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Analysis of risk correlations among stock markets during the COVID-19 pandemic

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ABSTRACT

The outbreak of the COVID-19 pandemic significantly negatively impacted the global economy and stock markets. This paper investigates the stock-market tail risks caused by the COVID-19 pandemic and how the pandemic affects the risk correlations among the stock markets worldwide. The conditional autoregressive value at risk (CAViaR) model is used to measure the tail risks of 28 selected stock markets. Furthermore, risk correlation networks are constructed to describe the risk correlations among stock markets during different periods. Through dynamic analysis of the risk correlations, the influence of the COVID-19 pandemic on stock markets worldwide is examined quantitatively. The results show the following: (i) The COVID-19 pandemic has caused significant tail risks in stock markets in most countries, while the stock markets of a few countries have been unaffected by the pandemic. (ii) The topology of risk correlation networks has become denser during the COVID-19 pandemic. The impact of the COVID-19 pandemic makes it easier for risk to transfer among stock markets. (iii) The increase in the closeness of the risk relationship between countries with lower economic correlation has become much higher than that between countries with higher economic correlation during the COVID-19 pandemic. For researchers and policy-makers, these findings reveal practical implications of the risk correlations among stock markets.

1. Introduction

Since the beginning of the 21st century, an increasing number of major emergencies has broken out around the world, thus bringing increasing attention to their impact on the economy, especially the stock market. The COVID-19 pandemic was declared a public health emergency of international concern by the World Health Organization on January 30, 2020; the pandemic has spread more widely and infected more people worldwide than the SARS epidemic (Chen et al., 2009) and the EBOLA virus (Del Giudice & Paltrinieri, 2017). By July 2021, there were nearly 180 million COVID-19 cases and 4 million COVID-19 deaths worldwide. COVID-19 has significantly adversely affected society, the economy, and the stock market. From late February to late March of 2020, many stock markets' indices experienced a continuous sharp decline, followed by frequent fluctuations and a slow recovery (Zhong & Wu, 2020). For example, the Dow Jones Industrial Average of the US declined from 29,290 to 20,087 between February and March 2020. Then, as various policies were implemented to deal with the pandemic,

the index gradually rose to 25,400 at the end of May 2020 (Hu, n.d.). In fact, in the increasingly closely connected international economic environment, preventing the rapid spread of financial risks during major emergencies around the world has become an important issue for government authorities and academia. This paper investigates whether COVID-19 has caused stock-market tail risks and how the pandemic affects the risk correlation of stock markets worldwide; the findings of this paper can help researchers and policy-makers better understand the risk correlations among stock markets.

Some studies have investigated the impact of COVID-19 on stock markets (Harjoto, Rossi, & Paglia, 2021; Onali, 2020; Ozili & Arun, 2020; Rizwan, Ahmad, & Ashraf, 2020). Harjoto et al. (2021) studied how the unprecedented adverse shock of COVID-19 on the countries' economic growth translated into a negative shock to the stock markets. The results showed that the impact of COVID-19 in emerging countries was different from that in developed countries. Au Yong and Laing (2021) examined the reaction of the US stock market to COVID-19 by focusing on firms' international exposure. The results showed that

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internationalization helps multinational firms be more resilient to economic shocks caused by COVID-19 in the long term. Baek, Mohanty, and Glambosky (2020) studied the impact of COVID-19 on US stock market volatility from the perspective of lower to higher volatility identified with a Markov-switching AR model. Al-Awadhi et al. (2020) used panel data analysis to test the effect of COVID-19 on the Chinese stock market. The findings indicated that the daily growth in both total confirmed cases and total cases of death caused by COVID-19 have significantly negatively affected stock returns across all companies. These studies examined the impact of COVID-19 on stock markets from the perspectives of returns and volatilities; however, the inherent risk correlations among the markets were not investigated.

Previous studies adopt various risk measurements to investigate the system risk in financial markets. In earlier studies, the cross-correlation coefficient (Hautsch, Schaumburg, & Schienle, 2015; Patro, Qi, & Sun, 2013) and principal component analysis (Kritzman et al., 2011) were widely used in risk measurement. In subsequent studies, value at risk (VaR) methods (Linsmeier & Pearson, 2000) and conditional value at risk (CoVaR) methods (Adrian & Brunnermeier, 2011; Xu et al., 2019; Zehri, 2021) became the most popular methods because of their accuracy estimation. Abuzayed et al. (2021) examined the systemic distress risk spillover between the global stock market and individual stock markets in the countries most affected by COVID-19 by using CoVaR and delta CoVaR. The empirical results revealed that bivariate systemic risk contagion between the global stock market and each individual stock market evolved during the sample period and intensified as COVID-19 spread worldwide. Zhang et al. (2020) investigated the tail risk of the Chinese stock market and found that according to the CoVaR model, during market crashes, the stock market is exposed to more systemic risk. The conditional autoregressive value at risk (CAViaR) model, which was proposed by Engle and Manganelli (2004), specifies the evolution of the quantile over time by using an autoregressive process and estimates the parameters by using a regression quantile. Allen, Singh, and Powell (2012) applied the CAViaR model to Australian stock market indices and a sample of stocks and tested the efficacy of four different specifications of the model in a set of in-sample and out-of-sample tests. Wu (2020) applied the CAViaR model to three different indices, namely, the Shanghai Security Composite index, Shanghai Stock Exchange B Share index and Shenzhen Security Component index of China's stock market. Compared with traditional VaR and CoVaR methods, the CAViaR model does not make any assumptions concerning the income distribution but directly investigates the behavior characteristics of the tail of the income distribution. The model adopts the form of autoregression to model the dynamic quantile. The CAViaR method has obvious advantages, especially for financial data that do not obey a normal distribution.

Traditional econometric methods can estimate the correlations between financial institutions; however, these methods may underestimate the systemic risk contribution of highly interconnected financial institutions because these methods cannot capture the risk correlation found in the topology of financial networks. Network theory has been a powerful tool for analyzing complex financial systems and is becoming more popular in the financial area. Network theory can abstract the financial system to a financial network with a set of nodes and edges, thereby revealing the underlying structure and complexity of the system (Levy-Carciente et al., 2015; Battiston et al., 2016; (Zhang, Chen, & Shao, 2021). (Billio et al., 2012) proposed a Granger-causality network (also known as a mean-spillover network) to study the interconnectedness and systemic risk among hedge funds, brokers, banks and insurers. Given the macroeconomic and market externalities, (Fang et al., 2018) constructed a tail risk network to present the overall systemic risk of Chinese financial institutions. The results showed that a firm's idiosyncratic risk could be affected by the firm's connectedness with other institutions. Compared with the macroeconomic state, firm characteristics and historical price movement, the risk spillover effect from other companies was the main driving factor of firm-specific risk. (Gong et al.,

2019) constructed a causal complex network of financial institutions by using a Granger-causality network and principal component analysis and further analyzed the network topology structure characteristics by using centrality indicators. Empirical studies have found that causal networks of Chinese financial entities possess small world and scale-free properties, with the number of connections increasing dramatically in periods of turmoil, thus indicating stronger interconnectedness in the financial system during crises.

In the aforementioned studies, the impact of COVID-19 on stock markets has been studied from different perspectives. However, most studies have focused on systemic risk in individual countries or financial markets during the COVID-19 pandemic. Additionally, few studies have combined the CAViaR model and network theory to investigate the risk correlations among stock markets in different countries. To bridge this research gap, using the CAViaR model, this paper measures the tail risk under the impact of COVID-19 by analyzing the risk correlation of the stock markets worldwide. The main contributions of this paper are threefold: (1) This paper applies the CAViaR model to measure the tail risks of stock markets worldwide during the COVID-19 pandemic. The results show that COVID-19 has caused significant tail risks in stock markets in most countries, while the stock markets of a handful of countries remain unaffected by COVID-19. (2) A risk correlation network is constructed to study the risk correlation among stock markets worldwide in different periods during the COVID-19 pandemic. The results show that the topology of the risk correlation network has become denser during the COVID-19 pandemic. (3) The daily change over time in the risk correlation between countries is examined in this paper. The results show that the increase in the closeness of the risk relationship between countries with lower economic correlation is much higher than that between countries with higher economic correlation during the COVID-19 pandemic.

The remainder of this article is organized as follows: Section 2 describes the method of risk measurement used in this paper. Section 3 describes the data. In Section 4, the impact of COVID-19 on stock markets and the risk correlation network during the COVID-19 pandemic are discussed. Finally, concluding remarks are given in Section 5.

2. Risk measurement

In this paper, the CAViaR model is used as the risk measurement to study the impact of COVID-19 on global stock markets. Because stock data do not usually obey a normal distribution, the CAViaR model has been proven to be a more effective method to measure the tail risk of stock markets (Abad, Benito, & López, 2014). The CAViaR model is a semiparametric equation based on the quartile regression (QR) model (Koenker & Bassett, 1978). The QR model regresses the independent variable according to the conditional quantile of the dependent variable to obtain the regression model under all quantiles. Therefore, compared with ordinary least-squares (OLS) regression, QR can describe the influence of only independent variables on the local changes in dependent variables, so QR can more accurately describe the influence of independent variables on the variation range of dependent variables and the shape of the conditional distribution. The QR model can capture the tail feature of the distribution when the independent variable affects the distribution of the dependent variable differently in different parts. For example, when there is a left or right deviation, the QR model can describe the characteristics of the distribution more comprehensively to obtain a comprehensive analysis. In addition, the coefficient estimation of the QR model is more robust than the OLS coefficient estimation is. The mathematical expression of QR is as follows:

$$F(y) = P(Y \leq y) \quad (1)$$

where y denotes a random variable that is the return of the index in this paper and $F(y)$ denotes the right continuous distribution function. Then, the corresponding quantile at τ is defined as:

$$Q(\tau) = \inf\{y : F(y) \geq \tau\}. \tag{2}$$

Equivalently, the formula can be transformed into an optimization problem:

$$Q(\tau) = \operatorname{argmin}_{\varphi} \left\{ \sum_{i: y_i \geq \varphi} \tau |y_i - \varphi| + \sum_{i: y_i \leq \varphi} (1 - \tau) |y_i - \varphi| \right\} \\ = \operatorname{argmin}_{\varphi} \left\{ \sum_i \rho_{\tau}(y_i - \varphi) \right\} \tag{3}$$

Engle and Manganelli (2004) were the first to propose the CAViaR model, which is based on the QR model. Compared to VaR, CAViaR does not need to estimate the tail distribution, which is calculated directly by using the mathematical optimization method. There are four quantile models of CAViaR: the Symmetric Absolute Value (SAV) model, Asymmetric Slope (AS) model, Indirect GARCH (IG) model and Adaptive (AD) model.

SAV:

$$f_i(\beta) = \beta_1 + \beta_2 f_{i-1}(\beta) + \beta_3 |y_{i-1}| \tag{4}$$

where y_{t-1} denotes the impact of the index; and where $f_i(\beta)$ denotes the conditional quantile of y_t , which represents VaR. Formula (4) shows that positive and negative shocks have the same influence on VaR.

IG:

$$f_i(\beta) = (\beta_1 + \beta_2 f_{i-1}^2(\beta) + \beta_3 f_{i-1}^2(\beta))^{1/2} \tag{5}$$

IG is similar to SAV in that there is no difference in VaR for the positive and negative impacts.

AD:

$$f_i(\beta) = f_{i-1}(\beta) + \beta_1 \{ [1 + \exp(G[y_{i-1} - f_{i-1}(\beta)])]^{-1} - \theta \} \tag{6}$$

AD describes the adjustment process of VaR itself; however, the AD model has been proven to be worse than other models, and later scholars have not conducted empirical research on it.

AS:

$$f_i(\beta) = \beta_1 + \beta_2 f_{i-1}(\beta) + \beta_3 |y_{i-1}| I(y_{i-1} > 0) + \beta_4 |y_{i-1}| I(y_{i-1} < 0) \tag{7}$$

where $I(\cdot)$ is a threshold function that will influence the impact term. The AS model distinguishes the different effects of positive and negative shocks on VaR.

As the above models show, the AS model differentiates positive and negative effects, while the SAV and IG models do not. To measure the tail risk of the stock market more accurately, this paper uses the AS model to calculate the CAViaR of the index.

3. Data

The data comprise daily closing price indices of 28 countries' stock markets. All indices were retrieved from the 'Gildata' database (<http://www.gildata.com>). The full sample period spans from January 2, 2019, to June 24, 2021, and the sample contains 644 daily observations. The sample period covers the COVID-19 outbreak period, thus enabling us to evaluate the effects on the risk correlation among stock markets

Table 1
Index codes and the corresponding countries.

Index	Country	Index	Country	Index	Country	Index	Country
AEX	Netherlands	MIB	Italy	DJI	US	SH	China
ATX	Austria	FCHI	France	AORD	Australia	HSI	Hongkong
BFX	Belgium	FTSE	UK	STI	Singapore	JKSE	Indonesia
IBEX	Spain	GDAXI	Germany	TWII	Taiwan	N225	Japan
OMXSPI	Sweden	RTS	Russia	MXX	Mexico	NZ50	New Zealand
OSEAX	Norway	GSPTSE	Canada	TA125	Israel	PSI	Philippines
SSMI	Switzerland	IBOV	Brazil	MERV	Argentina	KLSE	Malaysia

worldwide. The index codes and the corresponding countries are shown in Table 1.

In Table 1, data cover most of the well-known stock indices in the world, and focal countries were chosen based on the prevalence of COVID-19. The data cover 12 European countries and 9 Asian countries and regions. In addition, data on five important countries of the Americas (the US, Canada, Mexico, Brazil and Argentina) and two important countries in Oceania (Australia and New Zealand) are also included.

Fig. 1 shows the number of new COVID-19 cases daily worldwide. Data on new COVID-19 cases were obtained from the "WIND" database (<https://www.wind.com.cn/>). COVID-19 became a concentrated outbreak in the world in March 2020. In April 2020, the number of new COVID-19 cases rose rapidly and was nearly 100,000. Since then, the epidemic has been controlled to a certain extent, and the number of new COVID-19 cases has stabilized at approximately 100,000. By October 2020, the epidemic was out of control worldwide again, and the number of new cases rose from approximately 300,000 to approximately 800,000 by the end of 2020. Subsequently, the number of new COVID-19 cases fluctuated greatly between 300,000 and 800,000 in the first half of 2021.

Based on news reports from leading financial outlets (e.g., Bloomberg, Yahoo! Finance, the Wall Street Journal and the Financial Times), the pattern of the global financial market's response to perceived and actual threats from COVID-19 was identified after February 20, 2020 (Linsmeier & Pearson, 2000). To analyze the short-term effects of COVID-19 on the stock market worldwide, the period of the sample is split into three subperiods: January 2, 2019, to February 20, 2020 (Stage 1); February 21, 2020, to June 20, 2020 (Stage 2); and June 21, 2020, to June 24, 2021 (Stage 3). These subperiods represent three distinct phases of the premiddle and postepidemic period in the stock market. This classification enables us to evaluate the effects of the first wave of COVID-19 on stock markets worldwide and analyze the risk correlations between stock markets in different stages.

4. Results

This section combines the CAViaR model and network theory to conduct empirical research on the risk correlation of stock markets worldwide during the COVID-19 pandemic. By 100 times the log returns' difference, 664 daily returns of the selected 28 indices are calculated based on the following equation:

$$y_t = (\log p_t - \log p_{t-1}) \times 100 \tag{8}$$

where p_t denotes the closing price of the index at time t and y_t denotes the daily return of this index. Then, using the CAViaR model, we calculate the risk losses at 1% (i.e., $\tau = 0.01$ in Formula (2)). Furthermore, the dynamic quantile (DQ) test (Engle & Manganelli, 2004) is used to test the precision of the model used in this paper. The closer the value of the DQ test is to the corresponding confidence level, the more accurate the model is.

Table 2 presents the value of the estimated parameters, the corresponding standard errors and p values based on the AS model of CAViaR (see Formula (7)). Because of the limited length of this paper, six well-known stock markets are chosen to show in the table. The table shows

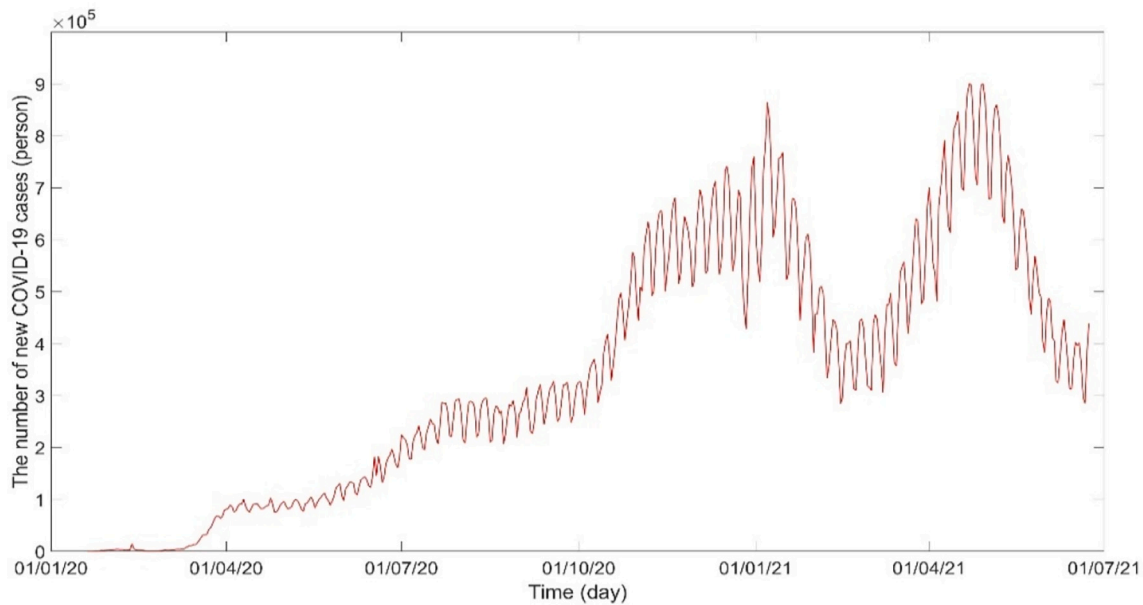


Fig. 1. The number of new COVID-19 cases worldwide.

Table 2
Estimates and relevant statistics for CAViaR specification of six countries' stock markets.

	DJI	FCHI	FTSE	HSI	STI	N225
Beta 1	0.1120	0.0559	0.0619	0.3034	0.1017	0.0694
Std.	0.0733	0.0228	0.0308	0.2271	0.0768	0.0340
p values	0.0633	0.0072	0.0223	0.0908	0.0927	0.0204
Beta 2	0.7717	0.9163	0.8856	0.7535	0.8187	0.9213
Std.	0.1034	0.0310	0.0498	0.1494	0.0707	0.0300
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Beta 3	0.0716	-0.0550	-0.0231	0.1187	0.0427	-0.0874
Std.	0.1431	0.0603	0.0987	0.1571	0.0876	0.0411
p values	0.3085	0.1809	0.4073	0.2250	0.3129	0.0169
Beta 4	0.7498	0.3361	0.4330	0.4219	0.4636	0.2949
Std.	0.1862	0.1701	0.2533	0.2004	0.1101	0.0642
p values	0.0000	0.0241	0.0437	0.0177	0.0000	0.0000
DQ Test (p values)	0.9381	0.9465	0.9674	0.9788	0.9945	0.9590

that the coefficients of the autoregressive terms (Beta 2) are always very significant. This finding confirms that the clustering of volatilities is also relevant in the tails. In addition, the adaptive model is not rejected by the DQ test, thus indicating that the CAViaR model performs very well in this paper. Similar to that of the six markets, the coefficients of the autoregressive terms (Beta 2) of the other 22 selected markets are significant too. And the results of the other 22 markets pass the DQ test.

4.1. The CAViaR of the stock markets during the COVID-19 pandemic

Since the COVID-19 pandemic is an extreme event that represents a source of tail risk from the stock markets (Sharif, Aloui, & Yarovaya, 2020), whether the outbreak of COVID-19 imposes a significant tail risk on the stock market is investigated in this section.

Based on the extent to which each market is affected by COVID-19, the 28 selected stock markets can be divided into those that are significantly affected and those that are relatively less affected. The CAViaRs of the two types of markets are presented in Figs. 2 and 3 respectively.

Fig. 2 illustrates the indices and CAViaRs of 16 countries' stock markets that are significantly affected by COVID-19. The blue and red lines represent the closing prices of the indices and the risk losses (i.e., the value of CAViaR) of each stock market during the whole sample

period. The lower the value of CAViaR is, the greater the tail risk the market suffers after being impacted by the event. More specifically, the indices of these countries' stock markets fluctuate within the normal range most of the time. However, from March 2020 to June 2020, almost all stock markets experience violent fluctuations (see the blue line in Fig. 2). This period coincides with the first major wave of COVID-19 around the world. The results show that the outbreak of COVID-19 significantly affects the indices of the stock markets in these countries. Potential reasons for the phenomenon include the following: first, stock markets are likely to react similarly to COVID-19 as to other disasters, such as natural disasters (Gao, Liu, & Shi, 2020) or terrorism (Wang & Young, 2020). The effects of COVID-19 on the overall economy will not only significantly influence domestic demand but also limit supply, negatively impact firms' future cash flows and foster public pessimism about the future (Goodell, 2020). Second, investors' risk preferences or moods toward certain events might vary considerably, thus leading to an increase in fear-induced sentiment (Zhang et al., 2021). Investor attention has negatively influenced global stock returns during the COVID-19 pandemic (Smales, 2021).

The results of CAViaRs are similar to the results of the indices (see the red line in Fig. 2). Before the concentrated outbreak of COVID-19, the risk losses of 16 countries fluctuate within a normal level, between approximately -3 and -5. However, after March 2020, the risk losses decline sharply and exhibit peaks in April 2020. As the stock markets gradually adapt to the epidemic and various policies are gradually applied in the financial markets, the risk losses begin to quickly reverse. Risk losses returned to relatively normal levels in June 2020. In addition, stock markets in different countries have different capacities to withstand the impact of the pandemic. The CAViaR of most countries, such as the Netherlands and Belgium, was approximately -10 to -20 during the outbreak of the epidemic. During this period, the CAViaRs of the stock markets in Italy and Brazil were lower than those of any other country; these CAViaRs were all beyond -30 (as shown in the red box in Fig. 2). These results imply that the stock markets in both countries were exposed to more tail risk during this period of the COVID-19 pandemic. There are two possible reasons for this phenomenon. First, these two countries have seriously suffered from the pandemic, which has greatly influenced the stock market. The economic downturn and the restricted circulation of people during the pandemic are the reasons for the outbreak of tail risk in the stock market. Second, the resilience of the two

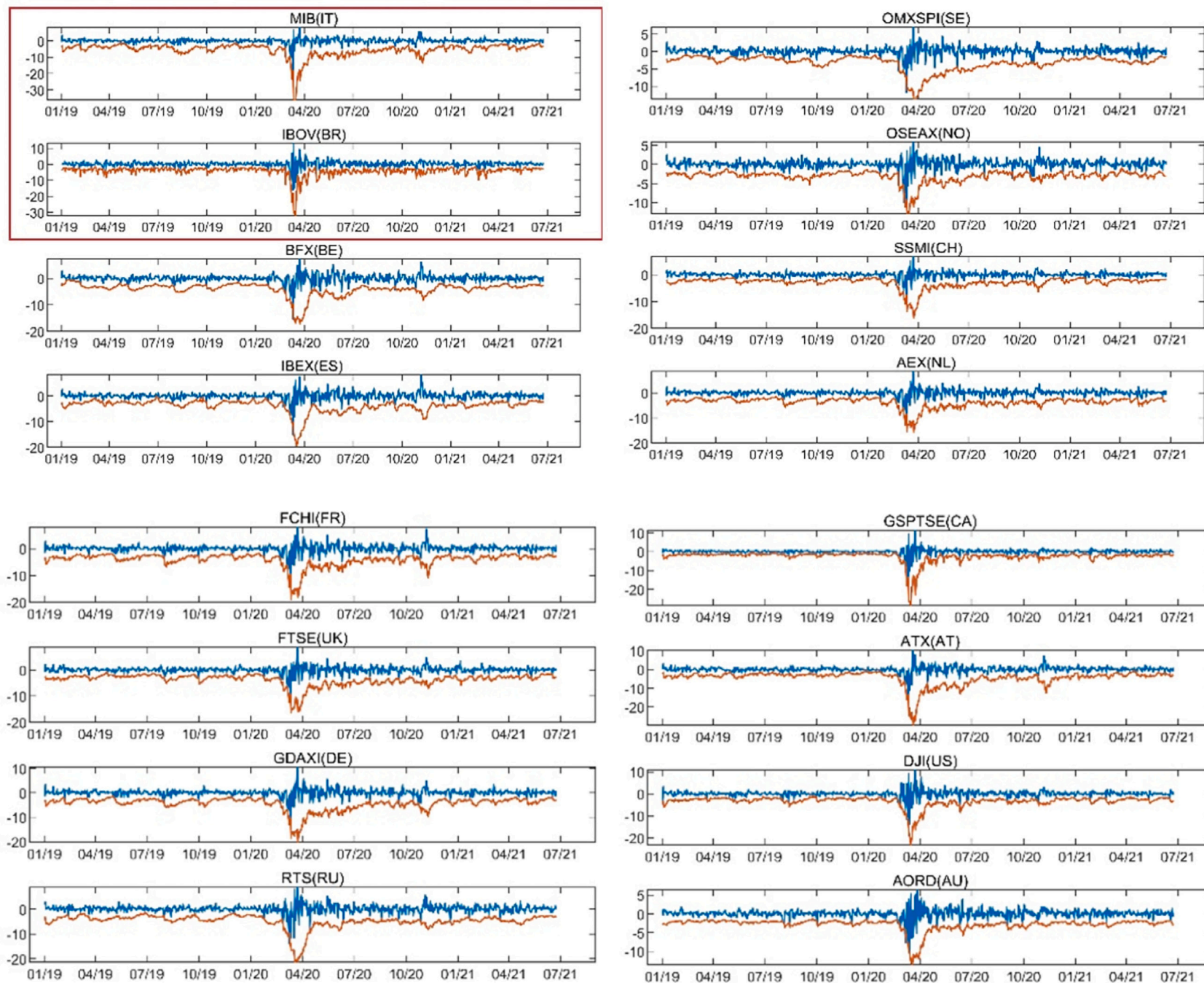


Fig. 2. Indices and CAViRs of the stock markets which are significantly affected by COVID-19.

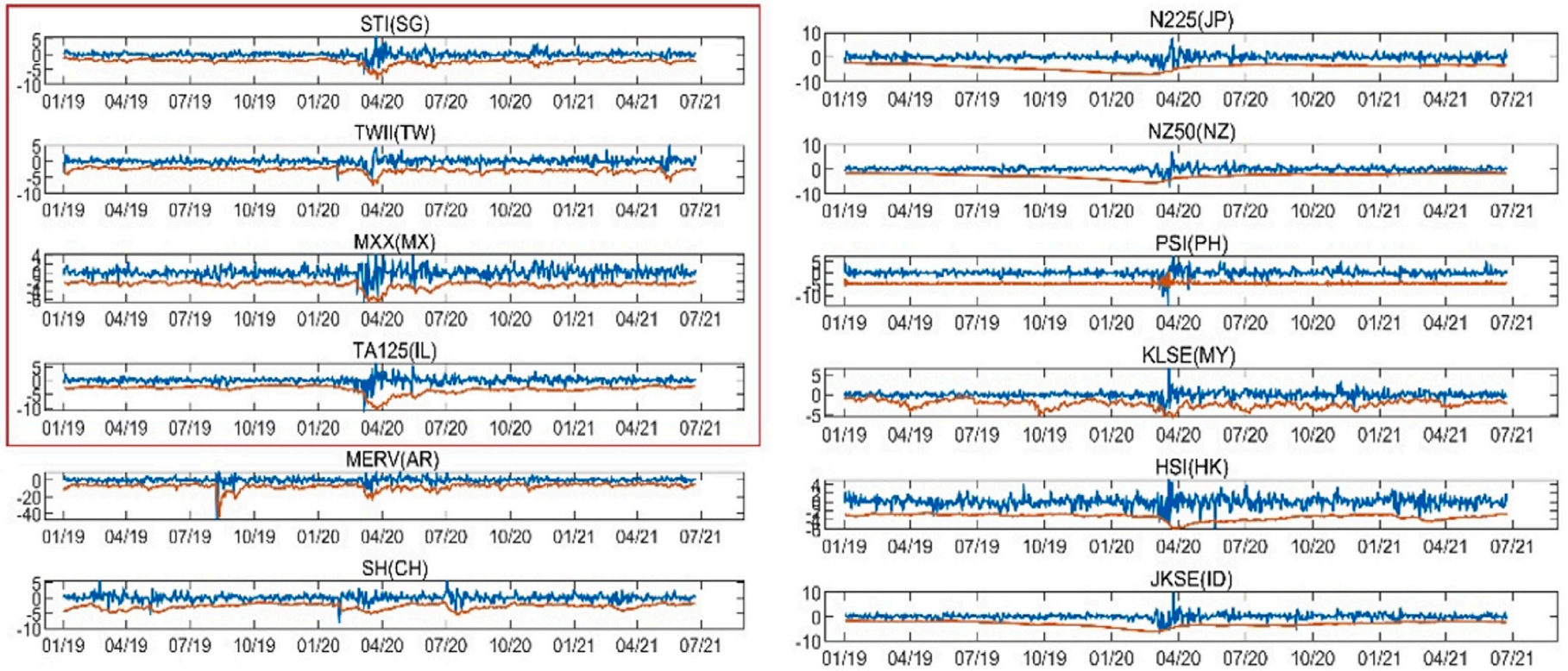


Fig. 3. Indices and CAViARs of the stock markets with lower fluctuations in CAViAR during the COVID-19 pandemic.

countries' stock markets is relatively weak. During a risk shock, the market reacts violently to the risk.

Another finding is that a small fluctuation appears at the end of 2020 in most countries' stock markets. Along with the volatility of the indices, risk losses also fell slightly in December 2020. This phenomenon is particularly true in some countries, such as Italy, Belgium, Spain, France, Germany, Switzerland, which are European countries. This result is consistent with the time of the second wave of COVID-19 in Europe. However, the CAViaR is higher than that in the first wave because the stock markets were already well prepared and experienced in responding to the pandemic shock.

Conversely, in some countries, there is no marked tail risk to the stock market from COVID-19 (see Fig. 3). Specifically, the stock markets of Singapore, Taiwan, Mexico and Israel (shown in the red box in Fig. 3) suffer from the limited impact of COVID-19. The CAViaRs of these countries are approximately -6 during the outbreak of COVID-19 and thus higher than those of the abovementioned 16 countries (whose CAViaRs are approximately -10 to -30). Additionally, there are still some countries whose stock markets are virtually unaffected by the outbreak; these countries include Argentina, China, and Japan. Fig. 3 shows that the CAViaRs of these indices have not fallen sharply since the outbreak of COVID-19. That is, tail risks do not occur in these markets, and the epidemic does not significantly affect the stock markets of these countries. Note that there was a significant tail risk in Argentina in August 2019. However, it was caused by internal problems in the country rather than COVID-19. The COVID-19 pandemic broke out at the beginning of 2020.

There are some possible explanations for this phenomenon. First, stock markets in countries such as Indonesia and Malaysia are relatively closed. Thus, stock markets are more resilient to shocks, such as COVID-19. Second, some countries and areas, such as China, Hong Kong and Singapore, took effective countermeasures quickly after the outbreak of COVID-19. The liquidity and stable panic of investors also reduce the influence of COVID-19 (Song, Chen, & Li, 2020). Unconventional monetary policies may also affect stock and exchange rate markets to some extent (Wei & Han, 2021). For example, when China detected its first case of COVID-19 in late 2019, the country responded quickly. The imposed restriction on internal movement and higher fiscal policy spending positively affected the level of economic activities. These actions allowed stock markets to be prepared before the pandemic hardly hit them. Generally, all these effects are driven solely by emerging markets and play no role in developed countries (Zaremba et al., 2021).

4.2. Risk correlation network of the stock markets during the COVID-19 pandemic

There is the conclusion that COVID-19 has affected most countries' stock markets and caused tail risk worldwide. To analyze the risk correlation between stock markets during the COVID-19 pandemic, this section uses the network method based on CAViaR to characterize the risk correlation of the stock markets worldwide. A risk correlation network of 28 countries during the whole period is constructed, and then the three stages of the network are compared and studied.

To build the risk correlation network, Pearson's correlation coefficient (PCC) is used to link the risk losses of 28 countries' stock markets.

$$\rho_{i,j} = \frac{E(CAViaR_i CAViaR_j) - E(CAViaR_i)E(CAViaR_j)}{\sqrt{Var(CAViaR_i)Var(CAViaR_j)}} \quad (9)$$

where $\rho_{i,j}$ denotes the PCC between country i and country j and CAViaR represents the risk loss of the stock markets.

By obtaining the correlation coefficient $\rho_{i,j}$, the correlation matrix between stock markets can be constructed by using the threshold method. To identify the positive correlations between stocks, the value of the matrix $e_{i,j}$ can be determined by the following rules:

$$e_{i,j} = \begin{cases} \rho_{i,j}, \rho_{i,j} > \theta, \\ 0, \text{otherwise} \end{cases} \quad (10)$$

where θ denotes the threshold of the PCC. When $\rho_{i,j}$ is greater than θ , the link is reserved, and the weight is set to $\rho_{i,j}$. Otherwise, the link is deleted. In this paper, θ is set to 0.6.

A network consists of nodes and edges, which are used to describe the relationships between nodes. The network method combines graph theory and topology to describe the relationship between different nodes. This paper uses network method metrics, namely, average degree, network density, average clustering coefficient and average path length, to measure the risk correlation between different stock markets. The average degree, average clustering coefficient and average path length are the three most robust measures of network topology. Network density shows the overall network correlation.

Fig. 4(a) shows the risk correlation network of the stock markets worldwide in stage 1 (before COVID-19). The figure shows that the risk correlation of the network is relatively sparse. Except for some European countries, most of the stock markets are relatively independent and have no risk correlation. However, after the outbreak of COVID-19, the correlation of the entire network increased significantly (see Fig. 4(b)). Moreover, risk correlations are relatively high across almost all countries. The risk correlations of the Netherlands, France, the UK and Germany are all beyond 0.9 (see the red line in Fig. 4). The same phenomenon has occurred in Japan, Indonesia and New Zealand. This finding indicates that the risk correlation of countries in the same economic region is relatively high. Fig. 4(c) shows that the risk network correlation decreases significantly after the first wave of COVID-19. Compared with Fig. 4(a), the risk correlation network is even thinner after the impact than it was before because of the stock market's ability to recover and resist shocks. Resilience to shocks varies from country to country, thus resulting in a slight decline in the risk correlation between countries after shocks compared with before shocks.

Table 3 shows the properties of the risk correlation network in different stages. Degree is the simplest but most important feature of a node. The higher the degree is, the more important the node is. The average degree is the average degree of all nodes. In Stage 2, the average degree is 19.786, which is higher than that in Stages 1 and 3. This result indicates that most stock markets have become risk centers during the COVID-19 pandemic and that risk can transfer more easily and quickly in the network. The network density shows that the risk correlation network is significantly tighter during COVID-19 (0.733) than before or after. The clustering coefficient is used to measure the degree of node aggregation. Under the influence of COVID-19, the risk correlation network is highly concentrated (0.919), thus indicating that the pandemic has made the risk of the stock markets worldwide more closely linked. The average path length is defined as the average distance between any two nodes. In the risk correlation network, shorter average path lengths result in the rapid spread of risk across the network. When the stock market is hit by COVID-19, the average path length is 1.222, which is lower than before (2.05) and after (2.095). This result shows that the impact of COVID-19 on the global stock market makes the entire risk correlation network more vulnerable, and risk transmission will be easier.

4.3. The changes in risk correlation between stock markets during the COVID-19 pandemic

The results show that COVID-19 has changed the topology of the risk correlation network worldwide. Furthermore, how the risk correlation between the stock markets of two countries changes during the period is worth continued study. By studying the dynamic changes in risk correlation over time, we can more clearly see the influence of COVID-19 on the risk correlation between two countries. Because the first wave of COVID-19 lasted approximately three months, we set the time window

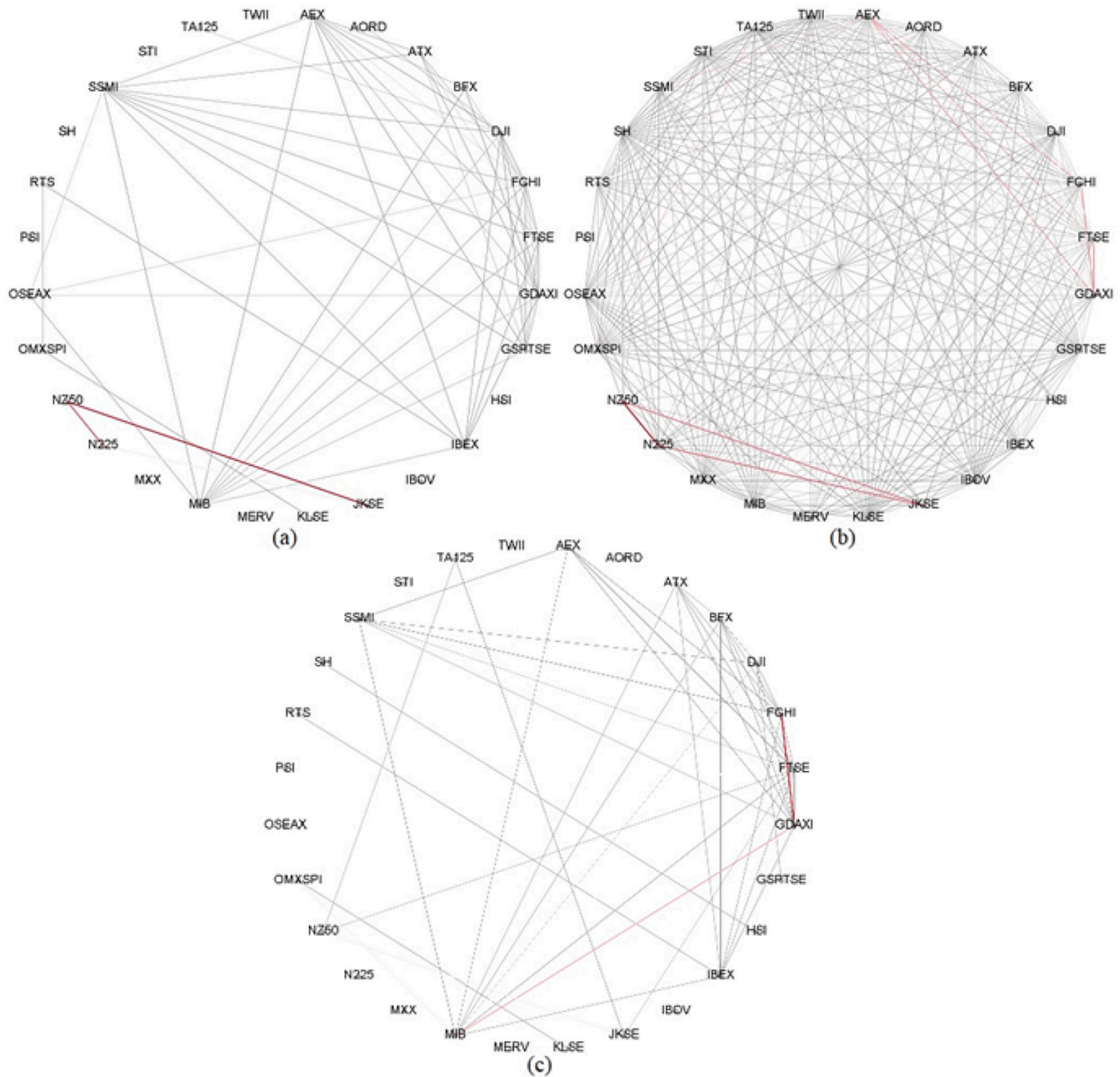


Fig. 4. Risk correlation network of the stock markets in different stages.

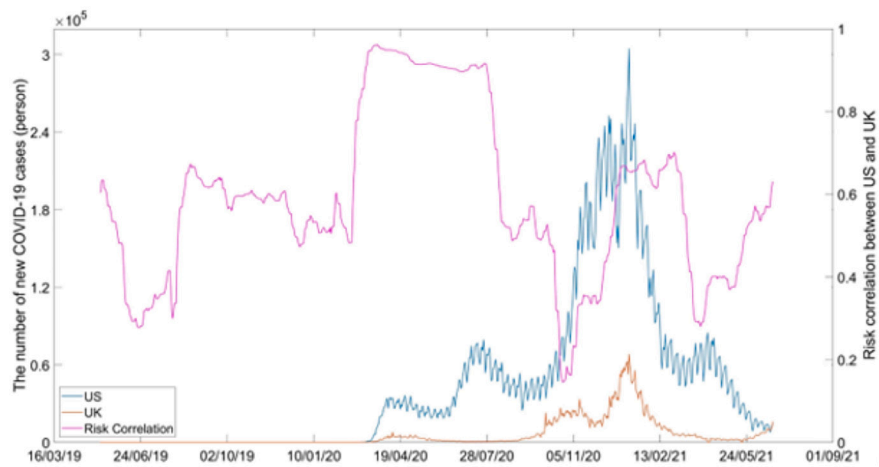
Table 3

The properties of the risk correlation network in different stages.

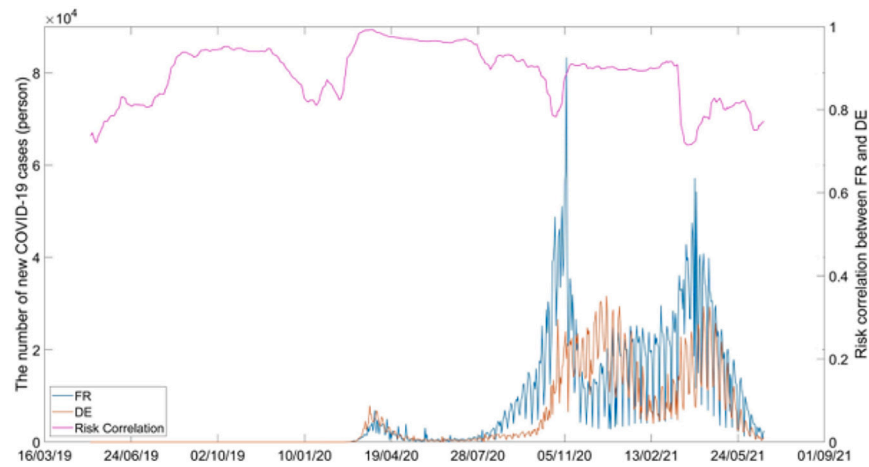
Stage	Average Degree	Network Density	Average Clustering Coefficient	Average Path Length
Stage 1	4.071	0.151	0.755	2.05
Stage 2	19.786	0.733	0.919	1.222
Stage 3	3.214	0.119	0.707	2.095

as 90 days; this period contains all information about the influence of COVID-19 on the stock markets. Then, PCC is used to calculate between the risk correlation between two countries according to CAViaR.

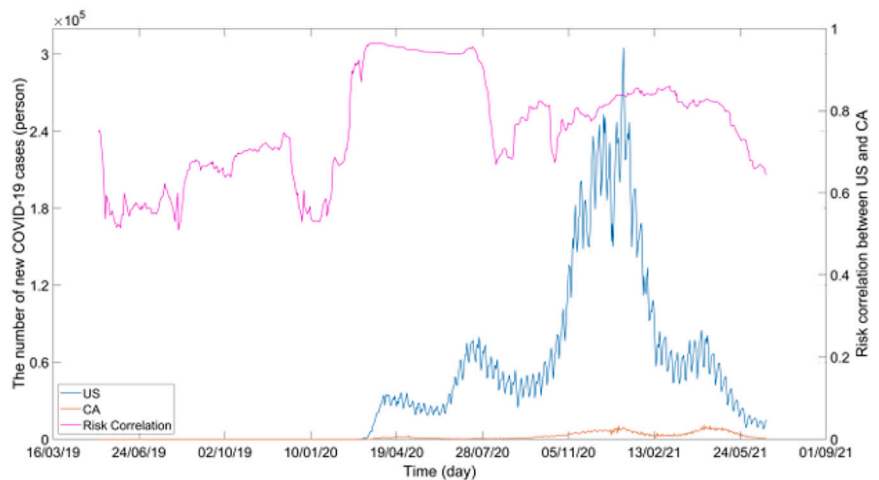
Fig. 5 shows the risk correlations between stock markets and the number of new COVID-19 cases during the sample period. In Fig. 5(a), before the outbreak of the pandemic, the risk correlation between the US and the UK is almost stable at approximately 0.3 to 0.6. In early March, the outbreak of COVID-19 began to cluster in both the UK and the US. The number of new cases in the US increased to approximately 30,000 within 15 days. Additionally, the number of new cases in the UK increased to approximately 7000. The sudden outbreak of the pandemic in these two countries has had an unexpected impact on the stock markets. As a result, since early March, the risk correlation between the stock markets of both countries has increased rapidly to 0.95 under the impact of the pandemic. At the end of July 2020, the number of new cases declined. During this period, the risk correlation also declined rapidly. Despite subsequent repeated outbreaks of COVID-19, the risk correlation fluctuated to a certain extent but did not exceed 0.6. The



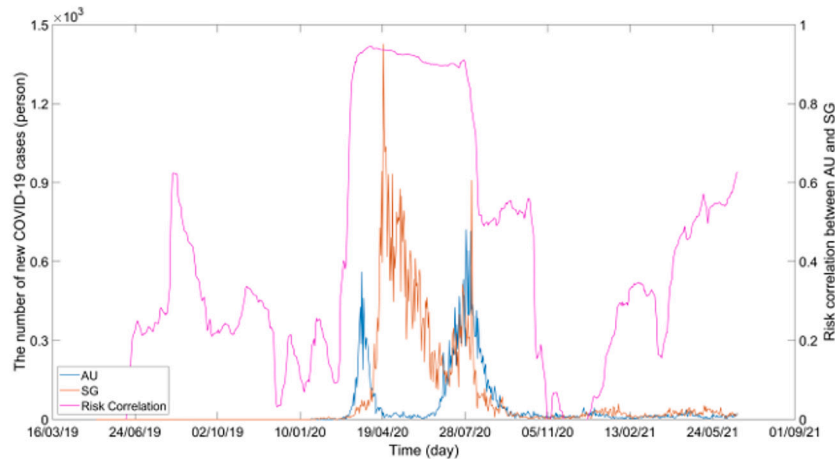
(a)



(b)



(c)



(d)

Fig. 5. Risk correlations between stock markets and the number of new COVID-19 cases in different countries: (a) the US and the UK; (b) France and Germany; (c) the US and Canada; (d) Australia and Singapore.

results suggest that the sudden outbreak of COVID-19 clearly affected the risk correlation between the US and the UK. However, as the stock markets adjusted to the shock, the pandemic had little impact on their risk correlation in the next period. In contrast, the risk correlation between the stock markets of France and Germany differs from that between the US and the UK (see Fig. 5(b)). Because both France and Germany are members of the European Community, they have a high economic correlation in common, thus making the risk linkage of their stock markets always strong. Therefore, the risk correlation of France and Germany improved slightly during the outbreak of COVID-19. However, COVID-19 has had limited influence on both of these countries, and they have remained highly correlated from approximately 0.8 to 0.95.

Fig. 5(c) presents the risk correlation between the stock markets of the US and Canada. These two countries are also highly correlated in their economies. It can be seen that, before the outbreak of COVID-19, the risk correlation between the markets of these two countries is stable at approximately 0.6 to 0.8, which is lower than that of France and Germany, and much higher than that of the US and the UK. After the outbreak of COVID-19, there was an obvious change in the risk correlation between these two markets, while the extent of the change is limited, which is similar to that of France and Germany. It is worth noting that the markets of Australia and Singapore have a low correlation ranging from approximately 0.1 to 0.5 (see Fig. 5(d)). After the outbreak of COVID-19, the risk correlation between these two markets increased rapidly (from 0.1 to 0.9), which reveals that the impact of COVID-19 on the risk correlation between the markets of Australia and Singapore is similar to that between the US and the UK.

These findings show that the increase in the closeness of the risk relationship between countries with a lower economic correlation (e.g., the US and the UK; Australia and Singapore) has been much higher than that between countries with a higher economic correlation (e.g., France and Germany; the US and Canada) during COVID-19.

5. Conclusion

The ongoing COVID-19 pandemic has dragged down the economy at the global and country levels since the beginning of 2020. Along with the outbreak of COVID-19 over time, the overall economic environment and economic activity have been depressed, as well as the stock markets worldwide. In this study, CAViAR is used to measure the tail risk of the stock markets worldwide during COVID-19. Based on the results of CAViAR, risk correlation networks are constructed to describe the risk correlations among the stock markets. The whole period is split into three stages that cover the premiddle and postepidemic periods. By analyzing the risk correlation network in the different stages, the impact of COVID-19 on stock markets worldwide is examined. Then, the dynamic changes in the risk correlation between countries' stock markets are grasped.

The main conclusion is as follows: First, COVID-19 significantly affects most countries' stock markets. Tail risks appear in most countries' stock markets along with fluctuations of the indices during COVID-19. Even so, there are still few countries' stock markets that are immune to COVID-19. These countries' stock markets are relatively closed, and effective countermeasures apply in these countries more quickly; this is the reason for this phenomenon. Second, in studying the risk correlation network, this paper finds that the outbreak of COVID-19 has changed the topology of the network. The impact of COVID-19 has made the risk correlation of the stock markets closer. In addition, the density of the network has become tighter. COVID-19 has made it easier for system risks to spread around the world. Finally, the results show that the increase in the closeness of the risk relationship between countries with lower economic correlation is much higher than that between countries with higher economic correlation during COVID-19.

CRedit authorship contribution statement

JunFeng Wu: Data curation, Methodology, Software, Visualization, Writing – original draft. **Chao Zhang:** Conceptualization, Investigation, Supervision, Validation, Writing – review & editing. **Yun Chen:** Supervision, Writing – review & editing.

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

I have shared the link to my data (e.g. <https://www.wind.com.cn> and <https://www.gildata.com>).

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