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The time-varying spillover effect of China’s stock market during the COVID-19 pandemic

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A B S T R A C T

The rapid spread of coronavirus (COVID-19) has a significant impact on the world economy, especially on the financial market. Investors are panicking about the future. This paper considers industry data and aims to investigate the impact of the pandemic on China’s stock market. The Asymmetric-GARCH-BEKK model and complex network theory were combined to construct the interaction networks. From the perspective of spillover effect, we investigated the time varying co-movement during the pandemic. The results indicate that the outbreak of COVID-19 weakens the mean spillover, but enhances the volatility spillover among China’s stock market. However, both mean spillover and volatility spillover decreased rapidly during the period of regular epidemic prevention and control. We also found that different industries have various sensitivity to the COVID-19 pandemic.

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1. Introduction

The pandemic of COVID-19 began to be widely concerned by people in the world at the end of January 2020. Due to the severity of the pandemic, Wuhan shut down at 10 a.m. on January 23, 2020. Subsequently, the COVID-19 spread rapidly in China and around the world. On March 11, 2020, the World Health Organization officially declared that COVID-19 has become a global pandemic. As of April 30, although there were still a lot of new cases in the world every day, the new cases in China were almost zero. One year later, the pandemic is still affecting our production and activities; however, the data show that the epidemic was under control in China quickly.

A lot of economic activities cannot run normally due to the pandemic, particularly in the financial market, such as the four times circuit breaker of US stock market in ten days. Obviously, the pandemic of COVID-19 has a significant impact on economic activities, especially on the financial market [1,2]. Rehman et al. examined the impact of COVID-19 on the G7 stock markets. They revealed the lead–lag co-movement across different countries and presented some suggestions for both policymakers and investment community [3]. Albulescu studied the effect of pandemic on the financial volatility in the United States. Their results indicated that the coronavirus pandemic is an important source of volatility risk [4]. In the research of Ben Amar [5], they used a spillover index to investigate the connectedness among six regional stock markets. The results showed that the epidemic could weaken the connection between markets. The peak of the pandemic has passed in China. Now it is necessary to investigate the impact of the pandemic on the co-movement in China’s financial market.

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Table 1
The abbreviation and identifier of ten sector indexes.

| Sector Indexes             | Abbreviation | Identifier | No. of Stocks |
|----------------------------|--------------|------------|--------------|
| Financials Index           | Financials   | F          | 60           |
| Materials Index            | Materials    | M          | 18           |
| Telecommunication Services | Telecom Serv | T          | 4            |
| Industrials Index          | Industrials  | I          | 31           |
| Utilities Index            | Utilities    | U          | 7            |
| Consumer Discretionary     | Cons. Discretionary | CD | 16         |
| Energy Index               | Energy       | E          | 5            |
| Consumer Staples Index     | Cons. Staples | CS | 12         |
| Information Technology    | Info. Tech.  | IT         | 8            |
| Health Care Index          | Health Care  | H          | 11           |

Scholars have proposed a variety of methods to characterize the co-movement of financial market. The correlation coefficient method [6,7], Granger causality method [8], Copula method [9,10], spillover method [11–17], transfer entropy [18] and Wavelet theory [19] are used for the research of co-movement. These methods describe and reflect the co-movement between markets from different perspectives. The correlation methods focus on whether there is linkage between markets and the strength of linkage, while the direction of co-movement is not the point. Different from correlation method, causality methods are more concerned with the direction of the linkage, so it can be used to study the problem of risk transmission between markets. The GARCH model can extract the weight and direction of linkages between markets. Therefore, GARCH family methods are widely used in the research of co-movement between markets [20,21].

In this study, GARCH-BEKK model is used to extract the interactions between financial time series. Too many estimation results need to be analyzed when there are many time series. Complex network theory provides a suitable solution to this problem [22,23]. Some researches focus on the application of complex network theory in the analysis of financial time series in recent years [24–29].

To sum up, this paper will study the time-varying impact of the pandemic on the co-movement of China’s stock market by constructing spillover networks. The results show that the initial outbreak of the pandemic has a significant impact on the volatility spillover in China’s stock market, but the stock market responded quickly after the initial shock.

2. Data and methods

2.1. Data

Our sample covers the daily data on the component stocks of SSE 180 Index, which can reflect the overall operation of the Shanghai stock market. The 180 stocks are selected from 10 industries. The details of the ten industries are shown in Table 1. The sample period is from January 1, 2019 to December 31, 2021, covering the outbreak period of COVID-19 pandemic and the period of regular epidemic prevention and control. Due to the lack of data on SSE 180 Index constituent stocks during this period, 172 stocks were selected as sample data. In order to study the time-varying volatility spillover, the sliding window method is used to divide the whole sample into 5 sub-period. According to the literature, we find that the window size ranges from about 200 to 1000 when using GARCH family models [30–33]. For a window with N observations, the overlap data can range from 0 to N−1 [32,34]. The window size used in this research is 12 months and the overlap length is 6 months. According to the COVID-19 pandemic in China, the Period 1, Period 2, Period 3, Period 4 and Period 5 represent the pre-stage, early-stage, middle-stage late-stage and post-stage of the pandemic respectively. The data was downloaded from the Wind database.

2.2. Methods

2.2.1. Spillover relation extraction

The mean spillover and volatility spillover relation are usually used to describe the direction and degree of the co-movement between financial markets. In this research, a bivariate GARCH-BEKK model is used to capture the spillover relationship between stocks. The GARCH-BEKK model is proposed by Engle and Kroner [35]. A bivariate GARCH-BEKK model consists of mean and variance equations [36].

The mean equation is defined as a vector autoregressive model (VAR) model:

\[
\begin{bmatrix}
R_1(t) \\
R_2(t)
\end{bmatrix} = \mu(t) + \begin{bmatrix}
\alpha_{11} & \alpha_{12} \\
\alpha_{21} & \alpha_{22}
\end{bmatrix} \begin{bmatrix}
R_1(t-1) \\
R_2(t-1)
\end{bmatrix} + \epsilon(t)
\]

(1)

where \( R(t) \) is the daily logarithmic return on day \( t \). \( \mu(t) \) and \( \epsilon(t) \) are \( 2 \times 1 \) vectors, representing the constant term and random error respectively. \( \alpha \) is the \( 2 \times 2 \) coefficient matrix.

The variance equation is defined as:

\[
H(t) = C'C + A'\epsilon_{t-1} \epsilon_{t-1}'(t) A + B'H_{t-1}B
\]

(2)
Fig. 1. Construction of spillover network.

\[
C = \begin{bmatrix}
  c_{11} & 0 \\
  c_{21} & c_{22}
\end{bmatrix}, \quad A = \begin{bmatrix}
  a_{11} & a_{12} \\
  a_{21} & a_{22}
\end{bmatrix}, \quad B = \begin{bmatrix}
  b_{11} & b_{12} \\
  b_{21} & b_{22}
\end{bmatrix}
\]

(3)

where \( H(t) \) represents the conditional variance–covariance matrix, \( A \) is the coefficient vector of the conditional residual, and \( B \) is the coefficient matrix of the conditional covariance.

The GARCH-BEKK model is estimated by maximizing the likelihood function \( L(\theta) \):

\[
L(\theta) = -T \ln (2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left[ \ln |H(t)| + \epsilon_t(\theta)'H_t'\epsilon_t(\theta) \right]
\]

(4)

where \( \theta \) represents the parameter to be estimated with a sample of size \( T \).

2.2.2. Spillover network construction

A complex network is the set of nodes and edges. It can be expressed as follows:

\[
N = (V, E)
\]

(5)

where \( N \) is the network, \( V \) is the set of nodes and \( E \) is the set of edges.

In this research, the nodes set \( V = \{ v_i; i = 1, 2, \ldots, 180 \} \).

The edges set \( E \) in the spillover network can be expressed as follows:

\[
E_m = \begin{bmatrix}
  e_{1,1} & \cdots & e_{1,180} \\
  \vdots & \ddots & \vdots \\
  e_{180,1} & \cdots & e_{180,180}
\end{bmatrix}
\]

(6)

In this paper, \( E \) is different in mean spillover network and volatility spillover network. According to the significance of the estimated coefficients, we can get whether there is such a relationship; According to the size of the coefficients, we can get the magnitude of the relationship. In the mean spillover networks, the linkages between nodes are captured by the mean equation (1). The coefficient \( \alpha_{12} \) can reflect the mean spillover from node 1 to node 2 [37]. Therefore, in the mean spillover network, \( e_{i,j} = \alpha_{i,j} \). In the volatility spillover networks, the linkages between nodes can be captured by the variance equation (2). According to the research [38,39], in the volatility spillover network, \( e_{i,j} = |a_{i,j} + b_{i,j}|. e_{i,j} \) represents the magnitude of mean and volatility spillover. The larger the value of \( e_{i,j} \), the stronger the spillover relationship.

The rules of spillover network construction are shown in Fig. 1. There are three nodes and three edges with significance indicated in parentheses. In this research, the significance was set at 10%. There is a spillover relationship between nodes if the significance of appropriate estimated parameters is less than 10%, otherwise, the edge will be deleted. The final sample spillover network is shown on the right.

3. Results and analysis

To ensure the stationarity, the logarithmic return series of each stock are obtained by the Eq. (7):

\[
R_i = \ln (x_{i,t}) - \ln (x_{i,t-1})
\]

(7)

where \( R_i \) is the logarithmic return series of stock \( i \), \( x_{i,t} \) is the original time series of stock \( i \) at time \( t \). \( x_{i,t-1} \) is the original time series of stock \( i \) at time \( t - 1 \).
3.1. Threshold-based spillover network filtering

In order to reduce the impact of weak linkages on the results, the network is filtered based on a threshold to extract the main structure. In this paper, we proposed a threshold selection method according to the literature [40]. We first calculate the cumulative distribution of the weights, and then find the point with the largest slope. The Fig. 3 shows the process of threshold determination. The X-axis represents the threshold, the Y-axis represents the number of edges in the corresponding weight interval. For the mean spillover networks (subfigure a), we can find that the largest edge density occurs in the range of 0.1–0.2 in five periods. For the volatility spillover networks (subfigure b), we can find that the largest edge density occurs in the range of 0.2–0.3 in five periods.

According to the literature [40,41], we set the thresholds for mean spillover networks and volatility spillover networks to 0.2 and 0.3, respectively. Fig. 2 shows the original mean spillover network and the filtered network in Period 1.

3.2. Overall mean and volatility spillover changing during the pandemic

A total of 73,530 ($C_{172}^2 	imes 5$) GARCH-BEKK models are estimated in the experiment. There are 10 spillover networks constructed (one mean spillover networks and one volatility spillover networks in each sample period).

Fig. 4 shows the spillover changing among SSE 180 stocks during the COVID-19 pandemic. In Fig. 4, the total spillover $S_w$ (blue histogram) can represent the strength of the spillover and the number of linkages $N$ (orange line) can represent the density of spillover network. $N$ is defined as the number of non-zero elements in the matrix $E$ and $S_w$ is defined as follow:

$$S_w = \sum_{1 \leq i < j \leq n} e_{i,j}$$  \hspace{1cm} (8)
It is obvious that the total mean spillover effect decreased (7%) meanwhile the total volatility spillover slightly increased (4%) in period 2. These results mean that the epidemic reduces the co-movement of price and increases the risk of volatility in Shanghai stock market. In the following periods, the mean and volatility spillover among markets show similar trends on the first order and second order. The trend is more significant for mean spillover. After the initial stage of the pandemic, the spillover relationship in the stock market dropped rapidly, which can be reflected in the reduction of total spillover and the number of linkages. More specifically, from period 2 to period 4, the mean and volatility spillover effect among stocks was significantly declined by 56% and 34%, respectively. These results indicate that the outbreak of COVID-19 weakened the co-movement of prices and risk of volatility among China’s stock market.

Fig. 5 shows the changes of the topology structure of unweighted mean spillover networks from Period 1 to Period 5. We investigate the connection changes between stocks in different periods using two topology indicators, the graph density (blue histogram) and modularity (transparent histogram). In Fig. 5, we found that the Graph Density decreased while the modularity increased after the outbreak of the pandemic. These results indicate that the epidemic reduced the spillover link between stocks, and the community structure of the stock network become clearly.

### 3.3. Big spillover senders

The influence strength of stocks in the spillover network can be expressed by the weighted out degree (WOD).

\[
\text{WOD}_i = \sum_{j=1}^{n} e_{ij}
\]  

(9)

The greater the weighted send, the greater the influence strength of this stock on other stocks.

For the mean spillover, it reflects the relationship of co-movement in the market. Table 2 shows the 10 biggest mean spillover senders with the magnitude of WOD in five periods. The IDs are the ticker symbol of the Shanghai Stock Exchange. The five state-owned banks (the big five SOBs) are highlighted with blue; other banks are highlighted with red. Obviously, the COVID-19 has changed the structure of the mean spillover relationship in China’s stock market from the perspective...
Table 2
Top ten mean spillover senders.

| Ranking | Period 1  | Period 2  | Period 3  | Period 4  | Period 5  |
|---------|-----------|-----------|-----------|-----------|-----------|
|         | ID        | WOD       | ID        | WOD       | ID        | WOD       | ID        | WOD       | ID        | WOD       |
| 1       | 600016    | 24.8      | 600016    | 16.8      | 601169    | 13.2      | 601006    | 10.4      | 601998    | 15.1      |
| 2       | 600015    | 20.4      | 600177    | 11.8      | 600177    | 10.9      | 600016    | 6.9       | 601288    | 4.5       |
| 3       | 601988    | 19.3      | 601668    | 9.5       | 601988    | 9.6       | 601169    | 4.6       | 601989    | 4.5       |
| 4       | 601998    | 18.6      | 601939    | 9.4       | 601998    | 7.6       | 601988    | 4.6       | 601988    | 4.5       |
| 5       | 601328    | 10.9      | 601988    | 9.0       | 601766    | 7.0       | 601288    | 4.3       | 600015    | 4.4       |
| 6       | 601939    | 8.4       | 601997    | 7.9       | 601668    | 5.8       | 600487    | 3.9       | 600016    | 3.1       |
| 7       | 601211    | 6.5       | 601998    | 7.8       | 601288    | 5.2       | 601077    | 3.3       | 601818    | 3.0       |
| 8       | 601169    | 6.4       | 601766    | 6.9       | 600016    | 4.6       | 600015    | 2.6       | 601169    | 2.8       |
| 9       | 601288    | 5.9       | 601600    | 6.4       | 601006    | 4.5       | 600875    | 2.6       | 601077    | 2.7       |
| 10      | 600030    | 5.2       | 600919    | 6.1       | 601997    | 4.5       | 601998    | 2.3       | 601328    | 2.6       |

Note: The IDs are the stock ticker of companies listed on the Shanghai Stock Exchange. The five state-owned banks are highlighted with blue; other banks are highlighted with red.

Fig. 6. Power changing of big mean spillover senders.

of spillover sender. It can be seen from Table 2 that banking stocks were the most influential nodes in the pre-stage of the pandemic, especially the large state-owned banks (highlighted with blue). The influence of banking stocks began to weaken after the outbreak of the pandemic. The influence of large state-owned banks has also decreased to varying degrees. The influence of the two companies (600177 and 601668) involving the real estate industry began to increase. This may be due to the fact that in the early stage of the epidemic, the real estate industry is a more affected industry.

According to Chinese characteristics, the big five SOBs are the vane of wind of all the banking sector [42,43]. It is necessary to analyze and evaluate the spillover changes of these five banks. Fig. 6 shows the change of spillover influence (WOD) of the five major state-owned banks in China over periods. The Y-axis represents the mean spillover strength. The X-axis represents the big five SOBs in different period. The change of WOD, defined in Eq. (9), in different periods can represent the change of influence power. These five banks are China Construction Bank (CCB), Bank of China (BOC), Bank of Communications (BCM), Industrial and Commercial Bank of China (ICBC) and Agricultural Bank of China (ABC). It can be seen from the figure that the influence strength of these five big banks shows different trends after the COVID-19 outbreak. On the one hand, BOC and BCM decreased rapidly, especially BOC. In April 2020, the futures price of WTI crude oil plummeted, with a transaction price of $-37 USD/barrel. The Bank of China has a financial product linked to it, which not only makes investors lose their principal, but also owes a lot of money to the bank. Investors lose confidence in this bank, which may be the main reason for the decline of the spillover influence of the Bank of China. On the other hand, ICBC and CCB have increased in varying degrees. Among all banks, ICBC and CCB have the highest capital adequacy ratio. The smaller capital risk makes them more influential in pandemic period. With the weakening of the pandemic, the influence of these banks declined greatly. Investors generally follow the trend towards large banks, but the data shows that the pandemic is changing this phenomenon in China’s stock market. After the outbreak of the pandemic, the spillover influence of the big five SOBs declined, especially the BOC, BCM and CCB.

Volatility spillover among stocks can reflect the risk in the market. The top ten volatility spillover senders with the magnitude of WOD in each period are shown in Table 3. The IDs are the ticker symbol of the Shanghai Stock Exchange. The five state-owned banks (the big five SOBs) are highlighted with blue; other banks are highlighted with red. As can be seen from the table, the banking stocks also act as an important role in the spillover of risk. Different from the mean spillover,
Table 3
Top ten volatility spillover senders.

| Ranking | ID   | Period 1 WOD | Period 2 WOD | Period 3 WOD | Period 4 WOD | Period 5 WOD |
|---------|------|--------------|--------------|--------------|--------------|--------------|
| 1       | 600015 | 166.2        | 601288       | 207.0        | 601288       | 155.9        |
| 2       | 600016 | 157.3        | 601988       | 194.5        | 601328       | 155.5        |
| 3       | 601288 | 143.6        | 600016       | 146.0        | 601006       | 148.5        |
| 4       | 601988 | 141.3        | 601169       | 143.8        | 600016       | 136.5        |
| 5       | 601006 | 132.7        | 600919       | 140.8        | 601988       | 135.5        |
| 6       | 601857 | 128.1        | 601006       | 132.0        | 600000       | 120.9        |
| 7       | 600795 | 125.2        | 601328       | 126.7        | 601169       | 102.6        |
| 8       | 601169 | 124.9        | 600015       | 125.1        | 600900       | 96.0         |
| 9       | 601398 | 118.3        | 600000       | 124.7        | 600919       | 93.0         |
| 10      | 601766 | 116.8        | 600900       | 121.3        | 601229       | 88.0         |

Note: The numbers are the stock ticker of companies listed on the Shanghai Stock Exchange. The five state-owned banks are highlighted with blue; other banks are highlighted with red.

except for the fourth period, banking stocks in the volatility spillover networks, including the five major state-owned banks, have a great influence in the whole sample period, especially Agricultural Bank of China (601288) and Bank of China (601988). In period 2, their influence increased significantly from 143.6 and 141.3 to 207 and 194.5 respectively. In addition, the influence of insurance companies (601318 Ping An Insurance and 601319 People’s Insurance) has increased in the late stage of the epidemic. The results indicate that the pandemic has led to increased attention to the insurance industry.

The distribution of $WOD_i$ over periods can observe the change of spillover influence from a macro perspective. The change of $WOD$ is defined as the difference of $WOD$ between two periods. For the mean spillover networks, we plot the stocks which change significantly over Period 1 (2019), Period 3 (2020) and Period 5 (2021). The following Fig. 7 shows the distribution of $WOD$ changes over periods for stocks. In the figure, the $X$-axis represents the codes of stocks, and the $Y$-axis is the weighted changes of $WOD_i$ over periods. It can be seen from the figure that most $WOD$ of stocks decreased significantly, especially stock No. 6 and stock No. 172 from Period 1 to Period 3. The influence of some stocks fluctuated slightly from Period 3 to Period 5. Considering the whole period, the influence of most stocks has been greatly reduced, especially 172, 6 and 157 stocks. The results indicate that after the outbreak of the pandemic, investors generally have a negative attitude, which reduced the spillover ability of the entire network. In terms of individual stocks, Huaxia Bank (6) and Minsheng Bank (172) decreased the most. This is because the pandemic first affected the financial and real estate industry. In a major emergency situation, risk aversion increases in the market. In addition, the performance of the two banks is poor, especially Minsheng Bank, which has the worst performance in the industry. The spillover ability of these two banks, therefore, decreased significantly.

For the volatility spillover, we studied two periods, before (Period 1) and after the pandemic (Period 5). The Fig. 8 shows the $WOD$ changes of volatility spillover networks. In Fig. 8, the $X$-axis represents the codes of stocks, and the $Y$-axis is the weighted changes of $WOD_i$ over periods. On the one hand, the pandemic led to energy shortage. The Fig. 8 indicates that the influence of energy stocks (No. 5 HUANENG power, No. 79 GUODIAN power and No. 146 CNPC) are greatly reduced in the volatility spillover network. On the other hand, the financial industry is the first to recover from the pandemic,
and some well-developed city commercial banks (No. 115 Shanghai Bank and No. 147 Zijin Bank) are gradually favored by investors. In addition, people are more concerned about health, making the stock (No. 121 PICC) a bigger volatility sender.

3.4. The dynamic spillover among industries

The 172 sample stocks selected in this study come from 10 industries. See Table 1 for the details of the ten industries. To highlight the spillover changing over periods, Fig. 9 shows the changing magnitude of mean spillover over two periods. Redder color intensities denote greater increase of spillover, while bluer color intensities denote greater decrease. From period 1 to period 2, we can find that the COVID-19 has a significant impact on the linkage of China’s stock market. The mean spillover among market has changed significantly. The change of spillover mainly comes from the financial industry to other industries and goes to the industrial sector. Obviously, the sensitivity of the industrial sector has increased and become a volatility receiver. Due to strict control measures after the pandemic outbreak, the factories shutdown by lack of workers and production materials, resulting in a negative impact on the industrial sector of stock market. On the one hand, the Industrials and Consumer Staples sectors have received more spillover. This is because these two industries are greatly affected by the pandemic. Most people need home quarantine and the consumption power is reduced in the first half of 2020. On the contrary, IT and Consumer Discretionary sectors are less affected and less sensitive to the financial sector. From period 2 to period 5, in general, the linkage among all industries has declined significantly, which is much lower than that before the COVID-19 outbreak. This means that the pandemic has reduced the overall co-movement of stocks in Shanghai stock market, and people’s investment expectations are lower than before.

Volatility spillover can reflect the risk in stock market. Fig. 10 shows the changing magnitude of volatility spillover across periods. Redder color intensities denote greater increase of spillover, while bluer color intensities denote greater decrease. From period 1 to period 2, different from the mean spillover, the volatility spillover within the financial industry showed a significant decline when the pandemic breakout. Major changes are that the volatility spillover from the financial sector has increased meanwhile the volatility spillover goes to the financial sector decreased. This result indicate that the financial sector act as a volatility spillover sender, not a receiver. This result means that the pandemic has shifted the volatility risk of the stock market from the financial industry to the real economy. From period 2 to period 5, the risk of the pandemic on the stock market began to weaken. We can find that the sensitivity of industrials and materials sector decreased fastest in sub-figure P2–P3 and P3–P4 in Fig. 10. Finance is a sector greatly affected by policies in China. At the executive meeting of the State Council in June 2020, the government announced that the financial system should transfer profits of 1.5 trillion to real enterprises, and many investors may be worried about the risks of banks. This has led to a sharp decrease of volatility spillover among the financial sector in sub-figure P3–P4 and P4–P5, and as a sender, volatility to other industries is enhanced in sub-figure P4–P5.

3.5. The dynamic volatility spillover between financial industry and health care industry

In the past two years, the company developing and producing vaccine of COVID-19 is undoubtedly a target of investors’ attention. As mentioned above, the pandemic mainly affects the volatility spillover between financial industry and other industries. This part will investigate the volatility spillover from the financial sector to three Vaccine R & D companies belonging to the health care industry.

Fig. 11 shows the volatility spillover changing from financial industry to three Vaccine R & D list companies. It can be seen from the figure that when the pandemic broke out, the volatility spillovers of the financial industry to the three
Fig. 9. The changing rate of mean spillover over two periods.

|   | P1-P2 | F   | M   | T   | I   | U   | CD  | E   | CS  | IT  | H   |
|---|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| F | -0.02 | -1.13 | 0.32 | -7.98 | -0.94 | -15.2 | -2.69 | 5.35 | -2.6 | 2.16 |
| M | 3.2 | 2.13 | 0 | 3.83 | 0.47 | 0.41 | -0.28 | -0.11 | 1.4 | 0.03 |
| T | -0.59 | 0.26 | -0.26 | 0.19 | 0 | -0.28 | 0 | -2.02 | -0.48 | 0.35 |
| I | 5.31 | -2.77 | 3.08 | 9.56 | 0.26 | -0.90 | 0.11 | 2.42 | -7.71 | 2.79 |
| U | -1.02 | 0.49 | 0.36 | 1.59 | 0 | -0.55 | 0.02 | -0.45 | -1.94 | 0.69 |
| CD | 0.59 | 1.25 | 1.83 | 3.64 | 0 | 2.82 | 0 | 0.39 | -0.45 | 0.4 |
| E | 6.65 | 0.98 | 1.16 | 1.91 | 0.32 | 1.29 | 0 | -0.08 | 0.56 | -0.07 | 0.23 |
| CS | -7.58 | -0.25 | 0 | -0.88 | 0 | -0.49 | 0 | -1.59 | -0.6 | -0.4 |
| IT | 0.47 | 0 | 0 | 0.08 | 0 | 0.22 | 0 | 0.2 | 0.22 | 0 |
| H | -8.68 | 1.4 | 0.22 | -1 | 0.15 | 0 | 0.55 | 0 | 0.18 | -0.28 | 0.54 |

|   | P2-P3 | F   | M   | T   | I   | U   | CD  | E   | CS  | IT  | H   |
|---|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| F | -2.87 | -10.9 | -3.39 | -17.2 | -7.5 | 2.17 | 0.21 | -7.77 | 4 | -0.92 |
| M | 3.52 | -2.6 | 0.2 | -4.51 | -7.56 | 0.33 | 0.28 | -0.49 | 0.25 | -1.49 |
| T | 0.41 | 0.35 | 0 | 0.31 | 0 | 0 | 0 | 0.64 | 0 | -0.01 |
| I | 0.31 | -0.33 | 0.73 | -8.81 | -1.04 | -0.31 | -0.35 | -2.28 | -2.61 | -1.37 |
| U | -1.66 | -2.46 | -0.36 | -1.48 | 0.25 | 0.68 | -0.32 | -1.09 | -0.95 | -0.04 |
| CD | -0.36 | -0.64 | -1.38 | -1.34 | 0.46 | -0.15 | 0 | -0.25 | -1.01 | 0.21 |
| E | 2.07 | -2.33 | -1.16 | -1.78 | -0.78 | 0.42 | 0.55 | 0.39 | -0.05 | 0.06 |
| CS | -0.14 | -1 | 0 | 0.07 | 0 | 0 | 0 | 0.65 | -0.09 | -0.54 |
| IT | -1.14 | 0.25 | 0 | -0.13 | 0 | 0.34 | 0 | 0.07 | -0.22 | 0 |
| H | -0.21 | -1.44 | -0.22 | -0.2 | 0 | -0.29 | 0 | -0.05 | 0 | 0.03 |

Fig. 10. The changing rate of volatility spillover over two periods.

|   | P3-P4 | F   | M   | T   | I   | U   | CD  | E   | CS  | IT  | H   |
|---|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| F | -2.99 | 0.84 | 0.44 | -0.71 | 0 | -1.71 | -0.65 | 0.09 | 0.43 | -0.29 |
| M | -0.34 | -0.92 | -0.55 | -0.07 | 0.53 | 0 | -0.08 | -0.22 | 0.58 | 0.47 |
| T | 0.09 | 0.47 | 0.44 | 0.78 | 0 | 0.01 | 0 | 0.25 | -0.07 | 0 |
| I | -1.84 | 3.03 | 0.68 | 1.13 | 0.29 | 1.87 | -0.26 | 0.06 | -0.08 | 1.5 |
| U | 1.4 | 0.25 | 0 | 0.12 | 0 | 0.25 | 0 | 0.06 | -0.22 | 0.27 |
| CD | -2.5 | -0.46 | -0.34 | -0.74 | -0.23 | 0.08 | 0 | -0.36 | -0.48 | 0.83 |
| E | 9.55 | 1.95 | -1.11 | 0.1 | 0.2 | -0.43 | -0.38 | -0.37 | 0.85 | 0.45 |
| CS | -0.7 | -0.95 | -0.47 | 0.44 | 0.08 | 0 | 0 | 0.64 | -0.09 | 0.03 |

|   | P4-P5 | F   | M   | T   | I   | U   | CD  | E   | CS  | IT  | H   |
|---|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| F | -2.99 | 0.84 | 0.44 | -0.71 | 0 | -1.71 | -0.65 | 0.09 | 0.43 | -0.29 |
| M | -0.34 | -0.92 | -0.55 | -0.07 | 0.53 | 0 | -0.08 | -0.22 | 0.58 | 0.47 |
| T | 0.09 | 0.47 | 0.44 | 0.78 | 0 | 0.01 | 0 | 0.25 | -0.07 | 0 |
| I | -1.84 | 3.03 | 0.68 | 1.13 | 0.29 | 1.87 | -0.26 | 0.06 | -0.08 | 1.5 |
| U | 1.4 | 0.25 | 0 | 0.12 | 0 | 0.25 | 0 | 0.06 | -0.22 | 0.27 |
| CD | -2.5 | -0.46 | -0.34 | -0.74 | -0.23 | 0.08 | 0 | -0.36 | -0.48 | 0.83 |
| E | 9.55 | 1.95 | -1.11 | 0.1 | 0.2 | -0.43 | -0.38 | -0.37 | 0.85 | 0.45 |
| CS | -0.7 | -0.95 | -0.47 | 0.44 | 0.08 | 0 | 0 | 0.64 | -0.09 | 0.03 |
companies of vaccine R & D companies were significantly enhanced. This shows that the three pharmaceutical companies have become more sensitive to the volatility from the financial sector. The risks of these three stocks have also increased. This may be due to the speculative psychology of investors, which can make stock price fluctuations more sensitive in the short term. At the early-stage of the pandemic in China, a large number of speculators pay more attention to the vaccine R & D stocks. The good news for vaccine companies is reported frequently. For example, Fosun Pharma has developed a detection kit for COVID-19 (2020.4.17); Wuxiapptec and Shanghai Pharmaceutical entered the field of drugs for COVID-19 (2020.4.2). As a result, from January 2020 to July 2020, the stock prices of the three vaccine companies rose sharply, from 25.3, 16.7 and 51.8 to 62.3, 25.5 and 94.8 respectively. However, with the effective control of the epidemic in China, the volatility spillover to these three vaccine R & D companies decreased in the following periods.

4. Conclusions and future work

COVID-19 has become an important event affecting global financial activities. The motivation of this paper is to explore the impact of the pandemic on the mean spillover and the volatility spillover among China’s stock market. We constructed ten spillover networks to capture the changing spillover relationship by applying the GARCH-BEKK model and complex network theory. The results are as follows:

(1) In general, the outbreak of the COVID-19 makes the mean and volatility spillover significantly decreased in the whole sample period. It indicates that the co-movement and volatility risk of the stock market are reduced by the pandemic. With the control of the pandemic and the adjustment of the market, the intensity of mean and volatility spillover has decreased rapidly. The results indicate that the pandemic has reduced the overall co-movement and volatility in Shanghai stock market, and people’s investment expectations are lower than before.

(2) From the perspective of industry, the intensity of mean spillover among SSE 180 stocks increased significantly in some industries such as Industrials sector and Consumer Staples sector, while the growth of volatility spillover were obviously reflected in consumer discretionary, health care and materials sectors in the early stage of the pandemic. In the late stage of the pandemic, the mean spillover and volatility spillover decreased significantly between most industries, but the intensity of volatility spillover increased from health care industry to other industries, especially to financial and consumer staples industry. Moreover, our results show that the volatility spillover from the financial sector to vaccine R & D companies in the health care sector increased significantly when the pandemic broke out.

In addition, although the intensity of mean spillover and volatility spillover in the market is much lower than that before the outbreak. Low spillover means that expectations of investors for the future are low and convergent. Small shocks may bring big fluctuations under this “crowded” consensus. Therefore, whether the low spillover effect in market will bring new uncertainties to the stock market is a problem to be solved in the future.

CRediT authorship contribution statement

Xueyong Liu: Methodology, Writing – original draft, Editing. Zhihua Chen: Visualization, Writing – review & editing. Zhensong Chen: Investigation, Language. Yinhong Yao: Software, Language.
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon request.

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