Scientia Iranica E (2022) 29(3), 1716–1728

SCIENTIA IRANICA

Sharif University of Technology
Scientia Iranica
Transactions E: Industrial Engineering
http://scientiairanica.sharif.edu

Dynamic correlation and volatility spillover between the stock markets of Shenzhen and Hong Kong

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Received 13 October 2019; received in revised form 23 May 2020; accepted 6 July 2020

KEYWORDS
SHSC;
Co-movements;
Copula function;
t-copula DCC-GARCH model;
BEKK-GARCH model.

Abstract. Considering the two-way spillovers of market information, this study establishes multivariate Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models to study the impact of Shenzhen-Hong Kong Stock Connect (SHSC) on the complex co-movement relationship between the stock markets of Shenzhen and Hong Kong in terms of dynamic correlation and volatility spillover. A *t*-copula Dynamic Conditional Correlation-GARCH (DCC-GARCH) model that combines the copula function with the DCC-GARCH model is established to model the return rate series of stock index at different stages and the characteristic that the dynamic correlation coefficient changes with time is analyzed emphatically. Moreover, a Baba, Engle, Kraft, Kroner-GARCH (BEKK-GARCH) model is established to measure the changes in the volatility spillover effect between the stock markets in Shenzhen and Hong Kong. The results show that the opening of SHSC has gradually increased the dynamic correlation coefficient of the two stock markets, and the openness degree of the two stock markets has increased. At the same time, the volatility spillovers of stock markets in Shenzhen and Hong Kong have shifted from one-way spillover to two-way spillovers, indicating that the SHSC mechanism has strengthened the correlation degree and improved the ability of risk spillover in the two stock markets.

1. Introduction

The reform and opening of China's capital market can not only meet the inflow of overseas capital, but also promote the innovation of the financial instruments. In 2014, the implementation of the Shanghai-Hong Kong stock connect mechanism connected the mainland market to the Hong Kong market for the first time, which was an important breakthrough for China's mainland market to open to the international market [1–3]. Although there were certain trading restrictions, the two markets had a certain trade basis. Shenzhen, adjacent to Hong Kong, has a strong advantage over Shanghai in terms of topography and cultural origin, and the trade transactions of Shenzhen and Hong Kong tend to be frequent. Therefore, it is necessary to further promote economic and trade cooperation between Shenzhen and Hong Kong. The opening of the SHSC in 2016 is a real interconnection of the three markets of Shanghai, Shenzhen, and Hong Kong [1,4,5], which has not only improved the level of China's opening-up, but also promoted the internationalization process of China's economy.

The Shenzhen-Hong Kong Stock Connect (SHSC) has been in operation for two years. It optimizes the

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doi: 10.24200/sci.2020.54637.3843

allocation of resources in the mainland and strengthens the two-way liquidity of funds in the Hong Kong and mainland markets. Therefore, it is complementary to some extent in terms of its target. There are many A-shares in Shenzhen, and the most dynamic listed companies in China are concentrated in Shenzhen. The inflow of foreign capital will make Shenzhen more active, and the differences between different sectors will continue to develop under the multi-level system. Moreover, the opening of the SHSC has brought some incremental funds and many mainland investors to Hong Kong stocks and made the Hong Kong stock market more diversified.

With the acceleration of global internationalization, the financial markets are more or less connected. China has basically completed the layout of the new two-way opening mode of capital markets, and the interconnection between the mainland and Hong Kong markets has opened a new era. Among them, the implementation of the SHSC mechanism has produced information impact on the two stock markets of Shenzhen and Hong Kong, which will cause local market fluctuations. Much of the current study has focused on the volatility of the stock market in a single market, but there is information transmission between stock markets. Therefore, in the stock markets of Shenzhen and Hong Kong, we should not only study the influence of this information transmission on the individual stock market volatility of Shenzhen and Hong Kong, but also analyze the influence degree of the SHSC mechanism on the complex co-movements relation of stock markets in these two cities by combining the effective information of market correlation.

Co-movements refer to a number of related things, one of which changes with respect to others. It is originally used in the business cycle to explain the tendency of many macroeconomic variables to change together in the business or economic cycle. Later, with the acceleration of the process of global economic integration, the rise or fall of different countries or stock market sectors occurred at the same time; thus, scholars applied co-movements to the mutual influence between stock markets, that is, the common change trend between different financial markets or different sectors [6–9]. The co-movements of stock markets are the result of mutual influence between different stock markets, different stocks, and individual stocks. Considering the role of information transmission between markets, the financial markets of various countries are sometimes more or less linked, and the fluctuations in a single market will be affected and restricted by the fluctuations of other markets or sectors to some extent [10–12].

This paper establishes relevant econometric models to study the impact of the SHSC on the complex co-movements relation between the stock markets in Shenzhen and Hong Kong. The study of co-movements will help investors to evaluate the stock market risks more effectively and provide certain investment references for investors in Shenzhen and Hong Kong. At the same time, it will also provide a decision-making basis for relevant departments to promote orderly opening of capital market as well as formulate and improve the policy of China's financial system.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 establishes a t-copula Dynamic Conditional Correlation-GARCH (DCC-GARCH) model that combines the copula function with the DCC-GARCH model to analyze the correlation changes of the Shenzhen-Hong Kong stock markets and then, establishes a Baba, Engle, Kraft, Kroner-GARCH (BEKK-GARCH) model to measure the changes in the volatility spillover effect of the stock markets in Shenzhen and Hong Kong. Section 4 provides the result analysis of SHSC on the co-movements between the stock markets of Shenzhen and Hong Kong. Section 5 concludes the paper.

2. Literature review

Most scholars have studied the complex co-movement relation of stock markets in terms of volatility spillover and dynamic correlation.

Crisis shocks often lead to changes in the interdependence of the stock markets. When a market suffers from information shock, the market will infect each other and the market co-movements will be significantly enhanced. Based on this background, Forbes and Rigobon [13] proposed a contagion test based on the correlation coefficient deviation under the condition of market volatility. The results demonstrated that the incidence of contagion decreased sharply compared with the results corresponding to the unadjusted correlation coefficient, and it was demonstrated that the high-level co-movements of many stock markets reflected the continuation of strong cross-market linkages. Different from the above results, Li and Majerowska et al. [14] investigated the relationship between emerging markets and mature markets by using the four-variable asymmetric BEKK model (named by Baba, Engle, Kraft, and Kroner), and the results showed that the interaction between markets was limited and the relationship between them was weak. Combined with previous studies, Rua and Nunes [15] employed a novel wavelet analysis method to evaluate the interaction between international markets, which could analyze the correlation between stock returns in time domain and frequency domain. Gjika and Horvath [16] studied the common role of western European stock markets according to the multivariate Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model with Asymmetric Dynamic Conditional Correlation (ADCC). The results indicate that the stock market shows asymmetry and conditional correlation in the conditional difference, and the Chinese stock market is closely correlated with western European stock markets, while the financial crisis has increased the correlation of stock markets.

Same with the above research results, Mensi et al. [17] established a DCC-FIAPARCH model combined with the revised incorrect-site algorithm and Value At Risk (VAR) to study the volatility spillover effect for the US and other five emerging stock markets. The empirical results show that the conditional volatility and dynamic correlation between stock markets in different countries have the features of asymmetric and long-term memory, and the occurrence of financial crisis solidifies the relationship between markets. Baris et al. [18] used ADCC and EGARCH models to deduce time-varying relationships among oil, gold, and international stock markets in terms of correlation. The results demonstrated that these relationships changed with the degree of correlation between these markets and affected diversification opportunities of global investment portfolios. Based on the above literature, Hassan et al. [19] explored the dynamic conditional correlation and volatility linkage between Islamic indexes and oil for BRIC countries. Akkoca and Civcir [20] proposed a SVAR-DCC-GARCH model to discuss the dynamic linkages between strategic commodities and stock market in Turkey.

In China, some scholars have gradually studied different aspects of the co-movements for different stock markets. For example, Song [21] established multiple GARCH models to study the volatility and intra-group dynamic relations of Asian stock markets. The results showed that there was significant volatility spillover and correlation infection among Asian stock markets, and DCC model was found to be better than other multivariate GARCH models. Different from the former research, Xiong and Han [22] used the Granger Causality-Multivariate Stochastic Volatility (GC-MSV) model to conduct the empirical analysis for the volatility spillover of the currency market and the stock market at different stages, and the result shows that with the change in RMB exchange rate, the spillover effect between them exhibits different characteristics. Subsequently, Li [23] employed different co-integration tests and BEKK-GARCH models to analyze the co-movement changes in the Asia-pacific stock markets before and after the crisis, and the results demonstrated that the stock market was affected by the crisis, and the co-movements of stock markets increased significantly regardless of one-way spillovers or two-way spillovers. At the same time, Gao and Guo [24] studied the co-movements of domestic and foreign stock markets using the same model as above. From the results, it can be found that China's stock market has left the relatively closed state and the market has an obvious trend of opening up.

Later, Yang et al. [25] analyzed the correlation of Chinese regional stock markets using the diagonal Vector Error Correction Heteroscedasticity (VECH) model and then, used DCC-GARCH model to study their co-movements. According to the results of data analysis, following the completion of the reform, the stock market fluctuations in Greater China converged and the stock market correlation significantly increased. Based on previous studies, Zhao and Yan [26] established a TVP-VAR model to explore the dynamic relationship between A, B shares and Hong Kong shares, and they found that the implementation of the Shanghai-Hong Kong stock connect mechanism improved the integration level of the stock market and accelerated the market reform. Yao and Liu [27] used the Dynamic Conditional Correlation-Mixed Data Sampling (DCC-MIDAS) model to study the co-movements of stock market in Shanghai and Hong Kong according to the mixed frequency data. The results demonstrated that the volatility of the two cities was more affected by the financial crisis than by the opening of the Shanghai-Hong Kong stock connect. Different from the above models, Xian and Pan [28] employed the regression equation to study the impact of Shanghai-Hong Kong stock connect on the co-movements of the stock markets in Shanghai and Hong Kong and concluded that the co-movements between these two cities were significantly enhanced in a short term through the regression fitting graph. Huo [29] took the global stock markets as the object and used the VAR model, the GARCH model, and the Vector Error Correction Model (VECM) and DCC models to study the dynamic financial connection and volatility transmission between different financial markets. Through the integration of the Variational Mode Decomposition (VMD) method with various static and time-varying copulas, Li and Wei [30] studied the dependence and risk spillover between crude oil market and China stock market over different investment horizons, before and after the recent financial crisis. Lin and Chen [31] presented a VAR(1)-DCC-GARCH(1,1) model and a VAR(1)-BEKK-AGARCH(1,1) model to study the problem of dynamic linkages and spillover effects among the CET market, the coal market, and the stock market of NEC. Xu et al. [32] investigated the presence of asymmetric response to volatility shocks using the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) model. Chang et al. [33] investigated the volatility spillover effects and dynamic correlations between China's emissions allowances and fossil energy markets by using the DCC-GARCH model.

To sum up, the existing literature generally investigates co-movements unilaterally from the correlation or volatility spillover effect of single or multiple capital markets. Furthermore, this study explores the impact of the SHSC on the co-movements of the Shenzhen-Hong Kong stock markets in terms of dynamic correlation and volatility spillover effect. This paper considers the nonlinear relationship which has been easy to ignore in the previous financial market research and establishes a new t-copula DCC-GARCH model to study the dynamic correlation between the stock markets of Shenzhen and Hong Kong by combining the copula function with DCC-GARCH model.

3. Impact analysis of SHSC on the co-movements

Co-movements mainly describe the tendency of one variable changing with the other, and it is described through the relationship of correlation, causality, volatility spillover, and so on. Because of the opening of SHSC, there is a certain complex co-movements relation between the stock markets of Shenzhen and Hong Kong. In this section, the copula DCC-GARCH model was established to judge the change of the dynamic correlation between these two stock markets and then, the BEKK-GARCH model was employed to analyze the volatility spillover effect of the stock markets in Shenzhen and Hong Kong at different stages.

In particular, before establishing the multivariate GARCH model, it is necessary to uniformly define the return rate variables of stock markets in Shenzhen and Hong Kong. Let the return rate double variants be $r_{1,t}$ and $r_{2,t}$, and they constitute the 2-dimensional column vector $\mathbf{R}_t = [r_{1,t}, r_{2,t}]'$ which can be decomposed into $\mathbf{R_t} = \mu_\mathbf{t} + \mathbf{a_t}$ that is, at time t; the return can be decomposed into $\boldsymbol{\mu}_t$ and $\boldsymbol{\alpha}_t$, $\boldsymbol{\mu}_t = E(\mathbf{R}_t|\mathbf{F}_{t-1})$ and $\alpha_t = \mathbf{H}_t^{1/2} \cdot \varepsilon_t$. The first term is the expected return at time t given the available information in the previous period, and the information set is expressed as $\mathbf{F}_{t-1}$. The unknown conditional covariance is defined as follows:

$$Cov(\alpha_t|\mathbf{F}_{t-1}) = \mathbf{H}_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}, \tag{1}$$

where $\boldsymbol{\varepsilon}_t$ is an independent identically distributed random vector with a mean of zero. From Eq. (1), since $\mathbf{H}_t'=\mathbf{H}_t$ is a symmetric matrix of the order 2×2, $\mathbf{H}_t$ must be positive definite for all t.

3.1. Data source and stage division

In order to analyze the impact of SHSC on the co-movements between the stock markets of Shenzhen and Hong Kong, the closing prices of Shenzhen Component Index (399001) and Hang Seng Index (HSI) of Hong Kong from December 4, 2014 to December 5, 2018 are selected as data samples in empirical analysis. The daily closing data of Shenzhen Component Index and HSI of Hong Kong is selected from the website Investing.com. Because of the differences in the holidays' regulations of Hong Kong and Chinese Mainland, the trading dates of stock markets in Hong Kong and Shenzhen have a slight discrepancy. Based on this background, we delete the data in inconsistent trading days of stock markets in Shenzhen and Hong Kong. After data processing, we get a total of 950 trading data sets.

3.2. Impact analysis of SHSC on the dynamic correlation

In order to quantify the correlation degree between the stock markets of Shenzhen and Hong Kong, the dynamic correlation between financial markets is used to measure the correlation degree. The data corresponding to financial assets do not all follow normal distribution, most of which have the property of thick tail and the nonlinear relationship between them may not be described using the general linear correlation coefficient. As a connection function, the copula function can describe the correlation structure between different distributed assets. Therefore, in order to avoid the limitations of the general model, this paper combines the copula function with the binary DCC-GARCH model to analyze the dynamic correlation degree of the stock markets in Shenzhen and Hong Kong.

3.2.1. Applicability test of copula function estimation

Figure 1 shows the steps of parameter estimation for

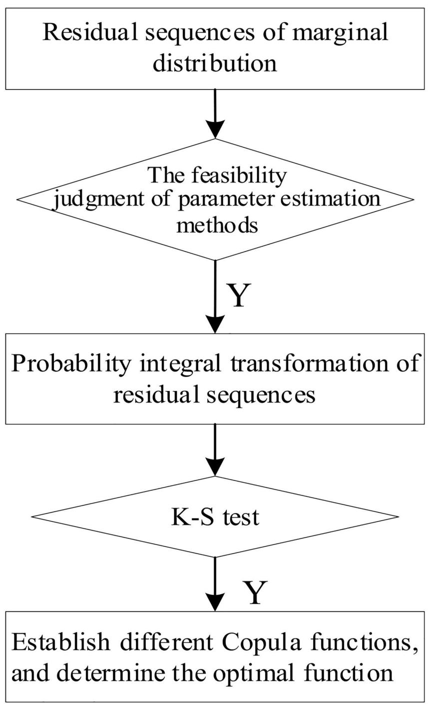

Figure 1. Flow chart for parameter estimation of copula function.

Table 1. Parameter estimation and test results of marginal distribution model.

Stage	RZ1	RK1	RZ2	RK2
K-S statistics	0.0347	0.0321	0.0337	0.0281
K-S Probability value	0.6071	0.7045	0.6378	0.8357

copula function. In this paper, the residual sequence of GARCH (1,1)-skewt model is used as the edge distribution, and the parameter estimation method is used to construct the optimal copula function.

In this section, MATLAB R2016a software is used to estimate the relevant parameters of the marginal distribution model of return rate sequence in different regions, and the probability integral transformation is employed to convert the sample from partial t distribution into a sequence subject to (0,1) uniform distribution, which is tested by the non-parametric test method (Kolmogorov-Smirnov, K-S). Table 1 shows the test results of the time series marginal model of the selected stock index return rates.

From Table 1, the following conclusions can be obtained.

1. The return rate sequences transformed by probability integral are all subject to an independent and uniform distribution (0,1). At a confidence level of 5%, the probability values of K-S are all greater than 0.05, so there is no reason to reject the null hypothesis;
2. The marginal distribution based on the GARCH(1,1)-skewt model is reasonable. The conditional marginal distribution is obtained by GARCH(1,1)-skewt model estimation for the time series of stock index returns of Shenzhen and Hong Kong in stages, and the new sequences transformed by probability integral are subject to uniform distribution; thus, the fitting effect of GARCH(1,1)-skewt model on the estimation of various return sequences of Shenzhen and Hong Kong is seen to be relatively ideal.

After determining the marginal distribution, the parameters of the copula function should be estimated. There are usually two kinds of parameter estimation methods [34-35], i.e., parametric method and non-parametric method, where the parametric method includes Maximum Likelihood Estimation (MLE) and Inference Function for Margins (MLE), and the non-parametric method mainly refers to the kernel density estimation.

In the application of copula function to describe the related structure of financial asset, the first step is to estimate the parameter values of copula function, and the most commonly used parameter estimation methods are MLE and IFM. In some applications, MLE estimation is difficult to implement due to the large number of unknown parameters or the complexity of models. Therefore, the IFM estimation method is used in this paper to estimate the parameters in copula function.

3.2.2. Determination and evaluation of the optimal copula function

The setting of the initial value of copula function depends on 5 kinds of common static copula models, namely normal copula, t-copula, Clayton copula, Frank copula, and Gumbel copula. The specific definition of each copula function is detailed in the literature [36–37].

In the financial field, suppose that there are m raw data sequences of n assets $(x_{i1}, x_{i2}, \cdots, x_{in})$, $i = 1, 2, \cdots, m$; then, the empirical distribution function of the corresponding asset can be obtained as $F_j(x_j), j = 1, 2, \cdots, n$ and substituted into the expression of copula empirical function; therefore, we have:

$$\hat{C}(u_1, u_2, \cdots, u_n) = \frac{1}{m}\sum_{i=1}^{m} I(D, (F_1(x_{i1}), F_2(x_{i2}), \cdots, F_n(x_{in}))). \quad (2)$$

Now, the method of IFM is used to estimate the parameters in the copula function, which is generally divided into two steps as follows.

Step 1: Estimate the marginal distribution parameters orderly. This step involves maximum likelihood estimation of the univariate margin and the following results can be obtained:

$$\hat{\theta}_1 = \arg\max \sum_{t=1}^{T} \ln f_1(x_{1t}; \theta_1), \quad (3)$$

$$\hat{\theta}_2 = \arg\max \sum_{t=1}^{T} \ln f_2(x_{2t}; \theta_2). \quad (4)$$

Step 2: Solve and estimate the parameters related to copula function. This step involves the maximum likelihood of dependent parameters, where the single variable parameter remains fixed as follows:

$$\hat{\theta} = \arg\max \sum_{t=1}^{T} \ln c \left(\mathrm{F}_1(x_{1t}; \hat{\theta}_1), \mathrm{F}_2(x_{2t}; \hat{\theta}_2); \theta_c\right). \quad (5)$$

Here, the software of MATLAB R2016a is employed to estimate the corresponding parameters of copula function. The parameter results of stock markets in Shenzhen and Hong Kong in the first stage are shown in Table 2. The relevant structure characterization of different copula functions is different. On the selection of optimal copula function, there are several

Table 2. The parameter estimation results of different copula functions in the first stage.

Copula	ρ	k	θ	**Euclidean distance**
Normal copula	0.4740	–	–	0.0457
t-copula	0.4572	14.6065	–	0.0348
Clayton copula	–	–	0.6413	0.0592
Frank copula	–	–	2.8670	0.0648
Gumbel copula	–	–	1.3712	0.0538

methods as follows:

1. According to the actual data statistical characteristics of stock markets in Shenzhen and Hong Kong, analyze the characteristics of copula functions and then, select the optimal copula function;
2. Select the optimal copula function from a given set according to the criteria of AIC, BIC, HQIC, distance minimum criterion, and so on;
3. Select the optimal copula function based on the likelihood function criterion.

On this basis, this paper uses the distance minimum criteria, that is, the square Euclidean distance of the empirical copula function and the theoretical copula function, to choose the best copula function. When the distance is smaller, the selected copula function has a stronger ability to describe the correlation structure between the stock markets of Shenzhen and Hong Kong, and the results reflected are closer to reality.

The expression of the square Euclidean distance is shown as follows:

$$d^2=\sum_{i=1}^{m}\left|C(u_{i1},u_{i2},\cdots,u_{in})-\hat{C}(u_{i1},u_{i2},\cdots,u_{in})\right|^2. \quad (6)$$

Table 2 shows the Euclidean distance results corresponding to different copula functions in the first stage. It can be found that the Euclidean distance corresponding to the t-copula function is 0.0348, which is the smallest. Therefore, the t-copula function with a parameter of 0.4572 and a freedom degree of 15 is the optimal copula function to describe the relative structure of the return rates in the first stage.

Kendall rank correlation coefficient and Spearman rank correlation coefficient are commonly used to measure the correlation of copula functions. They can measure the correlation structure between the stock markets of Shenzhen and Hong Kong from the perspective of linear and nonlinear relationships.

The related expression of Kendall rank correlation coefficient and the copula function is:

$$\tau = 4\iint C(u,v)dudv - 1, \quad (7)$$

and the Spearman rank correlation coefficient is:

Table 3. The Kendall and Spearman rank correlation coefficient in the first stage.

Rank correlation coefficient	τ	ρ
Normal copula	0.3144	0.4570
t-copula	0.3023	0.4377
Clayton copula	0.2428	0.3555
Frank copula	0.2835	0.7760
Gumbel copula	0.2707	0.5723
Direct estimation	0.2904	0.4195

Table 4. The Kendall and Spearman rank correlation coefficient in the second stage.

Rank correlation coefficient	τ	ρ
Normal copula	0.3635	0.5226
t-copula	0.3599	0.5084
Clayton copula	0.2658	0.3873
Frank copula	0.3573	0.8263
Gumbel copula	0.3246	0.5952
Direct estimation	0.3612	0.5145

$$\rho_s = 12\int_0^1\int_0^1 C(u,v)\,dudv - 3, \quad (8)$$

where the parameters u and v in Eqs. (7) and (8) represent the sequences after probability integral conversion. The software of MATLAB R2016a is used to calculate the corresponding τ and ρ_s of different copula functions and measure the Kendall rank correlation coefficient and spearman rank correlation coefficient in the first stage; the results are shown in Table 3. With the application of the same calculation method as in the first stage, the Kendall rank correlation coefficient and spearman rank correlation coefficient in the second stage can be calculated; the results are listed in Table 4.

Through a comprehensive comparison of the calculation results in Tables 3 and 4, we can conclude that the t-copula function is the best fitting function for the return rates of stock markets in Shenzhen and Hong Kong. In fact, the t-copula function is the optimal copula function to describe the relative structure of the return rates in the first stage and the second stage. Therefore, in the two-stage selection of copula function, the t-copula function is used as the basic function to analyze the dynamic correlation between the stock markets of Shenzhen and Hong Kong.

3.2.3. The t-copula DCC-GARCH model

Dynamic correlation can clearly show the daily correlation changes during the sample data and exhibit the impact on the stock markets of Shenzhen and Hong Kong more intuitively.

According to the optimal t-copula function selected in Section 3.2.2, the joint distribution function of residual vector after the standardization of marginal distribution is:

$$F(e_{1,t}, e_{2,t}) = C^{t}_{\mathrm{R},v}(u_{1,t}, u_{2,t}) \tag{9}$$

where R is the correlation coefficient matrix corresponding to the t-copula function, and v is the freedom degree of the t-copula function. In this paper, the copula model and DCC-GARCH are fused to establish a t-copula DCC-GARCH model. Thus, the copula model and the DCC-GARCH model are combined to establish a t-copula DCC-GARCH model. Then, Eq. (9) becomes:

$$F(e_{1,t}, e_{2,t}) = C^{t}_{R_t,v}(u_{1,t}, u_{2,t}). \tag{10}$$

In Eq. (10), R_t is the dynamic conditional correlation matrix of the sequence established by DCC-GARCH model [38–39].

Thus, the logarithmic likelihood function of the t-copula DCC-GARCH model is:

$$LL_{t-\text{copula}}(\theta) = -T\log\Gamma(\frac{v+k}{2})\Big/\Gamma(\frac{k}{2}) - kt \log\Gamma(\frac{v+1}{2})\Big/\Gamma(\frac{k}{2}) - \frac{v+k}{2}\sum_{t=1}^{T} \log(1+\frac{\tilde{u}_t' R_t^{-1}\tilde{u}_t}{v}) - \sum_{t=1}^{T}\log|R_t| + \sum_{t=1}^{T}\sum_{i=1}^{k}\log(1+\frac{\tilde{u}_{i,t}}{v}), \tag{11}$$

where $\tilde{u}_{i,t}= F_i^{-1}(u_{i,t})$ and $\theta = (v, \alpha, \beta)$ are the parameters in the t-copula DCC-GARCH model.

3.2.4. Dynamic correlation analysis based on t-copula DCC-GARCH model

For the t-copula DCC-GARCH model established in Section 3.2.3, we substitute relevant data and use the software of MATLAB R2016a to solve it and then, analyze the dynamic correlation between the stock markets of Shenzhen and Hong Kong in different stages.

Before the opening of SHSC

The parameter estimation results of the first stage are shown in Table 5. Table 5 shows that the parameters of the t-copula DCC-GARCH model are significant at a significance level of 1%. The correlation coefficient α is 0.0106, which indicates that the impact of the previous return rate shock is small. The correlation coefficient β is 0.7679, which indicates that the co-movements of Shenzhen-Hong Kong stock markets in the first stage are relatively strong. Figure 2 shows the graph of corresponding dynamic correlation coefficient.

Table 5. The parameter estimation results of t-copula DCC-GARCH in the first stage.

Parameters	Stock markets of Shenzhen and Hong Kong
ν	17.2383*
α	0.0106*
β	0.7679*

Note: * indicates that it is significant at the levels of 10%.

Table 6. The parameter estimation results of t-copula DCC-GARCH in the second stage.

Parameters	Stock markets of Shenzhen and Hong Kong
ν	19.6269*
α	0.0151**
β	0.9826**

Note: * and ** indicate that it is significant at levels of 10% and 5%, respectively.

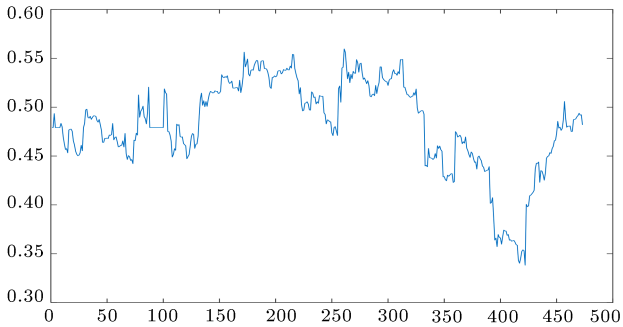

Figure 2. The graph of corresponding dynamic correlation coefficient in the first stage.

In the first stage, the average value of dynamic correlation coefficient is 0.4819. Together with Figure 2, we can conclude that when the SHSC is not opened, the correlation degree of the Shenzhen-Hong Kong stock market is in a stable state, which is related to the opening of the Shanghai-Hong Kong stock connect mechanism. After that, the correlation degree exhibits a downward trend. This is possibly affected by the stock market crash in 2015; thus, the stock market was depressed and the correlation degree between the two stock markets declined. The subsequent upswing may have been influenced by the news of the imminent implementation of SHSC.

After the opening of SHSC

The parameter estimation results of the second stage are shown in Table 6. As can be seen from Table 6, the parameters in the second stage are significant at a significance level of 1%, while the correlation coefficients α and β are significant at a significance level of 5%. The value of 0.9826 is obviously close

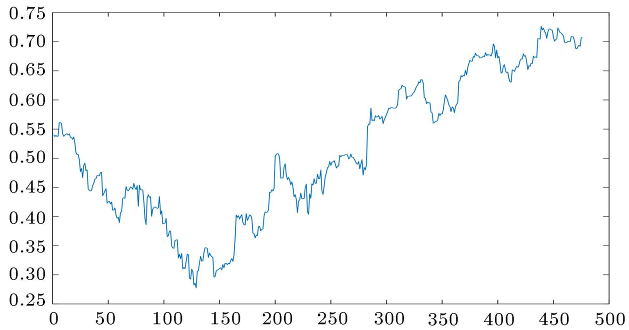

Figure 3. The graph of corresponding dynamic correlation coefficient in the second stage.

to 1, which indicates that the co-movements between the stock markets of Shenzhen and Hong Kong in the second stage have stronger sustainability than that in the first stage. In the second stage, the mean value of the dynamic correlation coefficient is 0.5143 and the maximum value is 0.7263. The graph of corresponding dynamic correlation coefficient is shown in Figure 3.

From Figure 3, after the opening of the SHSC, the correlation degree of the Shenzhen-Hong Kong stock markets has a significant change and an overall upward trend. In case of a high correlation between the two markets, the information will be transmitted between different markets, that is, there is a volatility spillover effect between the stock markets of Shenzhen and Hong Kong.

3.3. Impact analysis of SHSC on the volatility spillover effect

3.3.1. The BEKK-GARCH model for volatility spillover effect analysis

When studying the volatility spillover effect between the stock markets of Shenzhen and Hong Kong, based on Eq. (1), a BEKK-GARCH(1,1) model is given as follows:

The mean equation [40]:

$$\mathbf{R}_t = \gamma \mathbf{X}_t + \boldsymbol{\varepsilon}_t, \tag{12}$$

where γ is a $2 \times (p+1)$-order estimation coefficient matrix and $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]'$ is a residual term matrix.

The variance equation [40]:

$$\mathbf{H}_t = \mathbf{A}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{A}' + \mathbf{B}\mathbf{H}_{t-1}\mathbf{B}' + \mathbf{C}\mathbf{C}'. \tag{13}$$

where $\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ is an ARCH term coefficient matrix, $\mathbf{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$ is a GARCH term coefficient matrix, and $\mathbf{C} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$ is a lower triangular constant matrix.

In addition, considering Eq. (13) with Eq. (1), we have:

$$h_{11,t} = \mathrm{var}(r_{1,t}), \quad h_{22,t} = \mathrm{var}(r_{2,t}),$$

$$h_{12,t} = h_{21,t} = \mathrm{cov}(r_{1,t}, r_{2,t}).$$

Then, Eq. (13) can be expanded as:

$$\begin{aligned} h_{11,t} = {} & c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + a_{12}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{12}h_{12,t-1} \\ & + b_{12}^2 h_{22,t-1}, \\ h_{12,t} = {} & c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22}) \\ & \varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{12}h_{11,t-1} \\ & + (b_{21}b_{12} + b_{11}b_{22})\, h_{12,t-1} + b_{21}b_{22}h_{22,t-1}, \\ h_{22,t} = {} & c_{21}^2 + c_{22}^2 + a_{21}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + a_{22}^2\varepsilon_{2,t-1}^2 + b_{21}^2 h_{11,t-1} + 2b_{21}b_{22}h_{12,t-1} \\ & + b_{22}^2 h_{22,t-1}. \end{aligned}$$

In these expansion formulas, six factors, including the own volatility $h_{11,t-1}$ of the last period, the previous volatility $h_{22,t-1}$ of the opposing market, the covariance $h_{12,t-1}, h_{21,t-1}$ of the two different markets, the square of own former residual error $\varepsilon_{1,t-1}^2$, the square of the former residual error $\varepsilon_{2,t-1}^2$ of the opposing market, and the interaction term of the two markets $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ cause the volatility of $r_{1,t}$ or $r_{2,t}$.

3.3.2. Volatility spillover effect analysis of stock markets in Shenzhen and Hong Kong

Based on the BEKK-GARCH(1,1) models established in Section 3.3.1, the software of Winrats Pro 8.0 and the optimization algorithm of BGFS are used to estimate the parameters in the BEKK-GARCH(1,1) models before and after the opening of SHSC. The estimation results are listed in Tables 7 and 8, where Market 1 represents Shenzhen stock market and Market 2 represents Hong Kong stock market. Based on these results, we can further analyze the changes of volatility spillover effect before and after the opening of SHSC [41].

From Tables 7 and 8, we can get the following estimation result of the matrix parameters.

$$\mathbf{A}_1 = \begin{bmatrix} -0.3313 & -0.1584 \\ 0.064 & 0.133 \end{bmatrix}, \quad \mathbf{B}_1 = \begin{bmatrix} 0.7978 & -0.1573 \\ 0.4222 & 1.0597 \end{bmatrix},$$

$$\mathbf{A}_2 = \begin{bmatrix} -0.1024 & 0.0343 \\ -0.2003 & -0.1502 \end{bmatrix}, \quad \mathbf{B}_2 = \begin{bmatrix} -0.1024 & 0.0343 \\ -0.2003 & -0.1502 \end{bmatrix},$$

where $\mathbf{A}_1$ and $\mathbf{B}_1$ are the coefficient matrixes before

Table 7. Calculation results of BEKK-GARCH(1,1) model before the opening of SHSC.

Matrix	Estimated coefficient	Standard deviation	p value
C(1,1)	–0.2086*	0.1170	0.0746
C(2,1)	0.1754**	0.0727	0.0158
C(2,2)	0.0003	0.1891	0.9997
A(1,1)	–0.3313**	0.0450	0.0000
A(1,2)	–0.1584**	0.0263	0.0000
A(2,1)	0.0640	0.0680	0.3467
A(2,2)	0.1330**	0.0533	0.0125
B(1,1)	0.7978**	0.0199	0.0000
B(1,2)	–0.1573**	0.0123	0.0000
B(2,1)	0.4222**	0.0281	0.0000
B(2,2)	0.9319**	0.0194	0.0000

Note: * and ** indicate that it is significant at levels of 10% and 5%, respectively.

Table 8. Calculation results of BEKK-GARCH(1,1) model after the opening of SHSC.

Matrix	Estimated coefficient	Standard deviation	p value
C(1,1)	0.2156	0.1659	0.1937
C(2,1)	–0.1960*	0.0827	0.0178
C(2,2)	–0.0002	0.1907	0.9989
A(1,1)	–0.1024**	0.0511	0.0450
A(1,2)	0.0343*	0.0175	0.0502
A(2,1)	–0.2003**	0.0726	0.0058
A(2,2)	–0.1502**	0.0530	0.0046
B(1,1)	0.9395**	0.0836	0.0000
B(1,2)	–0.1239**	0.0076	0.0000
B(2,1)	0.1775**	0.0091	0.0000
B(2,2)	0.8572**	0.0435	0.0000

Note: * and ** indicate that it is significant at levels of 10% and 5%, respectively.

the opening of the SHSC, $\mathbf{A}_2$ and $\mathbf{B}_2$ are the coefficient matrixes after the opening of the SHSC. To determine whether the model estimation is covariance stationary, the conditions given in the theoretical description of the BEKK model are used. The Kronecker product (K) of $\mathbf{A}$ and $\mathbf{B}$ is:

$$\mathbf{K} = \mathbf{A}_i \otimes \mathbf{A}_i + \mathbf{B}_i \otimes \mathbf{B}_i, \qquad i = 1, 2.$$

We substitute the estimated coefficients of the BEKK model before and after the opening of the SHSC into the Kronecker product and set $\det(\mathbf{K} - \lambda\mathbf{I}) = 0$; then, we get the absolute eigenvalues corresponding to the two stages as follows:

$$\lambda_1 = [0.9126, 0.9126, 0.9727, 0.8779]',$$

$$\lambda_2 = [0.9277, 0.9113, 0.9113, 0.9198]'.$$

According to the above eigenvalues, the estimated absolute eigenvalues are all less than 1. Thus, the estimated model satisfies the condition of variance stability and it is reasonable to model the volatility spillover effect for the stock markets of Shenzhen and Hong Kong. Therefore, we can further analyze the meaning of volatility spillover expressed by model parameters.

As can be seen from Table 7, before the opening of the SHSC, there was a one-way volatility spillover between the stock markets of Shenzhen and Hong Kong. The values of off-diagonal elements a_{12} and b_{12} in parameter matrix are significant at a significance level of 5%, which shows that both ARCH effect and GARCH effect exist in Shenzhen stock market and Hong Kong stock market. There are the agglomeration effect and the lasting effect of volatility. In addition, there is also small volatility spillover between them. The reason may be due to the opening of the Shanghai-Hong Kong stock connect. However, the coefficient a_{21} is not significant at a significance level of 5%, which shows that there is no volatility agglomeration effect between the stock markets of Hong Kong and Shenzhen. Moreover, it is also indicated that there is no obvious volatility spillover between Hong Kong stock market and Shenzhen stock market.

According to Table 8, after the opening of the SHSC, there is a two-way volatility spillover between the stock markets of Hong Kong and Shenzhen. The values of off-diagonal elements a_{12}, b_{12}, a_{21}, and b_{21} in the parameter matrix are quite high at a significance level of 10% and are not zero at all, showing that there are both ARCH volatility effect and persistence effect of GARCH volatility in these two stock markets.

In this section, Wald statistics are constructed to test the volatility effect of BEKK-GARCH(1,1) model in the stock markets of Shenzhen and Hong Kong at different stages. The assumptions are presented below.

Assumption 1:

$$H_0 : a_{12} = b_{12} = a_{21} = b_{21} = 0.$$

That is, there is no two-way volatility spillover effect between the stock markets of Shenzhen and Hong Kong.

Assumption 2:

$$H_0 : a_{ij} = b_{ij} = 0 \qquad (i, j = 1, 2).$$

That is, there is no one-way volatility spillover effect from the Shenzhen or Hong Kong stock market to the other stock market.

The results obtained by Wald test are shown in Tables 9 and 10.

Table 9. The volatility spillover effect before the opening of SHSC.

Original hypothesis H_0	Wald value (Chi-square value)	p value	Conclusion
There is no volatility spillover effect between RZ1 and RK1 ($a_{12} = b_{12} = a_{21} = b_{21} = 0$)	77.6106	0.0000	Reject
There is no volatility spillover effect from RZ1 to RK1 ($a_{12} = b_{12} = 0$)	90.6293	0.0000	Reject
There is no volatility spillover effect from RK1 to RZ1 ($a_{21} = b_{21} = 0$)	101.1402	0.3241	Accept

Table 10. The volatility spillover effect after the opening of SHSC.

Original hypothesis H_0	Wald value (Chi-square value)	p value	Conclusion
There is no volatility spillover effect between RZ2 and RK2 ($a_{12} = b_{12} = a_{21} = b_{21} = 0$)	9.722813	0.0454	Reject
There is no volatility spillover effect from RZ2 to RK2 ($a_{12} = b_{12} = 0$)	2.528438	0.0295	Reject
There is no volatility spillover effect from RK2 to RZ2 ($a_{21} = b_{21} = 0$)	8.054070	0.0178	Reject

We use the Wald test to verify the estimated results of BEKK-GARCH(1,1) model, and find that after the opening of the SHSC, the volatility spillover relationship between the Hong Kong stock market and the mainland stock market changes, which indicates that the implementation of the SHSC mechanism has an impact on the volatility spillover between these two stock markets.

4. Result analysis of SHSC on the co-movements

Sections 3.2 and 3.3 analyze the co-movement changes of the stock markets in Shenzhen and Hong Kong before and after the opening of the SHSC from the perspectives of dynamic correlation and volatility spillover, respectively. Thus, some conclusions can be drawn on the impact of the opening of the SHSC on the co-movements between the stock markets of Shenzhen and Hong Kong as follows:

1. The dynamic influence of stock markets in Shenzhen and Hong Kong has been continuously enhanced. The parameters in Table 11 reflect the persistence of the volatility between stock markets in Shenzhen and Hong Kong. The value of β in the second stage is approximately 1, which indicates that these two stock markets have strengthened their market influence in the second stage and have a long term.
2. The correlation between the stock markets of Shenzhen and Hong Kong is changing dynamically, and the opening of SHSC strengthens the correlation degree between these two stock markets.

Table 11. Parameter estimation results of dynamic correlation.

Parameter	The first stage	The second stage
β	0.7679^{*}	0.9826^{**}

Note: * and ** indicate that it is significant at levels of 10% and 5%, respectively.

Before the implementation of the SHSC mechanism, the dynamic correlation coefficient between these two stock markets fluctuates around 0.5. Part of the reason is that the economic and trade cooperation between the mainland and Hong Kong is deepening and the mainland stock market is continuously reformed. In addition, opening to the outside world, especially the implementation of Shanghai-Hong Kong stock connect mechanism, makes the correlation coefficient of stock markets in Shenzhen and Hong Kong show moderate correlation. In 2015, China's stock market experienced a serious stock market crash, which lasted from June 2015 to February 2016. During this period, a large number of listed companies suspended their trading, the value of the A stock market plunged by 15 trillion yuan, the Shanghai securities composite index fell by 30%, and the stock market even fell by the daily limit of 1,000 shares. As a result, the stock market liquidity was extremely poor, the information transmission between the mainland and Hong Kong was not timely, and the correlation coefficient between the two stock markets finally exhibited a downward trend.

With the rational return of the markets, the value concept of cross-strait investors changes gradually, and the correlation degree between the stock markets of Shenzhen and Hong Kong has been rapidly strengthened. Observed from Figure 3, the dynamic correlation coefficient of the two stock markets exhibited a W shaped trend. After the opening of SHSC, the differences between the two stock markets need to be adjusted step by step. In addition, due to the ferment of Letv enterprise events, there was a short-term credit crisis in the market, and the correlation coefficient of the stock markets gradually increased and reached a record high after a period of adjustment.

From the estimated parameter a_{12} in Tables 7 and 8, we can see that the volatility effect becomes larger after the opening of the SHSC ($0.0343 > -0.1584$), which indicates that the intensity of volatility overflow increases with the implementation of the SHSC. The Wald test shows that the volatility spillover effect changed from one-way to two-way after the opening of the SHSC. This conclusion indicates that the transmission of risk information has changed from single transmission to mutual transmission. As a bridge and link between the two stock markets in Shenzhen and Hong Kong, the SHSC improves the risk transmission capacity of the two stock markets and the correlation degree between the two stock markets is further strengthened, which is also related to the information transmission rate of the two stock markets strengthened by the SHSC.

5. Conclusion

In this paper, the binary Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models were established to comprehensively analyze the complex co-movement effect of the SHSC on the Shenzhen-Hong Kong stock markets mainly in terms of dynamic correlation and volatility spillover. Specifically, considering the complex nonlinear relationship between financial markets, the t-copula Dynamic Conditional Correlation-GARCH (DCC-GARCH) model integrating copula function with DCC-GARCH was established to analyze the dynamic correlation between the stock markets of Shenzhen and Hong Kong before and after the opening of the SHSC. Based on the parameter estimation of different stages, we conclude that the volatility of the two stock markets in the second stage is persistent and has long-term influence. According to the analysis of dynamic correlation coefficient diagram, (a) the dynamic correlation coefficient between the stock markets gradually increased; (b) the correlation degree between the two stock markets increased after the opening of the SHSC; and (c) the openness of Shenzhen market increased. Moreover, the Baba, Engle, Kraft, Kroner-GARCH (BEKK-GARCH) model was established to study the volatility spillover effect of the stock markets of Shenzhen and Hong Kong before and after the opening of the SHSC. From the analysis result of the volatility spillover, the SHSC mechanism facilitated the capital flow between the stock markets of Shenzhen and Hong Kong and then, made the volatility spillover of stock markets change from one-way to two-way. In addition, due to the opening of the SHSC, the co-movements of the two stock markets were enhanced and the openness of these two stock markets was strengthened, which played a positive role in promoting the internationalization of China's securities market.

Compared with existing literature, the contribution of this paper is as follows. On the one side, the existing literature mainly analyzes the complex comovements relation of stock markets in Shenzhen and Hong Kong only from the perspective of correlation under the background of the SHSC, but there are some limitations. This paper analyzed the co-movements of the stock markets in Shenzhen and Hong Kong in terms of dynamic correlation and volatility spillover. On the other side, much of the existing literature is mainly based on DCC-GARCH model when studying the dynamic correlation of stock markets. However, there are many limitations in parameter estimation, information distribution hypothesis, and other issues. Accordingly, considering the nonlinear relationship that has been ignored in the previous financial market research, this paper integrated the copula function with DCC-GARCH model and then, established a new t-copula DCC-GARCH model to study the dynamic correlation between the stock markets of Shenzhen and Hong Kong.

On the basis of this paper, our further research can be conducted from the following angles in the future:

(i) This paper only concluded that the co-movements between the stock markets of Shenzhen and Hong Kong increased after the opening of the SHSC, without analyzing the specific influencing factors that lead to this phenomenon. This issue can be considered in the future and the importance of the influencing factors be ranked;

(ii) This paper found that the SHSC mechanism improved the openness of mainland capital market. In the future, the co-movements and risk spillover effect between mainland market and global stock market can be discussed based on the copula function in the context of connectivity mechanism;

(iii) There is a need to further study the VAR value of multi-asset portfolio or different optimized portfolio models for the stock markets of Shenzhen and

Hong Kong, which can provide decision-making references for rational investment of investors.

Acknowledgments

This work is supported by China Scholarship Council, the National Natural Science Foundation of China (No. 71671135), and the 2019 Fundamental Research Funds for the Central Universities (WUT: 2019IB013).

References

1. Wang, Q.Y. and Chong, T.T.L. "Co-integrated or not? After the Shanghai-Hong Kong and Shenzhen-Hong Kong stock connection schemes", *Economics Letters*, **163**, pp. 167–171 (2018).
2. Huo, R. and Ahmed, A.D. "Return and volatility spillovers effects: Evaluating the impact of Shanghai-Hong Kong stock connect", *Economic Modelling*, **61**, pp. 260–272 (2017).
3. Burdekin, R.C.K. and Siklos, P.L. "Quantifying the impact of the November 2014 Shanghai-Hong Kong stock connect", *International Review of Economics & Finance*, **57**, pp. 156–163 (2018).
4. Qu, S.J., Zhou, Y.Y., Zhang, Y.L., et. al. "Optimal strategy for a green supply chain considering shipping policy and default risk", *Computers and Industrial Engineering*, **131**, pp. 172–186 (2019).
5. Rao, C.J., Xiao, X.P., Goh, M., et al. "Compound mechanism design of supplier selection based on multi-attribute auction and risk management of supply chain", *Computers and Industrial Engineering*, **105**, pp. 63–75 (2017).
6. Liu, Z.H., Tseng, H.K., Wu, J.S., et al. "Implied volatility relationships between crude oil and the U.S. stock markets: Dynamic correlation and spillover effects", *Resources Policy*, **66**, 101637 (2020).
7. Xiao, Q.Z., Chen, L., Xie, M., et al. "Optimal contract design in sustainable supply chain: interactive impacts of fairness concern and overconfidence", *Journal of the Operational Research Society*, **72**(7), pp. 1505–1524 (2021). DOI: 10.1080/01605682.2020.1727784.
8. Zhou, W. and Xu, Z.S. "Envelopment analysis, preference fusion, and membership improvement of intuitionistic fuzzy numbers", *IEEE Transactions on Fuzzy Systems*, **28**(9), pp. 2119–2130 (2020). DOI: 10.1109/TFUZZ.2019.2930483.
9. Rao, C.J., Lin, H. and Liu, M. "Design of comprehensive evaluation index system for P2P credit risk of "three rural" borrowers", *Soft Computing*, **24**(15), pp. 11493–11509 (2020). DOI:10.1007/s00500-019-04613-z.
10. Kang, S.H. and Yoon, S.M. "Dynamic correlation and volatility spillovers across Chinese stock and commodity futures markets", *International Journal of Finance and Economics*, **25**(2), pp. 261–273 (2020).
11. Huang, R.P., Qu, S.J., Yang, X.G., et al. "Multi-stage distributionally robust optimization with risk aversion", *Journal of Industrial and Management Optimization*, **17**(1), pp. 233–259 (2021). DOI: 10.3934/jimo.2019109.
12. Rao, C.J., Goh, M., Zhao, Y., et al. "Location selection of sustainability city logistics centers", *Transportation Research. Part D: Transport and Environment*, **36**, pp. 29–44 (2015).
13. Forbes, K.J. and Rigobon, R. "No contagion, only interdependence: measuring stock market co-movements", *The Journal of Finance*, **57**(5), pp. 2223–2261 (2002).
14. Li, H. and Majerowska, E. "Testing stock market linkages for Poland and Hungary: a multivariate GARCH approach", *Research in International Business and Finance*, **22**(3), pp. 247–266 (2008).
15. Rua, A. and Nunes, L.C. "International comovement of stock market returns: a wavelet analysis", *Journal of Empirical Finance*, **16**(4), pp. 632–639 (2009).
16. Gjika, D. and Horvath, R. "Stock market comovements in central Europe: evidence from the asymmetric DCC model", *Economic Modelling*, **33**(3), pp. 55–64 (2013).
17. Mensi, W., Hammoudeh, S., Nguyen, D.K., et al. "Global financial crisis and spillover effects among the U.S. and BRICS stock markets", *International Review of Economics & Finance*, **42**(3), pp. 257–276 (2016).
18. Baris, K., Ramazan, S., Alper, G., et al. "Dynamic correlations between BRIC and US stock markets: the asymmetric impact of volatility expectations in oil, gold and financial markets", *Journal of Commodity Markets*, **7**(9), pp. 41–56 (2017).
19. Hassan, K., Hoque, A. and Gasbarro, D. "Separating BRIC using Islamic stocks and crude oil: dynamic conditional correlation and volatility spillover analysis", *Energy Economics*, **80**, pp. 950–969 (2019).
20. Akkoc, U. and Civcir, I. "Dynamic linkages between strategic commodities and stock market in Turkey: Evidence from SVAR-DCC-GARCH model", *Resources Policy*, **62**, pp. 231–239 (2019).
21. Song, X.J., *Application of Multivariate GARCH Model in Asian stock Market*, Xiamen University, Xiamen (2009).
22. Xiong, Z.D. and Han, L.J. "An empirical study on the volatility spillover effect between financial markets-GC-MSV model and application", *Chinese Journal of Management Science*, **21**(2), pp. 32–41 (2013).
23. Li, H.F., *An Empirical Analysis of Co-movement for Asian-Pacific Stock Markets*, Southwest University of Finance and Economics, Chengdu (2013).
24. Gao, M. and Guo, P. "Spillover effect of Chinese stock market price index and external stock market price index-an empirical study based on VAR-BEKK-GARCH model", *Price Theory and Practice*, **1**, pp. 101–102 (2014).

25. Yang, G.Y., Luo, Y., and Fang, Y.Y. "Research on the correlation and dynamic linkage of stock market volatility in greater China", *Statistics and Decision*, **22**, pp. 147–151 (2015).
26. Zhao, S.M. and Yan, H.L. "Study on the integration process of mainland and Hong Kong stock markets", *China Economic Studies*, **1**(1), pp. 124–135 (2016).
27. Yao, Y.Z. and Liu, Z.F. "Dynamic correlations among Shanghai, Shenzhen and Hong Kong stock markets: Based on DCC-MIDAS model", *Journal of Systems Science and Mathematical Sciences*, **37**(8), pp. 1780–1789 (2017).
28. Xian, J.C. and Pan, C.R. "Impact Analysis of Shanghai-Hong Kong stock Connect on Shanghai and Hong Kong stock markets", *Statistics and Decision*, (**17**), pp. 154–157 (2018).
29. Huo, R., *Modelling Dynamic Financial Linkages, Spillover Effects and Volatility Transmissions: Empirical Evidence from China and International Financial Markets*, RMIT University, Australia (2018).
30. Li, X.F. and Wei, Y. "The dependence and risk spillover between crude oil market and China stock market: New evidence from a variational mode decomposition-based copula method", *Energy Economics*, **74**, pp. 565–581 (2018).
31. Lin, B.Q. and Chen, Y.F. "Dynamic linkages and spillover effects between CET market, coal market and stock market of new energy companies: A case of Beijing CET market in China", *Energy*, **172**, pp. 1198–1210 (2019).
32. Xu, W.J., Ma, F., Chen, W., et al. "Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States", *Energy Economics*, **80**, pp. 310–320 (2019).
33. Chang, K., Ye, Z.F., and Wang, W.H. "Volatility spillover effect and dynamic correlation between regional emissions allowances and fossil energy markets: New evidence from China's emissions trading scheme pilots", *Energy*, **185**, pp. 1314–1324 (2019).
34. Na, O. and Kwon, S. "Residual-based copula parameter estimation", *Korean Journal of Applied Statistics*, **29**(1), pp. 267–277 (2016).
35. Ko, V. and Hjort, N.L. "Model robust inference with two-stage maximum likelihood estimation for copulas", *Journal of Multivariate Analysis*, **171**(5), pp. 362–381 (2019).
36. Li, X. *Financial Risk Measurement Based on Copula Theory*, Lanzhou University, Lanzhou (2018).
37. Zhang, X.W. and Jiang, H. "Application of copula function in financial risk analysis", *Computers & Electrical Engineering*, **77**, pp. 376–388 (2019).
38. Hou, Y., Li, S., and Wen, F.H. "Time-varying volatility spillover between Chinese fuel oil and stock index futures markets based on a DCC-GARCH model with a semi-nonparametric approach", *Energy Economics*, **83**, pp. 119–143 (2019).
39. Wang, Z.H., and Li, J.S.H. "A DCC-GARCH multi-population mortality model and its applications to pricing catastrophic mortality bonds", *Finance Research Letters*, **16**, pp. 103–111 (2016).
40. Yi, H.B., Lai, J.J., Dong, D.Y., et al. "Network forum affects the stock market: an empirical analysis based on multivariate GARCH-BEKK model", *Sociology*, **5**(2), pp. 137–145 (2015).
41. Kočenda, E. and Moravcová, M. "Exchange rate co-movements, hedging and volatility spillovers on new EU forex markets", *Journal of International Financial Markets, Institutions and Money*, **58**(1), pp. 42–64 (2019).

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