Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 221 (2023) 370–377

Procedia Computer Science

www.elsevier.com/locate/procedia

Tenth International Conference on Information Technology and Quantitative Management

Volatility and risk contagion of international stock market in the context of COVID-19

Wen Long[a,b,c], Yuhan Zeng[a,b], Man Guo[a,b,c] *

[a]School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100090, China;
[b]Research Center on Fictitious Economy & Data Science, Chinese Academy of Sciences, Beijing 100190, China;
[c]Key Laboratory of Big Data Mining & Knowledge Management, Chinese Academy of Sciences, Beijing, 100190 P.R. China

Abstract

In order to reveal the impact of the outbreak of COVID-19 epidemic on risk contagion in the international stock market, this paper establishes an ARMA-GARCH-Copula model based on the R-Vine structure to empirically analyze the stock index data of 19 important countries(regions) around the world, and uses complex network to display the risk contagion path. This research shows that the risk contagion correlation of the global stock market has significantly improved due to the impact of COVID-19; The correlation of risk transmission among European countries is significantly higher than that of other regions, reflecting a closer integration connection between EU countries; Finally, unlike previous literature, this article finds that stock market of Hong Kong in China has become an important node in the international stock market, playing an important role in the risk network before and after the epidemic.

Keywords: COVID-19; R-Vine-Copula; risk contagion; complex network

1. Introduction

The outbreak of novel coronavirus pneumonia at the end of 2019, as a major international public health event, has a huge impact on the socio-economic and capital markets. The development of global economic integration has led to increasingly close connections between financial markets in various countries, putting pressure on their stock markets during the epidemic period. The US stock market experienced 4 circuit breakers within 8 trading days, which is a rare

* Corresponding author. Man Guo.
E-mail address: guoman22@mails.ucas.ac.cn

10.1016/j.procs.2023.07.050

occurrence in history; European stock markets have also not been spared, with the EUSTX50, FTSE100 and other indices hitting their largest daily decline in history for several consecutive days. In this context, the study of risk spillovers in the international stock markets is particularly important.

This research has contributed to the issue of risk correlation in global stock markets. At present, most researches on risk correlation focus on the relationships between a few economies, such as Shanghai Composite Index, Nikkei Index, Nasdaq Index, etc.; It is relatively rare to study the stock markets of multiple important countries (regions) simultaneously. And from the perspective of research methods, this article adopts a relatively novel R-vine-copula model to study the correlation of residuals, and obtains upper and lower tail correlation results, which enriches the modeling methods for studying this problem.

In addition, this article can provide reference significance for global venture investors, which is conducive to building investment portfolios to hedge risk and obtain relatively stable investment return. At the same time, it can also enable regulators to correctly interpret market fluctuations, maximize risk avoidance, and avoid systemic risk.

2. Literature review

With the development of financial internationalization, the contagion of financial risk is gradually breaking national boundaries. And the existing research methods and models used to test and measure the contagion of financial risk mainly include the following categories.

Structural changes in correlation coefficient. Anastasopoulos et al.[1] utilized changes in Kendall's tau correlation coefficient to examine the impact of the Greek debt crisis on neighboring European countries, as well as the impact of the depreciation of RMB on major trading partners such as the United States and BRICS countries, and they found that both crises had risk contagion effects.

VAR model. Grillini et al.[2] used the Generalized Vector Autoregressive (VAR) model to study the total and paired average spillovers between eurozone countries, and found important evidence of contagion during crisis periods. Qin[3] conducted a structural VAR analysis of the financial system pressures in 20 countries and found that there is a clear contagion between the oil market and the financial system during periods of financial crisis and oil price collapse.

GARCH family models. Hung et al.[4] used the DECO-GARCH and Transfer Entropy methods to study the currency market during the Covid-19 crisis, revealing the existence of contagion effects. Li et al.[5] used the GARCH-BEK model to construct an regional volatility spillover network in Chinese stock market, and comprehensively analyzed the risk contagion effect between different regions.

Copula family models. Sklar[6] first proposed the Copula function, which can be used as a connection method to connect edge distribution and joint distribution. Embrechts et al.[7] first applied the Copula function to the field of financial research. Goel et al.[8] applied the time-varying C-Vine (Canonical Vine) copula to estimate the dependency structure of six markets, including the United States and China, during the pre and post financial crisis stages. The results confirmed that during recessions, these markets had contagion effects.

From the above, it can be seen that existing literature mostly use VAR, GARCH, and binary Copula models to study the correlation between a few markets, and high-dimensional vine structure Copula model is seldom used. The research scope is limited to the important events such as the subprime crisis and Asian financial crisis, which have occurred more than a decade ago. Thus, this paper will focus on the risk contagion effect of the international stock market in the context of the outbreak of COVID-19 epidemic and describe the contagion path.

3. R-Vine-Copula model

According to Sklar[6], the joint distribution can be decomposed into k edge distribution and a Copula function which is used to describe the nonlinear correlation between variables. When we study the overall risk correlation of multiple markets, the joint distribution of multivariate Copula function cannot accurately depict the correlation between them, existing a curse of dimensionality. Therefore, another structured Copula model is needed. Bedford and Cooke[9] first proposed a high-dimensional Copula model based on the vine model, which depicts the dependent structure between multiple markets through a tree like structure.

The Vine-Copula model can be used to measure the direct or indirect price transmission channel between financial markets, and to measure the correlation between different financial markets. The specific structures include

C vine, D vine, and R vine. In contrast, R-Vine-Copula model is more flexible and diverse, which can overcome the problem of "curse of dimensionality" to the greatest extent. Therefore, this article uses the Copula model with R vine structure to depict high-dimensional variable correlations between financial markets.

The R-vine structure can actually be regarded as a combination of a series of trees, where one edge of each tree corresponds to a copula function or a conditional copula function. n-1 trees can form an R-vine with n variables, and each tree is denoted as $H_1, H_2 \cdots H_{n-1}$, the node set of tree i is denoted as N_i, the edge set is denoted as $S_i (i = 1, 2, \cdots, n-1)$, the conditions they need to meet are as follows:

- Denote the node set of tree H_1 as $N_1 = \{1, 2, \cdots, n\}$, and edge set of tree H_1 as S_1;
- Denote the node set of tree i as $N_i = S_{i-1} (i = 2, 3, \cdots, n-1)$, namely the node set of tree i is the edge set of tree $i-1$;
- If two edges in tree H_i are also connected with edge in tree H_{i+1}, these two edges must have a common node in tree H_i.

Establish an n-ary R-vine statistical model with n-1 trees, and denote the nodes set as $N = \{N_1, N_2, \cdots, N_{n-1}\}$, edge set as $S = (S_1, S_2, \cdots, S_{n-1})$, edge in S_i as $s = j(s), k(s) \mid D(s)$, here $j(s)$, $k(s)$ are nodes which connected edge s, the connection condition set is $D(s)$, so we can represent the copula density function corresponding to edge s as $C_{j(s),k(s)|D(s)}$. Set n random variables $x_1, x_2, \cdots x_n$, and $X_{D(s)}$ is a vector determined by the condition set $D(s)$, denote the edge density function of the $i-th$ random variable as f_i, so the joint density function of X can be expressed as:

$$f(x_1, x_2, \ldots x_n) = \prod_{k=1}^{n} f_k(x_k) \prod_{i=1}^{n-1} \prod_{s \in S_i} C_{j(s),k(s)|D(s)}(F(x_{j(s)} \mid x_{D(s)}), F(x_{k(s)} \mid x_{D(s)})) \tag{1}$$

Finally, the maximum spanning tree is used to select the structure of R-vine-copula.

This article first uses the ARMA(p,q)-GARCH(1,1)-skewed t model on financial time series to construct sequence edge distribution, the order of ARMA(p,q) is selected based on AIC criteria, assumptions of the model are as follows:

$$\begin{cases} r_{i,t} = \varphi_0 + \varphi_1 r_{i,1} \cdot r_{i,t-1} + \cdots \varphi_p r_{i,p} \cdot r_{i,t-p} + \theta_1 \partial_{i,1} \cdot \varepsilon_{i,t-1} + \cdots + \theta_q \partial_{i,q} \cdot \varepsilon_{i,t-q} + \varepsilon_{i,t} \\ \varepsilon_{i,t} = \sigma_{i,t} \cdot \mu_{i,t} \\ \mu_{i,t} = skewed\ t(skew_i, shape_i) \\ \sigma_{i,t}{}^2 = \omega_i + \alpha_{i,1} \cdot \varepsilon_{i,t-1}{}^2 + \beta_{i,1} \cdot \sigma_{i,t-1}{}^2 \end{cases} \tag{2}$$

ε_i is intercept, $\varphi r_{i,1}, \cdots, \varphi r_{i,p}$ represent the logarithmic return parameter of the lagged p-period; $\theta\partial_{i,1}, \cdots, \theta\partial_{i,t-p}$ represent error parameter of lag p-period; $skew_i$, $shape_i$ are two parameters for skew t-distribution, $\omega_i, \alpha_{i,1}, \beta_{i,1}$ are parameters to be estimated。

Next, standardize the residuals obtained from the model, perform probability integral transformation, and obtain a new residual sequence. Use this new residual sequence to construct a Copula model with R-vine structure.

4. Empirical research on risk contagion in international stock market

This paper selects 19 major countries (regions) as research objects, covering major economies in Asia, Europe, the America, and Oceania, including Chinese Mainland, Hong Kong of China, Taiwan of China, Japan, South Korea, Australia, New Zealand, Russia, Brazil, India, Germany, France, the United Kingdom, Italy, Spain, the United States, Canada, Mexico, Chile. They are represented as market 1-19, respectively.

The time range of data is from January 2, 2019 to December 31, 2020. Taking January 20, 2020 as the time node, COVID-19 hasn't appeared or been recognized by the public before the node, and took an outbreak and spread after the node. The two-year time span includes important time such as the first outbreak in China, the successive outbreaks in the global scope, and the second outbreak in winter. Therefore, the time series data in this interval can better reflect the risk contagion effect.

This article also conducted a basic test on data and calculated the logarithmic rate of return. There is no autocorrelation or heteroscedasticity in the financial time series. The ARMA-GARCH model is used to calculate the edge distribution, and residual of edge distribution is standardized, then probability integration is performed to obtain a new residual sequence. Based on this new residual sequence, Copula model is constructed. We first select the optimal copula function according to the principle of maximum likelihood function value Loglik and minimum AIC, BIC and HB, then select the optimal vine structure according to Kendall correlation coefficient between variables. Finally, the risk contagion correlation and upper and lower tail correlation between international stock markets are obtained. Due to the research object includes 19 countries (regions), the R-Vine-Copula model will output an 18 layers tree structure diagram, displaying non-conditional and conditional vine structure respectively. Tables 1 and table 2 show the correlation results of the first two layers, respectively.

Table 1. Results of unconditional vine structure in the first layer before and after outbreak of COVID-19.

Edge	Risk contagion correlation before outbreak	Edge	Risk contagion correlation after outbreak
6,7	τ=0.24, λd=0.30	6,7	τ=0.29
4,6	τ=0.31	4,6	τ=0.40
5,4	τ=0.41	5,4	τ=0.44
2,1	τ=0.41	2,1	τ=0.40
2,3	τ=0.38, λd=0.46	5,3	τ=0.53, λu=0.24, λd=0.24
2,5	τ=0.42, λd=0.50	2,5	τ=0.51
2,10	τ=0.23	2,10	τ=0.38
13,8	τ=0.29	13,8	τ=0.46
12,13	τ=0.53, λu=0.30, λd=0.30	12,13	τ=0.71,λu=0.59, λd=0.59
13,2	τ=0.27, λd=0.34	12,2	τ=0.36, λd=0.44
16,9	τ=0.27, λu=0.34	16,9	τ=0.44
17,16	τ=0.49, λu=0.35, λd=0.35	17,16	τ=0.61
11,15	τ=0.58, λu=0.46, λd=0.46	11,17	τ=0.44
12,11	τ=0.65, λu=0.73	12,11	τ=0.78, λu=0.69, λd=0.69
12,14	τ=0.58, λu=0.44, λd=0.44	12,14	τ=0.76, λu=0.67, λd=0.67
12,16	τ=0.45, λu=0.20, λd=0.2	12,15	τ=0.73, λu=0.69, λd=0.69
18,15	τ=0.26	18,12	τ=0.38, λd=0.46
19,18	τ=0.25, λd=0.32	19,18	τ=0.33

Table 1 shows unconditional vine structure in the first layer. Taking markets 12(France) and 13(England) as examples, the Kendall correlation coefficient before the outbreak of COVID-19 was 0.53, and the upper and lower tail correlation was 0.3, indicating that the correlation between the same direction changes in return of these two markets was 0.53 before the outbreak, and when the French stock market skyrocketed or plummeted, the correlation of the UK stock market skyrocketed or plummeted in the same way was 0.3. While after the outbreak of the epidemic, the Kendall correlation coefficient reaches 0.71, and the upper and lower tail correlation coefficient rises to 0.59, indicating that the correlation of return changes in the same direction between these two markets during COVID-19 is 0.71, and correlation coefficient of the sudden rise and fall between the two markets is 0.59, which shows that there is a strong contagion and dependency structure between them.

Table 2 shows conditional vine structure in the second layer, namely the indirect contagion structure between two markets. Taking (5,6; 4) as an example, it represents the Kendall correlation between the stock markets of South Korea and Australia given the condition of Japanese stock market. According to the results, the Kendall correlation is 0.08 before the outbreak of COVID-19 and 0.22 after the outbreak, which also proves that the epidemic has exacerbated the risk contagion effect. In addition, it can be clearly seen that under the second layer of conditional vine structure, the values of risk contagion correlation significantly decrease. In fact, the higher the dimensionality of the vine Copula structure, the more indirect the infectious structure is, so the decrease in correlation is reasonable.

Table 2. Results of the conditional vine structure in the second layer before and after outbreak of COVID-19.

Edge	Risk contagion correlation before outbreak	Edge	Risk contagion correlation after outbreak
17,9;16	τ=0.04	17,9;16	τ=0.17, λd=0.22
12,17;16	τ=0.19	5,1;2	τ=0.08
4,7;6	τ=-0.02	4,7;6	τ=0.08
5,6;4	τ=0.08	5,6;4	τ=0.22
2,4;5	τ=0.19	2,4;5	τ=0.18
3,5;2	τ=0.24, λd=0.30	2,3;5	τ=0.18
3,1;2	τ=0.08	10,5;2	τ=0.14
10,3;2	τ=0.07, λu=0.01, λd=0.01	12,8;13	τ=0.12, λd=0.09
13,10;2	τ=0.08, λu=0.17	12,10;2	τ=0.21, λu=0.41
15,19;18	τ=0.13, λd=0.17	18,13;12	τ=0.08
11,18;15	τ=0.06	18,2;12	τ=0.06
12,15;11	τ=0.15, λu=0.20	11,16;17	τ=0.15, λd=0.19
14,11;12	τ=0.16, λd=0.21	12,17;11	τ=0.06, λd=0.13
8,2;13	τ=0.06	14,11;12	τ=0.12
12,8,13	τ=0.09	15,14;12	τ=0.24
16,13;12	τ=0.13, λd=0.17	18,15;12	τ=0.07, λu=0.15
16,14;12	τ=0.17, λd=0.22	19,12;18	τ=0.12, λd=0.17

Finally, from the Kendall correlation coefficient before and after the outbreak of COVID-19, the correlation coefficient between European countries is generally higher than that of other regions, reflecting a closer risk transmission path between European countries.

In addition, it’s also found that the correlation coefficient has generally improved during the epidemic, which supports that COVID-19 has strengthened the risk contagion effect between international stock markets.

Although the R-Vine-Copula model can better depict the risk contagion correlation between two markets, as the dimensions increase, the structure of conditional correlation becomes more complex, making it difficult to intuitively see the importance of a market in the global context. Therefore, this article introduces complex network to comprehensively display the risk contagion effect between 19 countries (regions). Specifically, taking 19 countries (regions) as network nodes, construct undirected network structure using the non-conditional correlation coefficient and conditional correlation coefficient of risk contagion as neighboring edges, calculate the degree centrality to measure the importance of each node in the network. The following operations are all implemented using UCINET software, and results are shown in table 3.

According to table 3, the degree centrality of Hong Kong and French stock markets before and after the outbreak of COVID-19 are all very high, indicating that these two markets are most important in the risk contagion network, which have the strongest contagion effect with other markets, and can cause the strongest impact on other markets or being hit by other markets intensely. In addition, from the perspective of the value of degree centrality, we can see that nearly all these 19 countries (regions) have a significant increase of degree centrality during COVID-19, which also reflect that the overall risk contagion intensity of the international stock market increases after the outbreak of COVID-19.

This article establishes two thresholds to study the risk contagion effect, which are 0.2 and 0.4, respectively. Based on the calculation results, it can be seen that as the vine structure continues to increase, the correlation of the higher-level structure decreases, both below 0.2. Moreover, 0.4 is an important node indicator for measuring correlation. Therefore, this article selects 0.2 and 0.4 as two thresholds. Since 0.2 indicates a lower degree of correlation, correlations below 0.2 means very weak and can be considered to have almost no correlation. And 0.4 means that the degree of correlation between the two markets is worthy of attention.

Table 3. Degree centrality of 19 countries (regions) in risk contagion network.

Degree centrality before outbreak of the epidemic		Degree centrality after outbreak of the epidemic	
Hong Kong(China)	3.410	France	5.560
France	3.270	Hong Kong(China)	3.550
Germany	2.830	South Korea	3.260
USA	2.380	Canada	2.870
Spain	2.300	Germany	2.830
South Korea	2.230	Mexico	2.660
England	2.140	Australia	2.420
Taiwan(China)	2.110	Spain	2.370
Italy	2.020	USA	2.360
Japan	1.960	England	2.330
Chile	1.880	India	2.280
Russia	1.880	Brazil	2.250
Australia	1.840	Taiwan(China)	2.240
Canada	1.820	Japan	2.190
Mexico	1.680	Russia	2.010
Chinese Mainland	1.520	Chile	1.930
Brazil	1.500	Italy	1.909
India	1.250	Chinese Mainland	1.679
New Zealand	0.980	New Zealand	1.660

Fig. 1 and Fig. 2 respectively reflect the risk contagion structure of domestic and foreign stock markets with a correlation of no less than 0.2 or 0.4 before and after the outbreak of the epidemic. It can be seen that the density of the network structure after the outbreak is higher, and there are more risk contagion pathways. Moreover, the Hong Kong stock market and the French stock market are still important nodes in the network with a correlation of 0.4, indicating that these two markets are the most important in the risk contagion network, and the contagion effect between them and other markets is the strongest, that is, their impact from and to other markets is the strongest. Furthermore, it can also be seen that the Hong Kong stock market is an important path for risk contagion between Chinese stock market and others.

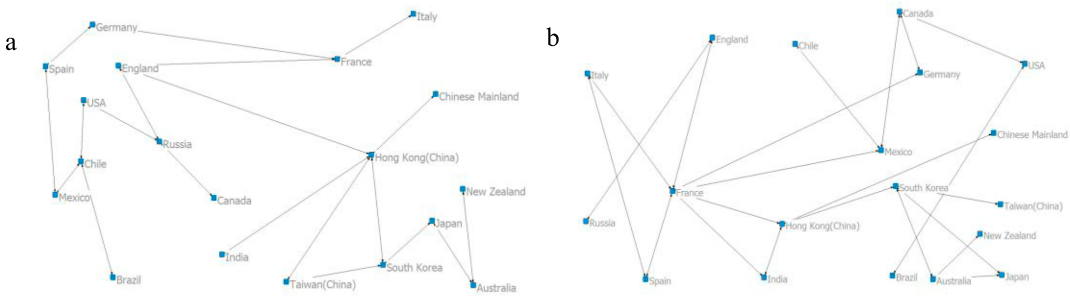

Fig.1. Risk contagion network before(a) and after(b) the outbreak(threshold=0.2)

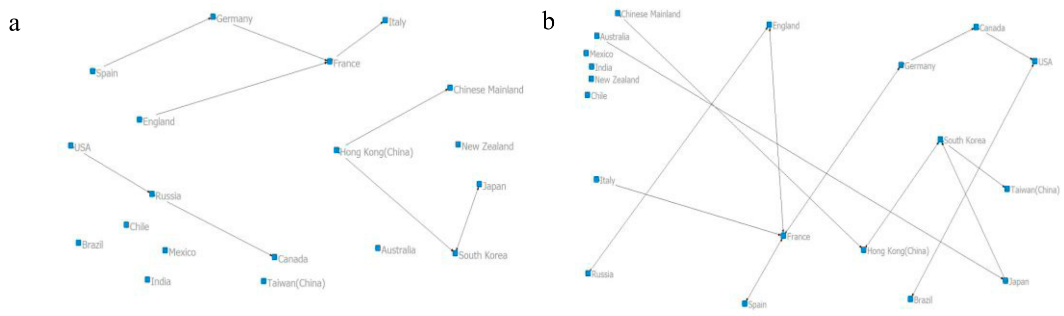

Fig.2. Risk contagion network before(a) and after(b) the outbreak(threshold=0.4)

5. Conclusion

This article aims to investigate the risk contagion effect between international stocks before and after the COVID-19. According to the risk contagion correlations among 19 countries (regions), we can not only see the impact of COVID-19 on the risk contagion effect, but also visually depict the risk contagion path between international stock markets. Main conclusions are as follows:

The ARMA-GARCH-Copula model with R vine structure can effectively analyze the correlation of risk contagion among international stock markets. The conditional and unconditional correlation results show that during COVID-19 the aggregation effect of stock market volatility in various countries has significantly increased, the correlation of risk contagion has significantly raised, and the correlation of top and bottom in some stock markets has also significantly increased.s

The risk contagion correlation between European countries is high, especially after the outbreak of the epidemic, reaching over 0.7, which reflects high degree of economic integration and trade internationalization among countries such as the European Union and the United Kingdom. It also reflects that the European stock market has a strong linkage in the face of COVID-19, and has a greater possibility of successive sharp rises and falls, especially it's more vulnerable when facing crisis.

According to the complex network model, the degree centrality of Hong Kong and French stock markets before and after the outbreak is very high, indicating that these two markets are the most important in the risk contagion network, with the strongest contagion effect. And under different levels of threshold conditions, it can be seen that Hong Kong and French stock markets both play an important role, and Hong Kong stock market becomes an intermediate path connecting the correlation between Chinese stock market and others.

Acknowledgements

This research was supported by the grants from National Natural Science Foundation of China (No.71771204, 72231010) and the Fundamental Research Funds for the Central Universities.

References

[1] Anastasopoulos, A. (2018). Testing for financial contagion: New evidence from the Greek crisis and yuan devaluation. *Research in International Business and Finance*, **45**, 499-511.

[2] Grillini, S., Ozkan, A., & Sharma, A. (2022). Static and dynamic liquidity spillovers in the Eurozone: The role of financial contagion and the Covid-19 pandemic. *International Review of Financial Analysis*, **83**, 102273.

[3] Qin, X. (2020). Oil shocks and financial systemic stress: International evidence. *Energy Economics*, **92**, 104945.

[4] Hung, N. T., Nguyen, L. T. M., & Vo, X. V. (2022). Exchange rate volatility connectedness during Covid-19 outbreak: DECO-GARCH and Transfer Entropy approaches. *Journal of International Financial Markets, Institutions and Money*, **81**, 101628.

[5] Li, Y., Zhuang, X., & Wang, J. (2021). Analysis of the cross-region risk contagion effect in stock market based on volatility spillover networks: Evidence from China. *The North American Journal of Economics and Finance*, **56**, 101359.

[6] Sklar, A., (1959). Fonctions de repartition a n dimensions et leurs marges. *Publ.inst.statist.univ.paris*.

[7] Embrechts, P., & Mcneil, A.. (2000). Correlation and dependence in risk management: properties and pitfalls. *Review of Economics and Statistics* **86(1)**.

[8] Goel, A., & Mehra, A. (2019). Analyzing contagion effect in markets during financial crisis using stochastic autoregressive canonical vine model. *Computational Economics*, **53**, 921-950.

[9] Bedford, T., & Cooke, R. M. (2001). Probability density decomposition for conditionally dependent random variables modeled by vines. *Annals of Mathematics and Artificial intelligence* **32**: 245-268.