the region of Lombardy together with 14 additional northern and central provinces in Italy. Amid the heightened uncertainty, the AIX soared to 89.45 on March 13, reaching the highest level in history. In response to the blow to the global economy and the market’s growing fear caused by COVID-19, the Federal Reserve issued a coordinated action statement with several other central banks, and announced a liquidity provision program on March 15. Until mid-June, the 7-day average of the daily confirmed cases in the U.S. and Europe remained at around 20,000 and 15,000, respectively, with near-zero growth rate. The western economies have contained the COVID-19 outbreaks to some extent in the second stage of the COVID-19 pandemic.

We use June 15, 2020 as the beginning of the third stage of COVID-19 pandemic, which is characterized by its large-scale worldwide growth. The pandemic deteriorated in several regions of the world throughout the summer months, most notably, the U.S., Brazil and India. The 7-day average of daily confirmed cases in the United States rose sharply from late June, reaching a second peak of 67,000 on July 20, which was more than doubling the highest case numbers during its first wave. The second wave in Europe also emerged as the weather turned colder. By the end of September, the 7-day average of daily confirmed cases in Europe was over 60,000. This figure jumped to around 280,000 in early November. Not surprisingly, the U.S. experienced another episode of rapid growth in winter due to the lack of coordinated public health measures. Its 7-day average of daily case numbers hovered around 17,000 in late November, and continued to grow towards the end of our sample.

In what follows we examine the estimated volatility connectedness network in these three stages separately. This exercise will provide a comprehensive analysis on how the development of COVID-19 pandemic altered the volatility spillover.

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3 We use the number of 7-day rolling average of daily confirmed COVID-19 case numbers to remove the weekly seasonal pattern due to testing constraints on weekends (Akovali and Yilmaz, 2020).
Fig. 7. Pairwise volatility spillover index among the 19 stock markets before and during COVID-19. Note: This figure shows the pair-wise volatility network connectedness between the 19 markets before and during the COVID-19 outbreak. We examine network in the two subsample periods: (1) January 1, 2019 to December 31, 2019, a total of 246 trading days, as the pre-COVID-19 period; and (2) January 1, 2020 to December 1, 2020, a total of 229 trading days, as the during-COVID-19 period. The countries are arranged according to the following order of continents: Europe, North America, South America, Oceania and Asia. The color in each block represents the level of volatility spillover from the market on the x-axis to the market on the y-axis. Darker color indicates weaker volatility spillover, and lighter color indicates stronger spillover. The prediction horizon is $H = 10$ for both subsamples. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
5.1. Volatility spillover from China

Results shown in Section 4.2 suggest that the volatility spillover from China to the rest of the global stock markets has dropped down to the near-zero level since the COVID-19 outbreak. The Chinese market seemed rather disconnected from the rest of the world during most of the COVID-19 period. In this section we specifically examine more closely pairwise connections among the global stock markets during the first stage of COVID-19 outbreak in China.

We compare the bipartite directed graph of pairwise connection network of each market on two dates before and after the outbreak in China: (1) December 30, 2019, the day before COVID-19 was first reported; and (2) February 14, 2020, when the 7-day rolling average of new confirmed cases in China peaked. It is worth noting that the days surrounding Chinese New Year are excluded from the sample of all markets, since some Asian stock markets are closed during that period. Fig. 8 shows the directed graph of the pairwise connection index on December 30, 2019 and February 14, 2020. Each node represents one market, and the node size is determined by the value of the TIX. The location of the nodes, indicating the average pairwise connectedness index, is determined by the algorithm ForceAtla2 proposed by Jacomy et al. (2014). The straight line between two nodes points from the spillover market to the receiver market, and the thickness of the line represents the strength of the pairwise connection. We have removed the pairwise connections with spillover index less than 5 to keep the figures readable.

Both Figs. 8a and 8b reveal the strong clustering in the Asia-Pacific markets and the Euro-American markets. In Fig. 8a, we can identify two main clusters: the Asian cluster around China, Japan, and Hong Kong, and the Euro-American cluster around Canada, U.S., Netherlands, France, and Germany. Australia and Singapore act as the link between the two clusters. In Fig. 8b, Australia and Japan become the center of the Asia-Pacific cluster, and connect with various Asia-Pacific countries, such as South Korea, Singapore, Thailand, China, Hong Kong and Indonesia. Countries with small financial markets, such as Mexico, Brazil, India, Philippines and Malaysia, appear on the periphery of the Euro-American cluster. Mexico and Brazil have close ties with the U.S. and Canada both

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4 We set the size of the smallest and largest node to be 0 and 150, respectively, as there is no market with TIX more than 150, and then assign other nodes linearly, so all network plots are comparable throughout the paper.

5 Specifically, the nodes repel each other according to their size, and attract each other according to strength of the connection, i.e., size of TIX or FIX, between them. The equilibrium position is determined when the repulsion and attraction reach a balance. Although the equilibrium representation is not unique, we only care about their relative position.
economically and financially. In particular, Mexico is a member of the North American Free Trade Area (NAFTA), and its largest trading partner is the U.S. It is worth noting that India, Philippines and Malaysia are Asian countries, they appear at the edge of the Euro-American cluster in both two network plots. One possible explanation is that these countries have a lot of economic and trade exchanges with the EU and NAFTA.

There are also a few distinctive features before and after the COVID-19 outbreak in China. First, the number of connections between the Asian markets have decreased significantly, especially with China. Second, the pairwise connections within the European and American markets changed very little, suggesting that the western economies have not been affected by the COVID-19 outbreak in China in mid-February, 2020. Third, the cross-continental connections between Asia and Europe/America have also decreased. When COVID-19 was the most severe in China in February, the Chinese stock market fluctuated wildly, but the other Asian markets did not follow suit. Therefore, the Chinese stock market had decreased level of synergy with the other Asian markets. The cross-continental connections decreased possibly due to similar reasons. The connections within the group of European and American markets have changed little.

5.2. COVID-19 outbreaks in Europe and America

When the Chinese government imposed strict lockdown measures to contain the outbreak, COVID-19 quickly spread to other parts of the world. On February 29, the United States reported its first death from COVID-19. On March 13, WHO announced that Europe has become the center of the pandemic. We compare the graphs of pairwise spillover network on two dates: (1) March 13, 2020, when US stock market experienced severe turbulence after US closed border to European countries; and (2) May 6, 2020, a day on the downward trend of 7-day average of COVID-19 infections after the first peak in the U.S. and Europe.

Figs. 9 and 10, respectively, depict the TIX and FIX among the 19 stock markets on these two dates. Fig. 9a and Fig. 10a show the pairwise connections on March 13, 2020, when the AIX reached a historical high. The results show a stronger clustering within the two groups on the two sides of the graph. It is evident that the cluster on the left tend to contain the Asia-Pacific countries around Hong Kong, and the cluster on the right side tend to contain the Euro-American countries. The Asian cluster and Euro-American cluster were mostly indirectly connected via Brazil and Australia, which are the only two economies that maintained high levels of direct cross-continent connections with other clusters. Compared with Fig. 8b when the connections within the Asian markets were almost non-existent during the COVID-19 outbreak in China, the intensity of the connection were extremely high in the second development stage. It is worth noting that South Korea appeared in the Euro-American cluster, and its connection with the Asian cluster only existed with Japan. In addition, we find that Australia, Brazil, Japan, the United Kingdom, and Germany were the largest risk source and risk receivers at the same time.

Figs. 9b and 10b plot the TIX and FIX for the pairwise connection network on May 6, 2020. The Asian cluster in these plots was centered on Singapore, which is an international financial center in Asia and to some extent conveys the sentiment of the Asian stock market. Comparing Figs. 9a and 9b, the following results stand out. First of all, the number of meaningful TIX connections between Brazil and the Asian markets has reduced from 9 in March to 5 in May. This could be a result of the different government policies in containing the COVID-19 pandemic in Brazil and the Asian countries. Most Asian countries implemented harsh lockdowns at the very early stage, while the Brazilian government was heavily criticized for their ignorance and lack of coordinated actions during this
period. Secondly, there are substantial changes in the Asian markets. The TIX of the Philippines and Malaysia have dropped significantly from 96.32 and 89.83 on March 13 to 10.85 and 49.99 on May 6, respectively. These two countries went through a phase of rapid growth in COVID-19 case numbers since late March. Combining Figs. 10a and 10b, Malaysia’s main connections switched from Asian markets on March 13 to European/American markets on May 6. In addition, Japan and South Korea have become more connected with the Asian markets from March to May, and have been less so with the Euro-American markets. South Korea, in particular, went from being on the periphery of the Euro-American cluster in March to being a connection between the two clusters in May. Last but not least, China has been disconnected from all other markets throughout this period, which is in sharp contrast to Fig. 8a when China was well connected before the pandemic.

Results shown in Figs. 9 and 10 are mostly consistent with the findings of Fig. 6 that the cross-continent connection are stronger than the within-continent connection. Although the connections within the Asian markets have increased, those in Europe and America have decreased. The cross-continent connections have grown substantially since March 2020.
5.3. Second and third waves in Europe and North America

Although the stock market turbulence in most advanced economies quickly ended in May, 2020, the COVID-19 pandemic continued to develop. Especially in the U.S., as the daily new case numbers consistently dropped after a few months of hard lockdown measures, most states eased restrictions in summer. As a result, the second wave of COVID-19 infections hit the U.S., and the 7-day average of new case numbers reached a peak on July 20, 2020. In Europe, the number of daily new confirmed cases sharply increased since October 2020 due to inadequate control of COVID-19. On November 8, the 7-day average of new case numbers in Europe reached its highest value in our sample of 280,000. Fig. 11 plots the 7-day average of daily confirmed case numbers in the U.S., U.K., France, Germany, and India, as well as North America, Europe, and Asia. The first three black vertical lines in the figure represent the peak of the 7-day average of daily confirmed cases in the U.S. during its second wave (North America), India (Asia), and Europe. The last vertical line represents the peak case number during the third wave in the U.S. and North America occurred on November 25, although it continued to grow after our sample ended on December 1, 2020. We take snapshots of the network connectedness on these four dates for comparison, in order to investigate whether the second and third waves of COVID-19 infections in Europe and North America had any impact on the strength of the global stock market connectedness.

Fig. 12 depicts the TIX among the 19 stock market indices on the four dates during the heights of the COVID-19 infections in Europe and North America. There is still the division between the Asian cluster on the left and the Euro-American cluster on the right. The Asian cluster centers on Singapore on the first three dates examined, and centers on China towards late 2020, when China was the first

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**Fig. 12. Pairwise connection among the 19 stock market indices.** Note: This figure shows the pairwise connectedness on July 20, 2020, September 17, 2020, November 9, 2020 and November 25, 2020. The node size represents TIX. The node location is determined by the algorithm ForceAtlas2. The arrows point from the spillover market to the receiver market, and the thickness of the line represents the strength of the pairwise connection. The line color is the same as the color of a node from which the line originated. Only connections with spillover index greater than 5 are shown on the figures. Parameter setting: window length \( w = 200 \), predictive horizon \( H = 10 \), and lag order \( p = 3 \). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
to resume production and life after the epidemic. However, the Euro-American cluster were polycentric. The two clusters were connected by Australia, Brazil and Japan.

Comparing with Fig. 9, one key distinction during the third stage of COVID-19 from stage two is the decreased connectedness within the Asian markets. In particular, Singapore has lost connections with other Asian markets that were connected during the second stage. Malaysia has been disconnected with the Asian markets since the second stage, and all of its connectedness were built with the European and American markets. Nonetheless the overall level and extent of within-continent connectedness were still much higher than either before- or first-stage of COVID 19, as could be seen by comparing Fig. 12 and Fig. 8. Among the Asian countries, only Japan, South Korea and Malaysia remained closely connected with the Euro-American markets, especially South Korea and Malaysia, which were located on the edge of the Euro-American cluster. It is worth noting that towards the end of our sample period, China is no longer independent of global stock market volatility spillover network. In contrast to the Panels 12a–12c, China became an integral part of the Asian markets on November 25, 2020, as is shown in Panel 12d.

Among the four dates in Fig. 12, there were far more connections within the Euro-American cluster than within the Asian cluster. Compared with the graphs on March 13 shown in Fig. 9a, the connections between Brazil and the Asian markets have decreased significantly. In addition, Australia maintained close connections with most of the other stock markets in all continents. Other than the change in the role of the Chinese market, there is little difference in the network graphs among the four dates. The global stock market remain at a highly connected level during the second half of 2020.

Our results so far show that the outbreak of COVID-19 in the U.S. and Europe in March 2020 strengthened the connectedness of global stock markets. The connectedness network still remained at a high level in the later development stages of the COVID-19 epidemic. Therefore, in the next section, we will investigate whether the COVID-19 infection can explain the increased connectedness between global stock markets using regression analysis.

5.4. Regression analyses

As the COVID-19 pandemic spread across the world in 2020, the volatility connectedness network among the 19 stock markets has strengthened and remained at a high level since March 2020. Therefore, the spillover index is likely to be positively correlated with the number of daily confirmed cases. We investigate how COVID-19 case numbers contributed to the increase of volatility spillover indices with regression analyses.

We regress the spillover index on the 7-day average of daily confirmed cases, among other variables. We take the logarithm of 7-day average of daily confirmed cases to remove the exponential growth shown in Fig. 11. Changes in governments’ economic policies in different periods are controlled for by including the Economic Policy Uncertainty Index (EPU) constructed by Baker et al. (2016) in the regressions. Baker et al. (2016) only provide the EPU index at monthly frequency, while our spillover indices are calculated daily. Therefore, we interpolate the monthly EPU index to daily frequency by cubic spline. The data are split into two sub-periods: (1) from October 24, 2016 to December 30, 2019 as the pre-COVID-19 period; and (2) from January 1, 2020 to December 1, 2020 as the during-COVID-19 period. To examine the explanatory power of the number of confirmed cases on the connectedness indices (Note that daily confirmed cases is always 0 in the period of pre-COVID-19), we conduct regression analysis separately in the two sub-periods. We first regress AIX on the logarithm of the 7-day rolling average of the total number of daily confirmed cases in 19 countries (denoted as log GCS) and Global Economic Policy Uncertainty (denoted as GEPU) (Davis, 2016), which is PPP-adjusted GDP-weighted average of national EPU indices for 21 countries, among which 13 countries overlap with the stock markets considered in this paper. The regression is

\[ AIX_t = \beta_0 + \beta_1 \log(GCS_t) + \beta_2 GEPU_t + \epsilon_t. \]  \tag{9} 

The regression results of Model (9) are tabulated in the first column of Panels A (pre-COVID-19) and B (during-COVID-19) of Table 3. We find that both log GCS and GEPU are statistically significant at the 1% level in all regressions across the two sub-periods. During COVID-19, \( \hat{\beta}_1 = 2.278 \) means that the number of 7-days rolling average of confirmed cases increases by 1%, AIX will increase by 2.278, which is an economically strong impact. GEPU also has a positive and statistically significant effect on AIX in both sub-periods, but the magnitude of the coefficient is small. We also find that since COVID-19 started, the addition of log GCS variable greatly enhance explanatory power for AIX with \( R^2 \) rising from 5.2% to 70.2% for Model (9).

We then turn to the directional volatility spillover indices. As the directional spillover indices are specific to each country, we use the national EPU index (denoted as EPU) as the control variable in addition to the logarithm of the 7-day rolling average of daily confirmed cases (denoted as log CS) of each country. There is no EPU data provided for Hong Kong, Indonesia, Mexico, Malaysia, Philippines, Thailand, hence the panel regression is applied to the remaining 13 markets. The TIX, FIX and NIX of each country are used as the regressor, respectively. We perform a fixed-effect panel regression of the following form to examine the relationship between the directional indices and the number of confirmed cases:

\[ y_{it} = \beta_0 + \beta_1 \log(\text{CS}_t) + \beta_2 EPU_{it} + \epsilon_{it}. \]  \tag{10} 

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6 See http://www.policyuncertainty.com.

7 The EPU of Australia, Brazil, Canada, France, Germany, India, Korea, United Kingdom and United States comes from Baker et al. (2016), Baker et al. (2013) provide the EPU for China, Arbatli et al. (2017) provide the EPU for Japan, and Davis (2016) provides the EPU for Singapore.
where $y_{it}$ denotes one of the directional indices $TIX_{it}$, $FIX_{it}$ and $NIX_{it}$ for country $i$ on day $t$. The panel regression results are shown in columns 2-4 of Panels A and B of Table 3. During the period of COVID-19, the coefficients on log CS are all significantly positive, showing that the COVID-19 case number has a positive effect on the directional indices. More importantly, the coefficient on log CS is larger in the regression for $TIX$ than that for the $FIX$, resulting in a positive and significant coefficient for the net spillover index $NIX$. Therefore, results in Table 3 reveal that increase in COVID-19 infections strengthens the volatility spillover in both directions, but the increment in the $TIX$ outweighs the increment in the $FIX$. On the other hand, EPU still has positive but small effects on both the $TIX$ and $FIX$ in both sub-periods, and the increment in the $FIX$ is larger. Comparing the results in Panels A and B, log CS variable has good explanatory power for connectedness indices with a substantial improvement in $R^2$ for Model (9) and Model (10), except for $NIX$.

Previous network analyses reveal strong clustering in the Asia-Pacific market and the Euro-American markets. Geographical characteristics of these financial markets may also play a role in the transmission of the COVID-19 shock. Therefore, we further divide the sample for the during-COVID-19 period into two groups: Euro-American markets and Asia-Pacific markets to estimate Model (10) for the two clusters separately. The regression results that control for geographical connections are shown in Panels C and D of Table 3. The coefficient on log CS remains highly statistically significant at the 1% level across all regressions, but its magnitude in the Asia-Pacific markets is much larger than in the Euro-American markets. In particular, the effect of log CS on NIX is positive in the Asia-Pacific market but negative in the Euro-American market. This suggests that the growth rate of daily confirmed cases has a promoting effect on the net risk spillover in the Asia-Pacific market, but has a restraining effect on the net risk spillover in the Euro-American markets.

The explanatory power of the number of confirmed cases for $TIX$ and $NIX$ is higher in the Asia-Pacific market, while its explanatory power for $FIX$ is higher in the Euro-American market. One possible explanation is as follows. Many Asia-Pacific countries implemented strict epidemic prevention measures, such as lockdown orders, as the number of daily confirmed cases grew during the pandemic. Therefore, market participants in this region are relatively more sensitive to the changes in the number of daily confirmed cases. Consequently, change in these numbers exacerbated risk spillovers in these markets. On the other hand, the social atmosphere in the Euro-American countries are relatively relaxed during the epidemic. With case numbers reached to much higher levels for the leading advanced economies in this region, less attention was paid to changes in the number of daily confirmed cases. However, these markets still receive spillover risk from the Asia-Pacific markets. Therefore, the growth rate of the number of confirmed cases promote risk spillover in the Asia-Pacific markets, and promote risk reception in the Euro-American markets from Asia-Pacific markets.
6. Conclusions

The outbreak of COVID-19 in February 2020 caused massive volatility surge in the global stock markets. This paper provides a dynamic analysis of volatility connectedness network among 19 stock markets from January 4, 2016 to December 1, 2020. We focus on the impact of COVID-19 on the connectedness network during different development stages of the COVID-19 epidemic. Compared with existing literature on the impact of COVID-19 on the stock market, this paper is one of the first attempts to investigate the volatility connectedness among different markets rather than examining the effect on market returns.

The empirical results show that the COVID-19 outbreaks in Europe and America in late February to March, 2020 have strengthened the overall volatility connectedness network, and the AIX reached its peak on March 13. At the same time, the directional spillover indices of each country, except China, have risen. The level of cross-continent connection has elevated more than the within-continent connection. We further examine the changes in connectedness network during different stages of COVID-19 development. China is shown to be disconnected from the global volatility network since March 2020 when the center of the COVID-19 pandemic moved from China to Europe and the U.S. We find strong empirical evidence that the volatility spillover in the global stock market is not transmitted from the Chinese market. The connectedness within the Asian markets is higher during the second stage of the COVID-19 pandemic, but has decreased in the third stage. The European, American, and Australian stock markets have been consistently closely connected during the COVID-19 pandemic.

There are several possible avenues for further research. The COVID-19 pandemic affects different sectors of the economy unevenly. It will be interesting to investigate the evolution of industry-level connectedness network in 2020. For example, healthcare and technology sectors might have benefited from the pandemic and the resulting changes in the work mode, while transportation and tourism sectors have experienced considerable loss. The use of realized volatility allows for a refined intra-day analysis for markets with similar trading hours. One potential area is the European stock markets where there are large overlaps in trading hours among many countries. We leave these for future research.

Appendix A

In this appendix, we first check the robustness of the model parameters, and then show more detailed calculations of each index, as well as the time path of TIX and FIX at continent level.

A.1. Robustness

Our analysis based on Diebold-Yilmaz volatility network model is related to three parameters: lag order $p$, window width $w$, and predictive horizon $H$. Here we conduct a robustness test, and we discuss the impact of different choices of parameter values on the results. We plot dynamic spillover index in Figs. A1–A2 for alternative these parameters. There are a total of three variable parameters in the model, and it is difficult to observe each parameter in one picture at the same time, therefore we focus on one or two parameters in each picture.

First, we keep lag order $p = 3$, let window width $w$ respectively take values of 150, 200, and 250 days, and let predictive horizon $H$ respectively take values of 5, 10, and 15 days, and then we see how the results change. Fig. A1 shows the result. Then, we keep window width $w = 200$ days and predictive horizon $H = 10$ days, let lag order $p$ respectively take values of 1, 2, 3, 4, 5, and 6, and then we see how the results change. Fig. A2 shows the result. The red line in Fig. A1 and Fig. A2 corresponds to the mean of Cholesky-based total connectedness measures based on 10,000 randomly-selected orderings of VAR variables, and the gray band corresponds to [min, max] interval based on 10,000 randomly-selected orderings, while blue line represents spillover index based on generalized orthogonal variance decomposition (GVD).

In general, the three parameters have no obvious influence on the spillover index based on generalized variance decomposition, that is, the result is robust.

In addition, we can find it from Fig. A1 that the larger the window length, the greater the deviation of spillover index between the orthogonal decomposition-based and the generalized variance decomposition-based. Moreover, it can be seen from Fig. A2 that if the lag order is selected too large or too small, it will lead to excessive deviation of the spillover index between Cholesky orthogonal decomposition and generalized variance decomposition. Therefore, the decision that we choose lag order $p = 3$, window width $w = 200$ days, and predictive horizon $H = 10$ days is reasonable.
Fig. A1. Robustness of Total Connectedness. When $p = 3$, we explore estimation window width $w$ of 150, 200 and 250 days and predictive horizon $H$ of 10, 15 and 20 days. In each graph, the blue line corresponds to generalized-based total connectedness measures, the red line corresponds to the mean of Cholesky-based total connectedness measures based on 10000 randomly-selected orderings, and the gray band corresponds to [min, max] interval based on 10000 randomly-selected orderings.
Fig. A2. Robustness of Total Connectedness. When $w = 200$ days and $H = 10$ days, we explore varying VAR lag order $p$ of 1, 2, 3, 4, 5 and 6.
A.2. Additional results

Table A1 and Table A2 show detailed calculations of TIX, FIX, NIX and AIX at country and continent level, respectively. Fig. A3 shows the time path of the TIX and FIX at continent level.

### Table A1
Spillover table schematic at country level.

| x₁   | x₂   | ⋮   | xₙ   | FIX      |
|------|------|-----|------|----------|
| ₁₁   | ₁₂   | ⋮   | ₁ₙ   | \sum_{j=1}^{N}X_{i,j}^{H} ≠ \theta_{i,j}^{H} |
| ₂₁   | ₂₂   | ⋮   | ₂ₙ   | \sum_{j=1}^{N}X_{i,j}^{H} ≠ \theta_{i,j}^{H} |
| ⋮    | ⋮    | ⋮   | ⋮    | ⋮        |
| N₁   | N₂   | ⋮   | Nₙ   | \sum_{j=1}^{N}X_{i,j}^{H} ≠ \theta_{i,j}^{H} |

Note: The N × N elements in the upper-left of the submatrix give the pairwise connection between N markets. \( \theta_{i,j}^{H} \) denote the generalized H-step-ahead forecast error variance decomposition from shock \( j \) to variable \( i \). The rightmost column (FIX) denotes from volatility spillover index, which is the sum of the row except the diagonal elements; the bottom row (TIX) denotes to volatility spillover index, which is the sum of the column except the diagonal elements; the bottommost row (NIX) denotes net volatility spillover index, which is TIX minus FIX; and the bottom-right element denote aggregate volatility spillover index, which is the mean of TIX or FIX.

### Table A2
Spillover table schematic at continent level.

| Asia  | CN | JP | KR | IN | HK | MY | PH | SG | TH | ID | US | CA | MX | BR | DE | FR | UK | NL | Oceania | AU | FIX |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|
| N.America | CA | MX |
| S.America | BR | DE | FR | UK | NL |
| Europe  | AU |
| Oceania | AU |

Note: The small grids that are not drawn represent the spillover table at national level, as shown in Table A1, and the large grids represent the spillover table at continental level. The value of each large grid is calculated by adding up the values of the small grids included in it, except for the diagonal elements of the small grid. The index Within is the sum of diagonal elements of the large grid, while the index Cross is the sum of non-diagonal elements. The same as Table A1 to calculate TIX and FIX, excluding the diagonal elements, adding up the elements in the matrix by column and row respectively to get TIX and FIX. The difference is that the TIX and FIX corresponding to each continent need to be divided by the number of countries included in the continent to compare between different continents. The time path of TIX and FIX at continental level is shown in Fig. A3a-A3b.
Fig. A3. Directional volatility spillover plot at continent level. Note: October 24, 2016 to December 1, 2020. window width $w = 200$ days, predictive horizon $H = 10$ days, and lag order $p = 3$.

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