A Study on the Network Effects of Risk Contagion Among Global Stock Markets Under the Impact of COVID-19

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Abstract. How the risk contagion network of the global stock markets changes under the impact of COVID-19 has always been a hot issue in academic circles. In this paper, the generalized variance decomposition method is used to construct the stock market risk spillover network of 11 countries in the world, and the dynamic correlation degree of stock market risk is obtained by the rolling window prediction method. On this basis, we investigate the changes and characteristics of the risk-contagion relationship among stock markets against the background of the COVID-19 outbreak. It is found that there is an obvious cross-industry spillover between stock markets, and the stock market risk contagion network has an obvious "small world" feature. During the outbreak of COVID-19, the density of risk transmission networks between markets increased. At the same time, the network connectivity is higher, and the infection path in the network is more direct. Under the impact of COVID-19, Australia and the United States are at the center of the network.

Keywords: Systemic risk · Risk overflow network · Generalized variance decomposition · Dynamic correlation degree

1 Introduction

With the increasing degree of global financialization, economies are increasingly interconnected and complex, and financial markets are gradually merging into an inseparable whole [2]. The stock market is an important part of financial markets, and stock markets across countries have also shown greater connectivity. This connectivity not only leads to better resource allocation, but also provides a channel for risk contagion [4, 5]. Under the spillover effect, the negative impact of the cyclical structure of the real economy may quickly disperse to neighboring financial markets and constantly spread to other financial markets, thus triggering a systemic crisis [1]. In recent years, major international emergencies occur frequently, repeatedly impacting the world's major stock markets. In 2020, the global economy was hit by the COVID-19 pandemic in a short period of

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time. Systemic financial risks continued to spread in international markets, and the stock markets of major economies also experienced dramatic fluctuations. In this context, the study of the complex volatility spillover connected network among the financial markets and its role in the connected network is a key link to effectively prevent the impact of global financial risks. This paper examines the risk contagion relationship among international stock markets under the impact of the novel coronavirus epidemic, and conducts in-depth research on the spread path of financial risks and the identification of risk sources of infection. The research of this paper is helpful for the financial regulators of each country to identify the position of their own financial markets in the global financial market connectivity network. They can also be helped to identify the sources of risk and the possible routes of transmission of the risk they are faced. This study provides a scientific basis for financial regulatory authorities to formulate more targeted domestic and foreign financial risk prevention policies, and also provides a reference for further strengthening the global financial risk prevention cooperation.

2 Data and Research Methods

2.1 Research Methods

Based on the marginal contagion index of the network topology method of Diebold and Yilmaz [3], we use the generalized variance decomposition technology to obtain the network contagion index and marginal contagion index. The generalized variance decomposition method can effectively solve the problem that the traditional variance decomposition results are not robust and better depict the risk contagion network between markets [6].

First of all, VAR(p) model with stable covariance of N variables is established, and P-order is selected in the lag period:

$$\mathrm{X_t} = \sum_{\mathrm{i}=1}^{p} \Phi_{\mathrm{i}} \mathrm{X}_{\mathrm{t - i}} + \varepsilon_t \tag{1}$$

where, $X_t = (x_{it}, \cdots, x_{Nt})'$ is the volatility series of N markets in period t, and the mean value of $\varepsilon_{\mathrm{t}} \sim (0, \Sigma)$ is 0, and the covariance matrix is Σ. Assuming that the covariance of this model is stable, Formula 1 is converted into moving average form

$$\mathrm{X_t} = \sum_{\mathrm{i}=0}^{\infty} A_{\mathrm{i}} \varepsilon_{\mathrm{t - i}} \tag{2}$$

where, $A_{\mathrm{i}} = \phi_1 A_{\mathrm{t - 1}} + \phi_2 A_{\mathrm{t - 2}} + \cdots + \phi_p A_{\mathrm{t - p}}$, A_0 is the N by N identity matrix, and when $i < 0, A_I = 0$.

Generalized variance decomposition was carried out for covariance Σ. The following formula is to measure the variance of prediction error at the i variable H step (the number of variance decomposition periods), which is impacted by the j variable part, among the rest $i \neq j$:

$$\theta_{\mathrm{ij}}^{\mathrm{H}} = \frac{\sigma_{ij}^{-1}\left(\sum_{h=0}^{H-1}\left(e_j' A_h \sum e_i\right)\right)^2}{\sum_{h=0}^{H-1} e_j' A_h \sum A_h' e_j}, H = 1, 2, \cdots \tag{3}$$

In the above equation σ_{ii}^{-1} is the standard deviation of the prediction error of the i variable,e_j is the N by 1 vector, the j element is 1, and the rest is $0.\theta_{ij}^{H}$ is impact of x_j on x_i.

In this study, the network topology method is used to construct the relational degree matrix, see in Table 1.

Where, the source of behavioral correlation is listed as the receiving place of correlation, ΔIV_1, $\Delta IV_2 \ldots\ldots \Delta IV_N$ represent 11 different stock markets. Elements in the matrix were obtained by variance decomposition to reflect the correlation degree between the two markets:

$$\mathrm{S}_{\mathrm{i}\leftarrow j}^{H} = \theta_{ij}^{H} \times 100 \tag{4}$$

By improving the above formula, the formula of net correlation index can be obtained, which reflects the difference of correlation degree between two markets. The formula is:

$$\mathrm{NS}_{\mathrm{i}\leftarrow j}^{H} = \mathrm{S}_{\mathrm{i}\leftarrow j}^{H} \text{ - } \mathrm{S}_{\mathrm{j}\leftarrow i}^{H} \tag{5}$$

In the FROM column of the matrix, each element is summed up by a corresponding column of non-diagonal elements. It is the sum of the impact of market i on other markets, namely the correlation degree of other markets to market i, which is called the degree of external correlation.

$$\mathrm{TS}_{IN,\mathrm{i}\leftarrow\cdot}^{H} = \sum_{\mathrm{j}} \mathrm{S}_{i\leftarrow j}^{H}, i \neq \mathrm{j} \tag{6}$$

Table 1. Correlation degree matrix

	$\Delta\mathrm{IV}_1$	$\Delta\mathrm{IV}_2$	…	$\Delta\mathrm{IV}_\mathrm{N}$	FROM
$\Delta\mathrm{IV}_1$	$\mathrm{S}_{1\leftarrow 1}^{H}$	$\mathrm{S}_{1\leftarrow 2}^{H}$	…	$\mathrm{S}_{1\leftarrow \mathrm{N}}^{H}$	$\sum_{\mathrm{j}} \mathrm{S}_{1\leftarrow j}^{H}, j \neq 1$
$\Delta\mathrm{IV}_2$	$\mathrm{S}_{2\leftarrow 1}^{H}$	$\mathrm{S}_{2\leftarrow 2}^{H}$	…	$\mathrm{S}_{2\leftarrow \mathrm{N}}^{H}$	$\sum_{\mathrm{j}} \mathrm{S}_{1\leftarrow j}^{H}, j \neq 2$
…	…	…	…	…	…
$\Delta\mathrm{IV}_\mathrm{N}$	$\mathrm{S}_{\mathrm{N}\leftarrow 1}^{H}$	$\mathrm{S}_{\mathrm{N}\leftarrow 2}^{H}$	…	$\mathrm{S}_{\mathrm{N}\leftarrow \mathrm{N}}^{H}$	$\sum_{\mathrm{j}} \mathrm{S}_{1\leftarrow j}^{H}, j \neq \mathrm{N}$
TO	$\sum_{\mathrm{i}} \mathrm{S}_{\mathrm{i}\leftarrow 1}^{H}, \mathrm{i} \neq 1$	$\sum_{\mathrm{i}} \mathrm{S}_{\mathrm{i}\leftarrow 2}^{H}, \mathrm{i} \neq 2$	…	$\sum_{\mathrm{i}} \mathrm{S}_{\mathrm{i}\leftarrow \mathrm{N}}^{H}, \mathrm{i} \neq \mathrm{N}$	$\frac{1}{\mathrm{N}} \sum_{\mathrm{i}} \sum_{\mathrm{j}} \mathrm{S}_{\mathrm{i}\leftarrow \mathrm{j}}^{H}, \mathrm{i} \neq \mathrm{j}$

Table 2. Marginal correlation matrix

	ΔIV_1	ΔIV_2	…	ΔIV_N	Marginal Net IN
ΔIV_1	0	$MNS^H_{t,1\leftarrow 2}$	…	$MNS^H_{t,1\leftarrow N}$	$\sum_j MNS^H_{t,1\leftarrow j}, j \neq 1$
ΔIV_2	$MNS^H_{t,2\leftarrow 1}$	0	…	$MNS^H_{t,2\leftarrow N}$	$\sum_j MNS^H_{t,2\leftarrow j}, j \neq 2$
…	…	…	…	…	…
ΔIV_N	$MNS^H_{t,N\leftarrow 1}$	$MNS^H_{t,N\leftarrow 2}$	…	0	$\sum_j MNS^H_{t,N\leftarrow j}, j \neq N$
Marginal Net OUT	$\sum_i MNS^H_{t,i\leftarrow 1}, i \neq 1$	$\sum_i MNS^H_{t,i\leftarrow 2}, i \neq 2$	…	$\sum_i MNS^H_{t,i\leftarrow N}, i \neq N$	

In the row of the matrix TO, each element in the row vector is summed up by a corresponding column of non-diagonal elements to reflect the sum of the impact of market j on other markets, which is called external correlation degree.

$$TS^H_{OUT,\cdot\leftarrow j} = \sum_i S^H_{i\leftarrow j}, i \neq j \tag{7}$$

In addition, the average of TO or FROM elements can obtain the total market correlation that reflects the overall market correlation:

$$NTS^H_i = TS^H_{TO,\cdot\leftarrow j} - TS^H_{FROM,i\leftarrow\cdot} = \sum_j NS^H_{j\leftarrow i} \tag{8}$$

Combined with the network topology method, the correlation degree matrix is further calculated to obtain the net correlation degree of the two markets. Then the marginal correlation matrix is obtained by sorting the difference by time, see in Table 2. Where, MNS is marginal net correlation index:

$$MNS^H_i = NS^H_{t,i\leftarrow j} - NS^H_{t-1,i\leftarrow j} = \left(S^H_{t,i\leftarrow j} - S^H_{t,j\leftarrow i}\right) - \left(S^H_{t-1,i\leftarrow j} - S^H_{t-1,j\leftarrow i}\right) \tag{9}$$

Each element in the corresponding row and column of "MNO" and "MNI" respectively reflects the total effect of the marginal net correlation degree from other markets to market i, and the total effect of the marginal net correlation degree from market j to other markets. The risk spillover network among stock markets of different countries is constructed by the matrix of volatility spillover network, and the characteristics of risk contagion in the financial system of stock markets of different countries are analyzed.

2.2 Data

From the perspective of financial market position and overall economic strength, we selected stock index data of 11 major economies including Australia, Germany, Russia, France, South Korea, the United States, Spain, Singapore, Italy, the United Kingdom,

Table 3. Stock indexes

market	abbreviations	Stock index
Australia	AUS	Australia s & P 200AS51.GI
Germany	DEU	Germany DAXGDAXI.GI
Russia	RUS	Russia RTSRTS.GI
France	FRA	France CAC40FCHI.GI
South Korea	KOR	Korea Composite Index KS11.GI
The United States	USA	Dow Jones Industrial Average DJI.GI
Spain	ESP	Spain IBEX35IBEX.GI
Singapore	SGP	Ftse Singapore Straits IndexSTI.GI
Italy	ITA	Ftse Italy MIBFTSEMIB.FI
Britain	GBR	UK FTSE 100FTSE.GI
China	CHN	Shanghai Composite Index 000001.SH

and China as the initial data based on the principle of data availability and representativity. And the specific indicators are shown in Table 3. The 11 countries include developed countries such as the United States and the United Kingdom, as well as emerging countries such as China and Russia. In addition, the total market value of these 11 stock markets accounts for more than half of the total market value of the global stock market, which is extremely representative and extensive. The sample range is from January 2, 2008 to September 27, 2022, containing the highest and the lowest price data of 2925 trading days of the stock index. The sample data span nearly 15 years, covering all kinds of major international emergencies. The data is from the Wind database.

The missing data caused by inconsistent working days were excluded from the samples, and the method of Diebold and Yilmaz (2014) was used for reference to measure the volatility of the stock market index with the daily range variance method. The calculation formula is as follows

$$\sigma_{it}^2 = 0.361[\ln(p_{it}^{max}) - \ln(p_{it}^{min})]^2 \tag{10}$$

$$\sigma_{it} = 100\sqrt{365 \cdot \sigma_{it}^2} \tag{11}$$

where p_{it}^{max} is the daily highest price for the stock index, p_{it}^{min} is the daily lowest price for the stock index,σ_{it} is the approximate daily volatility of the index.

3 Analysis of Risk Spillover Effect Between Global Stock Markets

The correlation of stock market volatility spillovers in different countries during the full sample period is shown in Table 4. The last row represents the external spillover index of the corresponding sample country. The larger the external spillover index is the greater the influence of the country on other countries. The last column shows the spillover index of the corresponding sample country. The larger the spillover index is the greater the influence of the country itself on other countries. After observation, the following analysis can be obtained: (1) The overall net spillover index of the whole research range is about 64.80%, indicating a high degree of risk spillover effect in various domestic stock markets. (2) By observing the diagonal data and comparing with other data, it can be concluded that the domestic stock market suffers from its own lagged volatility spillover effect significantly higher than the external market, and the strongest one is China, which is 78.1%. (3) The spillover effects of various domestic stock markets are asymmetrical. For example, the spillover degree of the US stock market to the stock markets of other sample countries is significantly stronger than that of other sample countries to the US stock market. (4) In terms of external volatility spillover degree, the volatility spillover degree of the US stock market has the greatest impact on the stock market of other sample countries, which is 108.7%. Followed by the French stock market and the stock market volatility spillover effect, 105.1%, 100.1% respectively; the Chinese stock market has the weakest impact on volatility spillovers of other sample countries, only accounting for 8.5%. On the extent of exposure to external volatility, the volatility exposure of the French stock market is the most affected by other countries, which is 79.0%, followed by Germany and Britain, which are 78.6% and 75.9%. At the bottom of the list is China's stock market, which is only 21.9% influenced by fluctuations in other countries. It can be seen that the stock market volatility is more affected by its own factors, it is difficult to be affected by the external stock market volatility.

By combining the intensity of external spillover and the intensity of inbound spillover, the net spillover fluctuation risk can be calculated as follows in order from greatest to smallest: The United States, France, the United Kingdom, Germany, Italy, Spain, China,

Table 4. Risk overflow table of sample countries (2008.1.2–2022.9.27)

	AUS	CHN	DEU	ESP	FRA	GBR	ITA	KOR	RUS	SGP	USA	FROM
AUS	30.9	1.4	7.0	6.7	9.1	12.9	6.8	4.1	2.5	4.4	14.2	69.1
CHN	2.8	78.1	2.5	1.0	2.4	2.7	1.2	1.8	0.8	3.8	3.0	21.9
DEU	2.2	0.7	21.4	11.7	17.8	11.6	13.9	3.2	2.5	3.2	11.7	78.6
ESP	2.0	0.4	12.8	26.1	16.9	10.1	17.9	1.6	2.1	1.6	8.6	73.9
FRA	2.5	0.7	16.3	14.2	21.0	12.3	14.8	2.2	2.7	2.4	10.9	79.0
GBR	4.7	0.8	11.6	9.5	13.3	24.1	10.5	3.8	3.3	4.1	14.3	75.9
ITA	1.7	0.3	14.3	16.4	16.4	10.6	25.6	1.5	2.5	2.3	8.4	74.4
KOR	5.2	1.1	6.4	4.4	5.2	9.0	3.8	39.6	1.5	9.0	14.7	60.4
RUS	2.3	0.4	6.7	4.9	7.3	8.0	6.3	1.7	51.0	2.7	8.6	49.0
SGP	4.4	1.8	6.7	4.1	6.0	10.2	4.9	10.6	2.6	34.5	14.4	65.5
USA	4.3	0.9	10.3	7.4	10.7	12.8	8.1	4.2	3.0	3.9	34.4	65.6
TO	32.0	8.5	94.6	80.4	105.1	100.1	88.3	34.5	23.5	37.4	108.7	64.80%

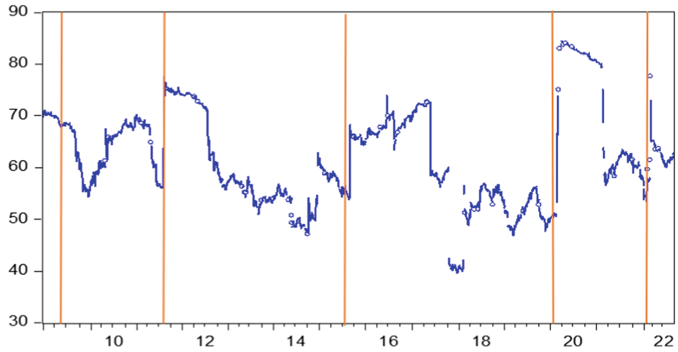


Fig. 1. Dynamic change of total overflow index (2008.1.2–2022.9.27)

Russia, South Korea, Singapore, Australia, the stock markets of the United States, France, the United Kingdom and Germany, which have positive and large net spillover effect index, are in the center of risk spillover. Once local risks occur, they are easy to have a big impact on other countries through their correlation networks, thus triggering global stock market shocks. However, the net spillover index of China, Russia, South Korea, Singapore and Australia is negative, which is the net absorber of stock market spillover risk.

The previous paper analyzes the risk linkage degree of various countries from the perspective of the full sample, and considers the static correlation of spillover effects of various countries from the perspective of static analysis. However, the static correlation cannot well describe the risk contagion network in the face of sudden extreme events. In order to better observe the situation of risk infection in various countries, the analysis is carried out from a dynamic perspective. In this paper, the ADF test is made on the range volatility of stock indexes of various countries during the whole sample period, and the test results show that all series are stable. Then, based on AIC criterion, a VAR model with a lag of 3 orders is constructed. A 200-day rolling window was used to measure the volatility spillover risk of various countries, and the variance decomposition period of the prediction error was set as 10, as shown in Fig. 1.We analyze the dynamic evolution characteristics of the total risk spillover level of the stock market in the sample countries during the whole sample period. It can be seen from the figure that the overall spillover level fluctuates between 30% and 90% during the fifteen years from 2008 to 2022, and the fluctuation fluctuation changes significantly.

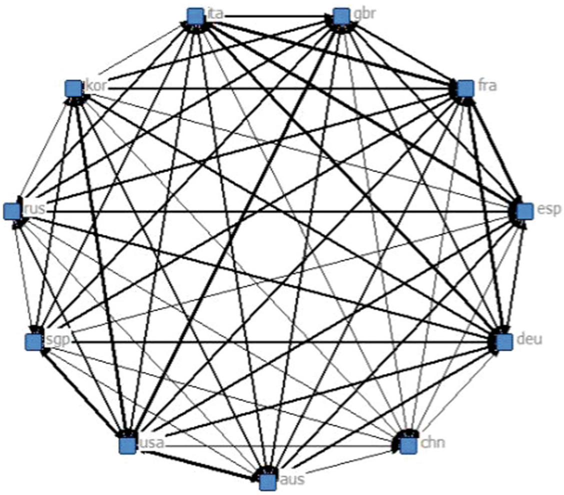
4 The Spillover Network Analysis Between Global Stock Markets Under the Impact of COVID-19

In early 2020, the novel coronavirus outbreak quickly swept the world, hitting global financial markets and causing severe shocks in the capital market. In order to further study the changes in connectivity between various countries, this paper selects March 23, 2020 as the time node to construct the marginal net spillover matrix of COVID-19. Then UCINET software was used to draw the risk infection network diagram of the day and calculate the network characteristic index. Using these indicators, we compared and analyzed the risk contagion and volatility of stock markets in different countries under the impact of COVID-19.

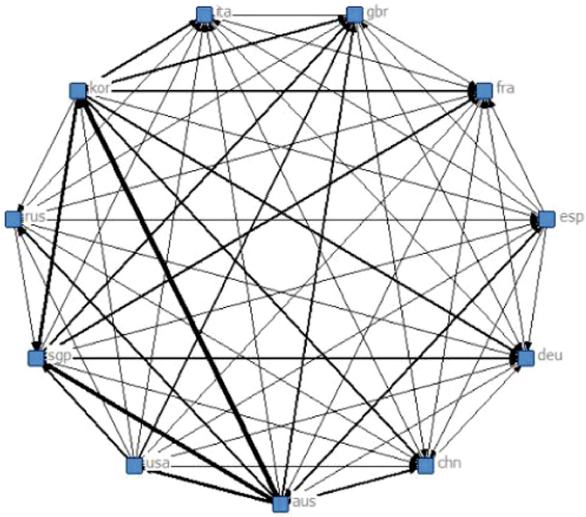
Each node in the network represents the corresponding sample country, and the directed line segment between nodes represents the input and output directions between sample countries. The thickness of the line represents the correlation between various domestic stock markets. The thicker the line, the stronger the correlation between sample countries. As shown in Fig. 2 (a), by observing the correlation diagram of the network structure during the whole sample period, it is found that the whole network structure diagram is circular, the connections between nodes have obvious directivity, and various countries are closely connected and influence each other. By observing the thickness of directed line segments, it can be concluded that the degree of correlation between different countries is not evenly distributed, among which the United States and the United Kingdom are the network center, and the connections between other countries and Australia, France and Italy are thicker, which indicates that the network risk contagion effect is strong. As shown in FIG. 2 (b), the network structure of the risk correlation degree of net spillovers between different countries shows that the degree of correlation among the sample countries has changed under the impact of COVID-19 on March 23, 2020. The connections between South Korea, Italy, Spain, the United Kingdom and France are thicker, and the effect of cyber risk contagion is stronger.

Through the comparison of network analysis indicators (see in Table 5), this paper quantitatively analyzes the volatility spillover network characteristics of major global stock markets under the impact of COVID-19. Compared with the case of full sample, the volatility spillover network features of major global stock markets have obvious "small world" characteristics. The specific analysis results are as follows: in both cases, the average centrality of the network is far greater than 1 and far less than the total number of industries 11. Although the network is sparse, it has a certain density, which ensures the possible structure of the network. The network density in these two cases is 0.646 and 0.5 respectively, indicating that the overall network density is high, the connectivity is strong, and the degree of dispersion is low during these two periods. At the same time, since the clustering coefficient is a value between 0 and 1, it can be seen that the fluctuation overflow network in both cases has a large clustering coefficient. For the spillover network of various domestic stock market volatility after the impact of COVID-19, the distance matrix is constructed to calculate the mean length of the path is 1, which is smaller than the full sample. It can be concluded that the mean distance of any two node countries in the correlation network is smaller and the transmission path is shorter.

In conclusion, the path of stock market risk transmission shows a significant centralized feature after the impact of COVID-19. Australia, Germany and France have significantly increased their intermediate centrality values and become the center countries of risk spillover. In terms of network structure, these three countries may be located on the risk infection path of the other eight sample countries, controlling the degree of risk spillover impact of other countries. They have a strong ability to influence and promote other sample countries, and play a role of mediating effect. Among them, Australia is the most centralized and located in the core part of the network structure. This may be



(a): Network structure of the full sample period



(b): Network structure during COVID-19

Fig. 2. Network structure of the full sample period **(b):** Network structure during COVID-19

due to the financial and economic crisis caused by public health events. In mid-March, Australia announced a second round of economic stimulus measures worth 66 billion Australian dollars to support the epidemic hit by the virus, which caused the stock market shock.

Table 5. Characteristics of industry volatility spillover network under the impact of COVID-19

indicators	Full sample	COVID-19
Mean degree of center	6.540	5.000
Density of network	0.646	0.500
Coefficient of clustering	0.841	1.000
Mean path length	1.145	1.000

5 Conclusions and Recommendations

In this paper, the risk contagion network among international stock markets is constructed from the perspective of risk spillover network, and the dynamic correlation degree of risk among stock markets is obtained by the method of rolling window prediction. On this basis, taking the COVID-19 outbreak in March 2020 as a landmark event, we analyzed the changes in the risk transmission network among stock markets in various countries when the shock event occurred, so as to identify the risk diffusion path and the source of the risk center. We draw the following conclusions.

First of all, the volatility of stock markets in various countries presents obvious cross-market spillover characteristics. Moreover, the analysis from the dynamic perspective finds that the risk spillover network among the stock markets of various countries is closely related to the current economic situation and the occurrence of social events. Specific shock events will have an impact on the risk contagion of the market, making the total dynamic spillover index rise significantly. The top three countries in the net spillover effect index of the stock market are the United States, France and the United Kingdom, indicating that the stock markets of these countries have higher external connectivity and are at the center of risk spillover. Once local risks arise in the US, France and the UK, it is easy to have a big impact on other countries through their networks, which will trigger global stock market shocks.

Secondly, the risk correlation network of each country's stock market has obvious "small world" characteristics. The situation of volatility spillover and risk transmission among stock markets is more complicated under the impact of COVID-19. Through the analysis of the characteristic indicators of social networks, the degree centrality of Australia and the United States belongs to the low entry degree to the high degree, which is less affected by other countries. They are in the core position of the network and have greater control. China, Germany, France, the United Kingdom, and Italy are countries with high input-low output-levels, indicating that the volatility of these countries after the impact of COVID-19 largely depends on the volatility of other countries, and their fluctuations have little impact on other sample countries.

Finally, through the analysis of the spillover effect of the stock market volatility in various countries under the impact of COVID-19, it is found that the density of the risk transmission network in the market after the occurrence of a major emergency is higher than the overall risk transmission network density, that is, the initial outbreak of a major health event may lead to investors' fear, and then trigger the herd effect, which will aggravate the risk transmission.

References

1. Allen F, Gale D. Financial contagion [J]. Journal of political economy, 2000, 108(1): 1-33.
2. Cotter J, Eyiah-Donkor E, Potì V. Predictability and diversification benefits of investing in commodity and currency futures [J]. International Review of Financial Analysis, 2017, 50: 52-66
3. Diebold F X, Yılmaz K. On the network topology of variance decompositions: Measuring the connectedness of financial firms[J]. Journal of econometrics, 2014, 182(1): 119-134.
4. Glasserman P., Young H. P. How Likely Is Contagion in Financial Networks?[J]. Journal of Banking & Finance, 2015, 50: 383-99.
5. Gross, C. ,and P. L. Siklos,"Analyzing Credit Risk Transmission to the Non-Financial Sector in Europe: A Network Approach", Journal of Applied Econometrics(2020),35(1) ,61–81.
6. YANG Z, ZHOU Y, Quantitative easing and volatility spillovers across countries and asset classes[J]. Management Science, 2016, 63(2): 333–354.