Study on the Dynamic Interdependent Structure and Risk Spillover Effect between Sino-US Stock Markets

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Abstract: This paper intends to explore the dynamic interdependence structure and risk spillover effect between Chinese and the US stock markets, using the multivariate R-vine copula-complex network analysis and R-Vine copula-CoVaR model, with a sample of CSI 300, S&P 500, and sub-sector indices from January 3, 2006 to July 3, 2019. The empirical results find that the Energy, Materials, and Financials sectors play leading roles in the interdependent structure of the Chinese and US stock markets, while the Utilities and Real Estate sectors are in the least important positions.The comprehensive influence of the Chinese stock market is close to that of the US stock market, but the differences in the influence of different sectors of the US stock market in the overall interdependent structure system are smaller. Over time, the interdependent structure of both stock markets changed, the sector status gradually became equal, the contribution of the same sector in different countries to the interdependent structure converged, and the degree of interaction between the two stock markets is positively correlated with the degree of market volatility. A further research shows that the lower tail interdependence coefficient between the Sino-US stock markets is larger than the upper tail interdependence coefficient and both display the volatility agglomeration effect. In contrast, the spillover risk of the US stock market to the Chinese stock market is higher than that of the Chinese stock market to the US stock market, and the US stock market play a more important role as the extreme risk sender in the interdependent structure.

Keywords: Interdependence Structure; R-vine Copula; Complex Network Analysis; CoVaR Model; Risk Spillover

1. Introduction

With the development of economic globalization, the relationship between financial markets around the world is becoming closer and closer, and the cross-market risk contagion and spillover effect are significant. The United States is the world's largest economy, with a GDP of US $21.43 trillion in 2019, accounting for about 24% of the world's total economy. Since the reform and opening up, China's economy has developed rapidly. In 2009, China overtook Japan to become the world's second largest economy, with a GDP of US $14.28 trillion in 2019. China and the United States have close political, economic, social, cultural, and educational exchanges, which is mainly reflected in the fact that the two countries are each other's largest trading partner, China is the largest creditor country of the United States, and the United States is one of the largest sources of foreign direct investment (FDI) in China. The economic and trade ties between China and the United States are increasingly strengthened and have become the most important bilateral economic relationship in the world. With the continuous improvement of the internationalization level of Chinese capital market, many Chinese enterprises listed in the United States, many

American institutions invested in the Chinese market, and the relationship between the financial markets of the two countries has also been strengthened. Especially since March 2018, trade disputes between China and the United States have escalated and intensified, affecting the sensitive nerves of the world capital market, especially the stock markets of China and the United States. In this context, it is of great practical significance to deeply study the dynamic relationship and risk transmission mechanism between China and the United States.

This paper mainly uses the multivariate R-vine copula-complex network analysis and R-Vine copula-CoVaR model, and takes the stock price indices and their sub-sector indices as samples to explore the dynamic interdependent structure and risk spillover effect between China and the United States. The main findings of this paper can be summarized as follows. First, different from most of the previous literature which is carried out from the linear framework, this paper uses the methods of nonlinear cointegration and R-vine copula function to explore the interactive relationship and risk spillover effect between Chinese and the US stock markets from the nonlinear perspective and investigates the long-term and short-term interactive relationship between Chinese and the US stock markets at the same time, which provides a more comprehensive picture for understanding the relationship between the two stock markets. Second, this paper puts forward the R-vine copula-complex network analysis method to creatively construct the interdependent network structure of the two stock markets, which not only overcomes the premise assumption of "linear correlation" in the general network analysis, but also can show the more correlated and complex stock price interdependent network more clearly and intuitively, which provides a new idea for the research of the interdependent structure of the financial markets. Third, this paper combines the generalized CoVaR method with the R-vine copula function, introduces the stock market decline and rise risk, and further discusses the risk spillover effect between Chinese and the US stock markets from the static and dynamic perspectives.

2. Literature Review

The interaction between international stock markets has always been an important content concerned by researchers. Most studies focus on the main stock markets of European and American developed countries (Fratzscher, 2002; Barberis et al., 2005), but in recent years, more and more studies begin to turn their attention to the stock markets of developing countries (Travkin, 2015; Kayalar et al., 2017). Since China and the United States are the two most important economies in the world, the interactive relationship between their stock markets is also one of the hotspots studied by many scholars

Theoretically, the early relevant exploration of the stock market linkage mechanism can be divided into two hypotheses: the economic basis hypothesis (Alder and Dumas, 1983; McQueen and Roley, 1993) and the market contagion hypothesis (King and wadhwani, 1990; Connolly and Wang, 2000). Based on the traditional financial theory that investors are completely rational, the former believes that the basic bread of each economy, including economic cycle, macroeconomic information, international trade, exchange rate fluctuations and capital flows, plays a major role in the strength of the correlation between the stock markets; the latter believes that the linkage of the stock markets can not be completely explained by the observable correlation of macro fundamentals. It should also consider the sensitivity of the financial market and the behavior of investors, including market price information and investors' psychological expectations. Since then, some studies have made a more comprehensive and specific interpretation of the above two hypotheses from the perspective of stock market information spillover (Hong et al., 2009), and the explanation of stock market linkage from this perspective can be expanded into two mechanisms: direct information spillover mechanism and indirect information spillover mechanism. In fact, the interaction between different markets includes both economic connection factors (Beine and Candelon, 2011) and market contagion factors (Hudson and Green, 2013), and scholars have different emphases in their research.

From the perspective of methodology, the existing studies on the interdependence of financial markets can be divided into the following four categories:

(1) Long-term equilibrium test method. Such methods can be divided into Granger causality test under stationary conditions (Ghysels et al., 2016) and cointegration test under non-stationary conditions which includes cointegration test under linear and nonlinear framework (Chan et al., 2015). Since the financial sequence is usually non-stationary and the interaction relationship is often nonlinear, the nonlinear cointegration test is a more accurate method to investigate the long-term equilibrium relationship of the financial market.

(2) Dynamic conditional correlation method (DCC). This method consists of a flexible GARCH model and a correlation coefficient model with concise parameters, which can be used to study the time-varying correlation degree of nonlinearity between variables (Engle, 2002). The DCC method can also be combined with the vector autoregressive (VaR) model to characterize the time variability of correlation coefficients (Primiceri, 2005). This linear model with time-varying parameters is essentially a general nonlinear model, which can simultaneously consider the nonlinear characteristics of information spillover through rolling window analysis (Diebold and Yilmaz, 2014). However, the DCC method is difficult to describe the interdependent structure and multiple interactive relationships between financial markets.

(3) Network analysis method. This method mainly constructs the association network structure of all nodes according to the linear correlation coefficient between nodes. Tumminello et al. (2007) used the plane maximum filter graph (PMFG) method to build a relevant network for 300 stocks on the New York Stock Exchange and studied the changing trend of topological indicators such as average path length, node intermediary number, and degree in the network. Diebold and Yilmaz (2014) and Acemoglu et al. (2015) used the method of network analysis to characterize the correlation and transmission of extreme risks between financial markets, revealing the correlation structure and overall level of global systemic risks. The limitation of the

network analysis method is that the description of interdependent degree between financial markets is mainly based on the Pearson coefficient measuring linear correlation, which can not well reflect the nonlinear interaction between financial markets, and the network analysis method assumes that each node is independent of each other, which is inconsistent with the reality of spillover impact between financial markets.

(4) Copula function method. The copula function was first proposed by Sklar (1959), and then the concept, properties, and form of the copula function were continuously improved. Copula function is not constrained by the theoretical framework of traditional "linear" and "normal distribution", and can measure the nonlinear structure between financial markets. However, when the financial market changes from binary to multivariate, the parameter estimation of the copula function will become very complicated, resulting in the "curse of dimensionality" problem. In this regard, Bedford and Cooke (2001) extended the form of the copula function and proposed the R-vine copula model, which can decompose the multivariate interdependent structure into various specified marginal distributions and the coupling between these marginal distributions relationship, while taking into account the tail interdependencies between pairs. Brechmann et al. (2012) found that the vine copula function can effectively solve the "curse of dimensionality" problem of multi-dimensional parameter estimation, and found that the most important interdependencies exist in the first 4-6 trees by constructing the interdependent structure between Norway and the international market. Dißmann et al. (2013) confirmed that the R-vine copula function is more flexible than the C-vine and D-vine copula functions, and used the R-vine copula to construct the interdependent structure of 16 indices during the financial crisis. The vine copula function can better remedy for the defects of the traditional copula function. Under the premise of considering the interaction between different markets, it can describe the nonlinear interdependent structure between different financial markets, which is also a big difference compared to the previous three methods.

Based on the linkage characteristics of the stock market, some studies further explore the issue of risk spillovers between different markets. Stock market risk spillover is a phenomenon of extreme risk interaction based on interdependence. Currently, there are three commonly used methods to describe extreme risks in financial markets: the value-at-risk method (VaR), expected shortfall method (ES), and conditional value-at-risk method (CoVaR). Among them, the value-at-risk is a very classic risk measurement method, but this method has shortcomings such as lack of sub-additivity, convexity, inconsistent consistency, and is not easy to supervise (Kratz et al., 2018). In 2010, Basel III proposed to replace the traditional VaR indicator with the expected shortfall indicator to measure the value at risk of the financial sector, making the risk measurement indicator more tail sensitive and effective (Du and Escanciano, 2016). Since then, an improved marginal expected shortfall (MES) method based on the ES method was proposed to describe the overall level of systemic risk in financial markets (Acharya et al., 2017).

Compared with the VaR and the ES method, the advantage of the CoVaR method is that it can measure the direction and degree of risk spillover. Adrian and Bruunermeier (2008) first established the CoVaR model that reflects the risk spillover relationship among financial institutions. Compared with the VaR model, this model introduces the concept of conditional probability and more comprehensively examines the risk conduction and spillover between financial markets. Later, Girardi and Ergün (2013) improved the former's definition of the CoVaR model, changing the definition of the financial crisis from an institution that is in its VaR to an institution that is at most in its VaR, making the model more applicable. Although the CoVaR model was proposed late, a large number of scholars have applied it to the study of risk spillover effects in financial markets. The CoVaR model can be used in conjunction with the copula function, and its advantage is that it can better characterize the interdependent structure and spillover effects between financial markets (Karimalis and Nomikos, 2018). In addition, Reboredo et al. (2016) established a generalized CoVaR model, proposed the concept of downside and upside spillover risk based on investor expectations, and measured the two-way risk spillover degree of stock markets and exchange rates in developing countries such as Brazil, Chile, Colombia, and India. On this basis, Warshaw (2019) further expanded the Copula-CoVaR model, introduced the copula function into the generalized CoVaR model, investigated the risk spillover effect between the stock markets of developed countries such as the United States and Canada, and studied the asymmetry of upside and downside risk spillovers.

3. Methodology

The interdependence between financial markets often presents non-linear characteristics, which includes both the overall market linkage and the risk spillover in extreme cases. First, this paper uses linear and non-linear cointegration tests based on the Logistic STAR model to examine the long-term equilibrium relationship between China and the United States. Second, this paper examines the complex short-term interdependence structural relationship between Chinese and the US stock markets by combining the R-vine copula model with complex network analysis. Third, this paper uses the generalized CoVaR model based on R-vine copula to examine the relationship between Chinese and the US stock markets risk spillovers from the perspective of downside and upside risks

3.1 Nonlinear Cointegration Model

Before studying the short-term interdependent structure, we first use co-integration analysis to test the long-term relationship between Chinese and the US stock markets return series. Since most of the stock market data are high-frequency and volatile, and the linkages and interdependencies of different markets often show nonlinear characteristics, the cointegration test under the traditional linear framework may have certain limitations. In addition to the traditional linear cointegration analysis, this paper also refers to the smooth transition autoregression model (STAR) of Chan et al. (2015) and establishes a Logistic STAR model to conduct nonlinear cointegration analysis on the return series of Chinese and the US stock markets to explore whether there is a long-term equilibrium relationship between the total indices and their sub-sector indices of two countries' stock markets. Based on the general STAR model, it is extended to the LSTAR in the following form:

$$y_t = \varphi' X_t + F(S_{t-d}, \gamma, c)\theta' X_t + \varepsilon_t \tag{1}$$

Where $X_t = (x_t, x_{t-1}, x_{t-2}, \dots, x_{t-p})'$ represents the financial market return series, $\varphi = (\varphi_0, \varphi_1, \varphi_2, \dots, \varphi_p)'$ and $\theta = (\theta_0, \theta_1, \theta_2, \dots, \theta_p)'$ are the correlation coefficients. c represents the position parameter, γ represents the transfer velocity variable, also known as the scale parameter, and d represents the lag parameter. $F(S_{t-d}, \gamma, c)$ is a smooth transfer function, which represents a mechanism conversion process, where S_{t-d} is a transfer variable, and the value is generally y_{t-d}. The value range of $F(S_{t-d}, \gamma, c)$ is [0,1], and when $F(S_{t-d}, \gamma, c)$ is 0, it can be considered that there is only a linear correlation between random variables, otherwise there is a non-cointegration relationship between random variables. Where the logistic function representation of the smooth transfer function $F(S_{t-d}, \gamma, c)$ is $\{1 + e^{-\gamma(S_{t-d}-c)}\}^{-1} - \frac{1}{2}$. In this paper, the third-order Taylor expansion approximation at $\gamma = 0$ is used to replace the nonlinear logistic smooth transfer function, and the final form can be expressed as:

$$\begin{aligned} y_t &= \mathrm{Coef}_0' X_t + \mathrm{NCoef}_1' X_t S_{t-d} + \mathrm{NCoef}_2' X_t S_{t-d}^2 + \mathrm{NCoef}_3' X_t S_{t-d}^3 + u_t \\ &= c + \sum_{i=0}^{p} \left(\mathrm{Coef}_{0i} X_{t-i} + \mathrm{NCoef}_{1i} X_{t-i} S_{t-d} + \mathrm{NCoef}_{2i} X_{t-i} S_{t-d}^2 + \mathrm{NCoef}_{3i} X_{t-i} S_{t-d}^3\right) + u_t \end{aligned} \tag{2}$$

Where $u_t = \varepsilon_t + \theta' X_t R$, R is the remainder of the third-order Taylor expansion, then the cointegration relationship between the test variables is transformed into a hypothesis test problem, where Coef_0 represents the linear coefficient, NCoef_1、NCoef_2、NCoef_3 respectively represents the nonlinear parameters under the condition of Taylor expansion of order 1-3. In addition, the null hypothesis H_0 of the test indicates that $\mathrm{NCoef}_1 = \mathrm{NCoef}_2 = \mathrm{NCoef}_3 = 0$, and the alternative hypothesis H_1 indicates that NCoef_1、NCoef_2、NCoef_3 are not 0 at the same time.

3.2 R-Vine Copula - Analysis of Complex Networks

Copula function can get rid of the constraints of linear and normal distribution, and connect low-dimensional distribution functions into multi-dimensional joint distribution functions. When examining the correlation between multiple financial markets, the use of the traditional copula function may ignore the interdependence between marginal distribution functions, and excessive parameter estimation may cause the "dimension disaster", which in turn results in a certain estimation bias. Therefore, this paper uses the R-vine copula function to describe the interdependence structure of Chinese and the US stock markets. Compared with the other two types of C-vine and D-vine copula functions, the R-vine copula has better properties and is more flexible to use.

According to the definition of Dißmann et al. (2013), the joint distribution density function $h(x_1, \dots, x_n)$ of n-dimensional random variables can have $n!/2$ construction methods to describe the interdependent structure, so an n-dimensional vine copula structure can use n-1-level tree structure representation, which is decomposed into $n(n-1)/2$ edges. In the n-dimensional copula tree structure, the tree T_j at the jth level has n-j+1 nodes and n-j edges, each edge represents a pair copula function, and the independent variable in each pair copula function can be expressed as two the respective edge distribution functions of each node. The form of the R-vine copula density function can be expressed as:

$$h(x_1, \dots, x_n) = \prod_{i=1}^{n} h_i(x_i) \times \prod_{t=1}^{n-1} \prod_{e \in E_t} c_{j(e),k(e)|D(e)} \left(F\left(x_{j(e)}|x_{D(e)}\right), F\left(x_{k(e)}|x_{D(e)}\right)\right) \tag{3}$$

The above density function form can be described as an n-1 layers tree structure decomposition of the joint density function of n-dimensional random variables, forming an R-vine interdependent structure. Note that the node set is $\Psi = \{\Psi_1, \Psi_2, \dots, \Psi_{n-1}\}$, and the edge set is $E = \{E_1, E_2, \dots, E_{n-1}\}$, where $e = j(e), k(e)|D(e)$ is an edge in the set E. Also, $j(e)$ and $k(e)$ are the two nodes connected to edge e, and $D(e)$ are all nodes except $j(e)$ and $k(e)$, where $j(e)$ and $k(e)$ is the adjusted set, $D(e)$ is the adjustment set, and $c_{j(e),k(e)|D(e)}$ represents the conditional binary pair copula function corresponding to edge e, $x_{D(e)} = \{x_i | i \in D(e)\}$ represents the random variable in the $D(e)$ node set. Therefore, the joint distribution function of the random variables x_j and x_k represented by the two nodes $j(e)$ and $k(e)$ is $F\left(x_j, x_k\right) = c(F_j\left(x_j\right), F_k(x_k))$, the joint density function is $f\left(x_j, x_k\right) = c(F_j\left(x_j\right), F_k(x_k)) f_j(x_j) f_k(x_k)$. Correspondingly, each edge e (or each pair copula function) corresponds to an empirical Kendall τ coefficient to represent the degree of interdependence between nodes $j(e)$ and $k(e)$. All edges of the R-vine copula function, and ultimately the structure of the R-vine, can be determined by solving the following optimization problem:

$$\max_{e} \sum_{e=\{j,k\}} |\tau_{jk}| \tag{4}$$

Where τ_{jk} represents the value of the empirical Kendall τ interdependence coefficient between nodes j and k, and its positive and negative values only indicate that the interdependence is positive or negative, and does not affect the degree of interdependence. In order to further detect the network characteristics of the interdependence structure of Chinese and the US stock markets, this paper introduces complex network analysis on this basis and replaces the original linear Pearson correlation coefficient with the nonlinear Kendall τ interdependence coefficient in the R-vine copula function to establish the network interdependence structure between the stock markets of the two countries. This method makes the constructed network interdependent structure free from linear constraints, and at the same time considers the influence of exogenous subjects on the interdependence between subjects.

Specifically, the Kendall τ interdependence coefficient in the R-vine copula function is used to represent the degree of correlation between the subjects, and the distance s_{jk} in the traditional

$S(j,k)$ network association matrix is replaced to form a new interdependence coefficient matrix $K(j,k)=(\tau_{jk})_{N\times N}$, which determines the edges and nodes of the stock market interdependence network. In order to analyze and present accurately, and prevent the relatively weak interdependencies from affecting the overall distribution of the network structure, this paper implements binarization processing on the elements in the network matrix, and comprehensively considers the tree level of the R-vine copula and the size of the interdependent coefficient τ_{jk} to set the binarization criterion:

$$\widetilde{K(j,k)}=\begin{cases}1, & \tau_{jk}\geq m \text{ and Tree Level } \leq n\\ 0, & \tau_{jk}< m \text{ or Tree Level } > n\end{cases} \tag{5}$$

Meanwhile, this paper also introduces the concept of network centrality to measure the influence and relative importance of different sectors in the interdependent structure of Chinese and the US stock markets. The network centrality of a node mainly measures the number of other nodes connected to it, and the centrality analysis describes the status and role of each node in the associated network (Diebold and Yilmaz, 2014). According to the interdependence coefficient matrix $\widetilde{K(j,k)}$, the interdependence network structure of Chinese and the US stock markets can be constructed. The higher the network centrality is, the more stock indices are connected to it, which further means that the sector represented by the node is in the entire interdependence network has more influence in the structure.

$$DC_j=\sum_{k=1}^{N}\widetilde{K(j,k)}\,,j=1,2,\dots,N \tag{6}$$

The distribution of the financial market return series is mostly characterized by fat tail, so the selection of the marginal distribution function F_i of the copula function should take the fat-tailed distribution into consideration. This paper uses the generalized pareto distribution (GPD) to describe the marginal distribution. The GPD is a typical distribution in extreme value theory (EVT), and its advantage is that it does not need to assume the initial distribution type, focuses on the tail characteristics of the distribution and can more accurately assess extreme risks. According to Lee and Kim (2017), this paper sets u as the selected threshold and $Z_i(i=1,2,\dots,N)$ as the residual sequence of stock returns, where N is the number of samples. If $Z_i>u$, then Z_i is called the over-threshold sequence, and $Y_i=Z_i-u$ is the excess amount. When the threshold u is sufficiently large, the excess distribution function $F_u(y)$ will converge to the GPD, which can be written as:

$$F_u(y)\approx G_Y(y)=\begin{cases}1-\left(1+\dfrac{\xi y}{\sigma(u)}\right)^{-\frac{1}{\xi}},\xi\neq 0\\ 1-e^{-\frac{y}{\sigma(u)}},\xi=0\end{cases} \tag{7}$$

Where $\sigma(u)$ and ξ are the position parameters and shape parameters of the excess distribution function, respectively, when $\xi\geq 0$, $y\geq 0$; when $\xi<0$, $0\leq y\leq -\sigma(u)/\xi$, and

$\sigma(u) > 0$. For the relationship between the distribution of the yield residual Z_i, the excess y, and the threshold u, according to the definition of the conditional excess distribution function:

$$F_u(y) = P(Z - u \le y | Z > u) = \frac{P(u < Z \le y + u)}{P(Z > u)} = \frac{F(y+u) - F(u)}{1 - F(u)} \tag{8}$$

After sorting, the relationship between the distributions can be obtained as $F(Z) = F_u(y)\big(1 - F(u)\big) + F(u)$. If Z is the residual greater than the threshold u, $F(Z)$ is the tail distribution of the yield residual series. If the upper and lower tail distributions are considered at the same time, the upper tail threshold is set as u_U, the lower tail threshold is set as u_L, the middle part is fitted with an empirical distribution function, and finally the residual distribution of yield can be obtained as (only the general case of $\xi \neq 0$ is considered):

$$F(Z) = \begin{cases} 1 - \big(1 - F(u_U)\big)\left(1 + \dfrac{\xi_U y}{\sigma_U(u)}\right)^{-\frac{1}{\xi_U}}, Z > u_U \\ \widetilde{F(Z)}, u_L \le Z \le u_U \\ F(u_L)\left(1 - \dfrac{\xi_L y}{\sigma_L(u)}\right)^{-\frac{1}{\xi_L}}, Z < u_L \end{cases} \tag{9}$$

3.3 R-Vine Copula - Generalized CoVaR Model

The CoVaR model can be used to measure the risk spillover to another market when one market is at extreme risk. Compared with the traditional VaR model, it has the advantage of introducing conditional probability, which can more comprehensively examine the direction and degree of risk transmission between financial markets. According to the definition of Girardi and Ergun (2013), there is $P\left(X^j \le CoVaR_q^{j|k} | X^k \le VaR_q^k\right) = q$, where q is the confidence. If $CoVaR_q^{j|k}$ represents the CoVaR faced by financial market j when the rate of return of financial market k is at the level of VaR_q^k (extreme risk situation), and deduces $CoVaR_q^{j|k} = F_{j|k}^{-1}\big(q|VaR_q^k\big)$. In practice, The CoVaR can be solved by using the conditional distribution function of each pair copula in the R-vine copula function①. Specifically, according to the decomposition form of the pair copula density function is $f(x_j, x_k) = c\left(F_j(x_j), F_k(x_k)\right) f_j(x_j)\, f_k(x_k)$, so it has $f_{j|k}(x_j|x_k) = c\left(F_j(x_j), F_k(x_k)\right) f_j(x_j)$. Integrating both sides of this equation at the same time gives:

$$F_{j|k}(x_j|x_k) = \int_{-\infty}^{x_j} c\left(F_j(x_j), F_k(x_k)\right) f_j(x_j) dx_j \tag{10}$$

The solution x_j of the above formula can be used as the value of $CoVaR_q^{j|k}$. According to the research of Reboredo et al. (2016) and Warshaw (2019), affected by investor sentiment, risk accumulation is easy to occur during the stock market surge, and the probability of stock price crash will also increase. Therefore, the upside risk of the stock market is also worthy of attention. Referring to the practice of Warshaw (2019), this paper expands the traditional CoVaR method and uses the generalized CoVaR model to simultaneously examine the upside risk spillover $CoVaR_{\beta,t}^U$ and the downside risk spillover $CoVaR_{\beta,t}^D$. The calculation method is as follows:

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① Pair copula function is the optimal copula function connecting two nodes in the tree structure constructed by R-vine copula.

$$P\left(R_{j,t} \leq CoVaR_{\beta,t}^{D,j|k} | R_{k,t} \leq VaR_{\alpha,t}^{D,k}\right) = \beta \tag{11}$$

$$P\left(R_{j,t} \geq CoVaR_{\beta,t}^{U,j|k} | R_{k,t} \geq VaR_{1-\alpha,t}^{U,k}\right) = \beta \tag{12}$$

$VaR_{\alpha,t}^{D,k}$ and $VaR_{1-\alpha,t}^{U,k}$ for downside risk and upside risk, respectively, are given by:

$$P\left(R_{k,t} \leq VaR_{\alpha,t}^{D,k}\right) = \alpha \tag{13}$$

$$P\left(R_{k,t} \geq VaR_{1-\alpha,t}^{U,k}\right) = \alpha \tag{14}$$

There are $t = \{1,2,\dots,T\}$, and the specific forms of $VaR_{\alpha,t}^{D,k}$ and $VaR_{1-\alpha,t}^{U,k}$ can be obtained according to the marginal distribution of the return series:

$$VaR_{\alpha,t}^{D,k} = \hat{\mu}_{D,t} + F_{r_t}^{-1}\left(\alpha; \hat{\theta}_j\right)\hat{\sigma}_{D,t} \tag{15}$$

$$VaR_{1-\alpha,t}^{U,k} = \hat{\mu}_{U,t} + F_{r_t}^{-1}\left(1-\alpha; \hat{\theta}_j\right)\hat{\sigma}_{U,t} \tag{16}$$

where $\hat{\mu}_t$ and $\hat{\sigma}_t$ represent the conditional mean and standard deviation of financial markets, $F_{r_t}^{-1}\left(\alpha; \hat{\theta}_j\right)$ and $F_{r_t}^{-1}\left(1-\alpha; \hat{\theta}_j\right)$ are the α and $1-\alpha$ quantiles of the return series distribution function, respectively. According to the definition of conditional probability, (11) and (12) can be rewritten as:

$$C_t\left(F_j\left(CoVaR_{\beta,t}^{D,j|k}\right), F_k\left(VaR_{\alpha,t}^{D,k}\right)\right) = \alpha\beta \tag{17}$$

$$1 - F_j\left(CoVaR_{\beta,t}^{U,j|k}\right) - F_k\left(VaR_{1-\alpha,t}^{U,k}\right) + C_t\left(F_j\left(CoVaR_{\beta,t}^{U,j|k}\right), F_k\left(VaR_{1-\alpha,t}^{U,k}\right)\right) = \alpha\beta \tag{18}$$

There is $F_j(\cdot) = F_{r_t}\left(\cdot; \hat{\theta}_j\right)$, and let $\omega_t^i = F_j\left(CoVaR_{\beta,t}^{i,j|k}\right)$, $\omega_t^{*i} = \omega_t^i\left(\alpha, \beta, C_t\left(\cdot; \hat{\theta}_{ic}\right)\right) \in [0,1]$, $i = D, U$ represent the maximum solutions of equations (17) and (18), respectively. Referring to the two-step method of solving $CoVaR_{\beta,t}^{j|k}$ by Reboredo and Ugolini (2015), ω_t^{*i} and corresponding $C_t\left(\cdot; \hat{\theta}_{ic}\right)$ for given α and β can be obtained, then $CoVaR_{\beta,t}^{j|k}$ can be expressed as:

$$CoVaR_{\beta,t}^{i,j|k} = VaR_{\omega_t^{*i},t}^{j} = \hat{\mu}_{j,t} + F_{r_t}^{-1}\left(\omega_t^{*i}; \hat{\theta}_{ij}\right)\hat{\sigma}_{j,t} \tag{19}$$

$CoVaR_{\beta,t}^{D,j|k}$ and $CoVaR_{\beta,t}^{U,j|k}$ in the above formula respectively represent the downside CoVaR and upside CoVaR of the j market when the k market is at extreme risk, respectively. In order to avoid the dimensional influence, according to Adrian and Brunnermeier (2008), the relative conditional value at risk %CoVaR is generally used to measure the risk spillover degree of the stock markets of the two countries. The indicator is defined as follows:

$$\%\text{CoVaR}_q^{j|k} = \frac{\text{CoVaR}_q^{j|X^k=\text{VaR}_q^k} - \text{CoVaR}_q^{j|X^k=\text{Median}^k}}{\text{CoVaR}_q^{j|X^k=\text{Median}^k}} \quad (20)$$

Where $\%\text{CoVaR}_q^{j|k}$ represents the degree of conditional risk spillover from market k to market j. Referring to the practice of Reboredo et al. (2016) and Warshaw (2019), q is usually selected as 0.05, and Median^k usually selects $\text{VaR}_{0.5}^k$ as an approximate value.

4. Empirical Study

4.1 Data

This paper selects the CSI 300 and S&P 500 stock indices and their sub-sector indices as samples to examine the interdependence between the stock markets of China and the United States. Where each country's stock market includes 11 sectors including Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financals, Information Technology, Communication Services, Utilities and Real Estate①. It should be noted that in the GICS classification standard, the CSI 300 sector indices does not include the Real Estate. In order to correspond to the US stock sector indices, the Real Estate index in the CSI 300 secondary sector index is selected to be included in the sample. Due to the closed market and small scale, the level of internationalization of the Chinese stock market in the early stage was low, and taking into account the matching and availability of data, this paper selects transactions from January 3, 2006 to July 3, 2019 daily closing price as base data②.Where the S&P 500 index and its sector indices each have 3398 observations (except the Real Estate sector index, which started on May 30, 2008③); the CSI 300 index and its sector indices each have 3281 observations.

In view of the lack of data on non-common trading days between the two stock markets, a strategy of excluding data on non-common trading days was adopted. In the end, the CSI 300 and S&P 500 stock indices and their sector indices both had 3178 observations (the US Real Estate index got 2614 observations). Taking into account the impact of the time difference, the trading hours of the stock markets of China and the United States do not overlap. The trading hours of the US stock market on day t correspond to 9:30 p.m. on day t in Beijing, China to 4:00 a.m. on day t+1, and the trading hours of the Chinese stock market on day t correspond to 9:30 p.m. to 3:00 a.m. EST on day t-1. Therefore, the two-way information spillover mechanism of short-term information in Chinese and the US stock markets generally shows that the Chinese stock market price is affected by the information overflow of the US stock market the previous day, and the US stock market price is affected by the information overflow of the Chinese stock market on the

① The industry classification refers to the standard revised in September 2018 by *the Global Industry Classification Standard* (GICS). GICS is an industry classification system launched by Standard & Poor's (S&P) and Morgan Stanley (MSCI) in August 1999. The standard provides a unified economic sector and industry definition for the global financial market.

② As early as 2005, China's A-share market had little linkage with international stock markets, and was little affected by fluctuations in international stock markets. Therefore, data selection began in 2006.

③ The subsequent empirical analysis involving the US's stock real estate index began on May 30, 2008.

same day. When examining the linkage between the two stock markets and the US stock market's risk spillover effect on the Chinese stock market, this paper lags the S&P stock price by one period, and the return adopts the continuous compound daily return of the index closing price. The formula for calculating the rate of return is as follows:

$$\mathrm{R_t} = (\ln \mathrm{P_t} - \ln \mathrm{P_{t-1}}) \times 100\% \tag{21}$$

Where $\mathrm{R_t}$ represents the daily rate of return of the index, and $\mathrm{P_t}$, $\mathrm{P_{t-1}}$ represent the closing price of the t-th trading day and the t-1th trading day, respectively. The data are all taken from the WIND information system. From the descriptive statistics of the sample series, as shown in Table 1. The kurtosis of the return of the stock market and sector indices of the two countries is significant and almost all greater than 3, and the p-value corresponding to the J-B statistic is less than 0.05, showing a sharp peak, fat tail and non-normal distribution. Through ADF unit root test and ARCH-LM test, it is found that each return series is stable but has heteroscedasticity. According to results of the autocorrelation test, partial autocorrelation test, and AIC test, ARMA(1,1)-EGARCH(1,1) model was used to fit the sequence.

Table 1 Descriptive statistics of returns of Chinese and the US stock markets sample indices

Index	Mean	S.D.	Min	Max	Skewness	Kurtosis	J-B Statistics	P-value
Panel A: Chinese Stock Market								
CSI 300	0.0005	0.0182	-0.1301	0.0893	-0.5879	4.2198	2545	0.0000
CSI Energy	0.0001	0.0211	-0.1304	0.1178	-0.2814	3.2876	1476	0.0000
CSI Materials	0.0003	0.0210	-0.1299	0.0864	-0.5870	2.8562	1265	0.0000
CSI Industrials	0.0003	0.0198	-0.1262	0.0955	-0.5696	3.8187	2107	0.0000
CSI Consumer Discretionary	0.0006	0.0197	-0.1222	0.1109	-0.5966	3.4352	1754	0.0000
CSI Consumer Staples	0.0009	0.0190	-0.0986	0.0967	-0.2331	2.8321	1093	0.0000
CSI Health Care	0.0008	0.0197	-0.1315	0.1230	-0.3691	3.6849	1874	0.0000
CSI Financials	0.0006	0.0204	-0.1450	0.1003	-0.2527	4.0087	2166	0.0000
CSI Information Technology	0.0003	0.0228	-0.1157	0.0955	-0.5879	2.4254	964	0.0000
CSI Communication Services	0.0003	0.0224	-0.1258	0.0960	-0.2623	3.1894	1386	0.0000
CSI Utilities	0.0002	0.0174	-0.1320	0.0847	-0.6978	5.1307	3750	0.0000
CSI Real Estate	0.0007	0.0243	-0.1520	0.1348	-0.1815	2.5408	874	0.0000
Panel B: the US Stock Market								
S&P 500	0.0003	0.0124	-0.1378	0.1096	-0.5881	14.4826	27991	0.0000
S&P Energy	0.0001	0.0176	-0.1758	0.1696	-0.3903	13.9993	26063	0.0000
S&P Materials	0.0002	0.0163	-0.2063	0.1247	-0.7630	15.1545	30756	0.0000
S&P Industrials	0.0003	0.0138	-0.1547	0.0952	-0.6721	10.7632	15599	0.0000
S&P Consumer Discretionary	0.0004	0.0139	-0.1556	0.1232	-0.4404	12.5420	20958	0.0000
S&P Consumer Staples	0.0003	0.0089	-0.0665	0.0884	-0.0477	9.9855	13222	0.0000
S&P Health Care	0.0003	0.0108	-0.0922	0.1171	-0.2551	10.5983	14927	0.0000
S&P Financials	0.0000	0.0206	-0.1864	0.1720	-0.1827	15.9883	33907	0.0000
S&P Information Technology	0.0004	0.0139	-0.1599	0.1146	-0.4524	10.8412	15692	0.0000
S&P Communication Services	0.0001	0.0130	-0.1106	0.1292	0.0593	11.5843	17794	0.0000
S&P Utilities	0.0002	0.0116	-0.1222	0.1269	-0.0773	14.9230	29527	0.0000
S&P Real Estate	0.0002	0.0230	-0.2042	0.1885	-0.2428	17.6993	34193	0.0000

4.2 long-term Equilibrium Relationship Test

In this paper, the linear and nonlinear co-integration methods are used to test the linear and nonlinear long-term equilibrium relationships between China and the United States, respectively, as shown in Table 2. The results of the Johansen cointegration test[①] show that the maximal eigenvalue statistic and the trace statistic of each group of samples except the Sino-US

[①] The ADF unit root test shows that each stock index sequence is an I(1) sequence (that is, a first-order single integral sequence), so the stock index sequence can be used for the Johansen cointegration test.

Communication Services are less than the 5% critical value, and the null hypothesis cannot be rejected, that is, there is no linear cointegration relationship. For the income series of the Communication Services sector in China and the United States, the trace statistics reject the null hypothesis at the 5% significance level, but the result of the maximal eigenvalue is the opposite. Since there is no cointegration relationship between the market total indices of the two countries and the Communication Services of the other party, so it is also determined that there is no linear cointegration relationship between the Sino-US Communication Services indices.

According to the non-linear co-integration test results, the test statistic between the CSI 300 and S&P 500 return series is significant at the 5% level, indicating that there is a significant non-linear co-integration relationship between the two indices. From an sector perspective, for the Chinese stock market, except that there is no significant non-linear cointegration relationship between the CSI 300 index and five the US sectors of Materials, Industrials, Consumer Staples, Utilities, and Real Estate indices, there is a nonlinear cointegration relationship between the CSI 300 index and more than 50% of the US sector indices, which indicates that there is a certain nonlinear equilibrium relationship between the Chinese stock market total index and the US sector indices. For the US stock market, except that there is no significant nonlinear cointegration relationship between the S&P 500 index and Chinese sectors of Utilities and Real Estate indices, and between the two countries' Communication Services and Utilities indices, there are certain non-linear co-integration relationships between the rest of the return series at the 10% significance level, which indicates that there is also a certain nonlinear equilibrium relationship between the US stock market total index and the Chinese sector indices. In general, there is a long-term equilibrium relationship between the stock markets of China and the United States to a certain extent, but it is mainly manifested in a nonlinear structure rather than a linear interactive relationship, which provides the necessity for the subsequent analysis of the nonlinear short-term interdependent network structure.

Table 2 Cointegration test results of Chinese and the US stock markets indices

Panel A: Total Index – Sector Index

Form	Linear Cointegration Test						Nonlinear Cointegration Test													
Index	CSI 300			S&P 500			CSI 300							S&P 500						
	Cointegration Statistics		Reject H_0?	Cointegration Statistics		Reject H_0?	$NCoef_1$		$NCoef_2$		$NCoef_3$		Reject H_0?	$NCoef_1$		$NCoef_2$		$NCoef_3$		Reject H_0?
OPPO-total index	7.30	7.56	N	7.30	7.56	N	4.40**	-4.45**	-2.54**	2.67**	0.39**	-0.40**	Y	4.40**	-4.45**	-2.54**	2.67**	0.39**	-0.40**	Y
							(1.96)	(1.93)	(1.22)	(1.21)	(0.19)	(0.19)		(1.96)	(1.93)	(1.22)	(1.21)	(0.19)	(0.19)	
OPPO-Energy	10.36	14.67	N	7.45	7.96	N	-20.50**	25.60***	17.50***	-19.33***	-3.41***	3.64***	Y	6.55*	-7.81**	-4.04*	4.50**	0.61*	-0.65**	Y
							(8.15)	(8.01)	(6.00)	(5.97)	(1.12)	(1.11)		(3.96)	(3.93)	(2.28)	(2.27)	(0.33)	(0.33)	
OPPO-Materials	6.96	8.82	N	6.69	7.12	N	1.67	-2.79	-1.40	2.04	0.27	-0.37	N	5.93***	-5.86***	-3.49***	3.56***	0.53***	-0.54***	Y
							(2.69)	(2.46)	(2.11)	(2.10)	(0.45)	(0.45)		(1.86)	(1.82)	(1.15)	(1.14)	(0.18)	(0.18)	
OPPO-Industrials	7.17	7.19	N	7.07	7.41	N	1.75	-2.16	-1.23	1.54	0.23	-0.28	N	6.31***	-4.39**	-3.16**	2.65**	0.46**	-0.40**	Y
							(1.53)	(1.52)	(1.20)	(1.20)	(0.24)	(0.24)		(2.00)	(1.97)	(1.24)	(1.24)	(0.19)	(0.19)	
OPPO- Consumer Discretionary	6.90	8.08	N	9.56	9.79	N	3.27***	-3.02***	-2.17***	2.21***	0.40**	-0.40***	Y	5.00***	-2.87	-2.24**	1.71	0.31*	-0.26	Y
							(1.04)	(1.03)	(0.81)	(0.80)	(0.16)	(0.16)		(1.79)	(1.76)	(1.11)	(1.10)	(0.17)	(0.17)	
OPPO-Consumer Staples	6.71	6.74	N	4.69	5.54	N	-3.60	0.56	1.89	-0.52	-0.30	0.11	N	3.83*	-4.65**	-2.08*	2.42**	0.28*	-0.32**	Y
							(2.70)	(2.67)	(2.09)	(2.08)	(0.41)	(0.41)		(2.08)	(2.08)	(1.11)	(1.11)	(0.15)	(0.15)	
OPPO-Health Care	7.22	7.41	N	9.37	9.52	N	3.83**	-4.19**	-2.71**	2.99**	0.50**	-0.53**	Y	2.74	-2.91*	-1.53	1.73	0.23	-0.26	Y
							(1.85)	(1.83)	(1.34)	(1.34)	(0.24)	(0.24)		(1.77)	(1.75)	(1.09)	(1.09)	(0.17)	(0.17)	
OPPO-Financials	10.43	12.95	N	7.60	7.81	N	3.25*	-2.80	-2.01	1.96	0.35	-0.34	Y	-1.30***	1.72***	0.44***	-0.45**	-0.56**	0.46*	Y
							(1.84)	(1.83)	(1.50)	(1.50)	(0.31)	(0.31)		(0.21)	(0.49)	(0.13)	(0.22)	(0.22)	(0.24)	
OPPO-Information Technology	7.25	9.75	N	9.90	10.20	N	3.90***	-2.99***	-2.30***	2.10***	0.39***	-0.37***	Y	6.82***	-3.57**	-3.03***	2.15**	0.41***	-0.32**	Y
							(1.08)	(1.07)	(0.79)	(0.78)	(0.14)	(0.14)		(1.63)	(1.59)	(1.00)	(1.00)	(0.16)	(0.16)	
OPPO-Communication Services	10.15	16.77	N	8.99	9.28	N	-12.16**	4.57	8.33	-4.58	-1.73	1.13	Y	3.52**	-3.27**	-1.90*	1.93*	0.28*	-0.29*	Y
							(5.59)	(5.50)	(5.21)	(5.20)	(1.23)	(1.23)		(1.69)	(1.65)	(1.04)	(1.03)	(0.16)	(0.16)	
OPPO-Utilities	8.29	8.59	N	7.71	7.85	N	-5.31	4.73	4.68	-4.28	-1.02	0.96	N	2.87	-0.31	-0.92	0.24	0.12	-0.05	N
							(3.29)	(3.25)	(2.85)	(2.84)	(0.62)	(0.62)		(5.30)	(5.27)	(3.21)	(3.21)	(0.49)	(0.49)	
OPPO-Real Estate	6.65	6.95	N	8.83	9.05	N	-1.88	1.37	2.36	-1.94	-0.66	0.58	N	2.57	-4.20	-1.67	2.25	0.25	-0.30	N
							(2.11)	(2.09)	(2.04)	(2.03)	(0.49)	(0.49)		(3.59)	(3.58)	(1.96)	(1.96)	(0.27)	(0.27)	

Panel B: Sector Index – Sector Index

Index	S&P Sector Index			S&P Sector Index						
	Cointegration Statistics		Reject H_0?	$NCoef_1$		$NCoef_2$		$NCoef_3$		Reject H_0?
CSI Energy	10.21	13.23	N	3.48**	-2.95**	-1.72***	1.70	0.25	-0.25	Y
				(1.47)	(1.33)	(0.53)	(1.52)	(0.22)	(0.22)	
CSI Materials	7.17	8.15	N	3.39	-4.11*	-2.69	3.13	0.54	-0.60	Y
				(2.29)	(2.25)	(1.93)	(1.92)	(0.41)	(0.41)	
CSI Industrials	6.71	6.71	N	-4.46	6.98*	3.52	-4.13*	-0.55	0.61*	Y
				(4.14)	(4.10)	(2.43)	(2.42)	(0.36)	(0.36)	

CSI Consumer Discretionary	9.26	10.26	N	3.40***	-2.43**	-2.00***	1.77**	0.35**	-0.32**	Y
				(0.95)	(0.95)	(0.74)	(0.73)	(0.14)	(0.14)	
CSI Consumer Staples	2.79	2.86	N	-9.61***	3.42	5.38**	-2.73	-0.90**	0.54	Y
				(2.91)	(2.89)	(2.25)	(2.25)	(0.44)	(0.44)	
CSI Health Care	9.73	9.85	N	3.07*	-3.73**	-2.25*	2.66**	0.41*	-0.47**	Y
				(1.63)	(1.62)	(1.18)	(1.18)	(0.21)	(0.21)	
CSI Financials	10.14	11.85	N	4.62**	-5.35***	-1.46	2.90	0.26	-0.40	Y
				(1.27)	(1.23)	(1.79)	(1.78)	(0.25)	(0.25)	
CSI Information Technology	9.74	11.85	N	4.76***	-2.29***	-2.37***	1.61**	0.37***	-0.28**	Y
				(0.89)	(0.88)	(0.64)	(0.64)	(0.12)	(0.12)	
CSI Communication Services	12.07	19.10	N	1.21	-7.20	-3.64	6.60	1.05	-1.52	N
				(4.85)	(4.76)	(4.49)	(4.49)	(1.06)	(1.06)	
CSI Utilities	7.42	7.77	N	6.65	-3.62	-2.87	2.11	0.38	-0.31	N
				(4.78)	(4.76)	(2.89)	(2.89)	(0.44)	(0.44)	
CSI Real Estate	6.65	6.79	N	11.00***	-5.81*	-4.23**	3.07*	0.50*	-0.41	Y
				(3.57)	(3.37)	(1.89)	(1.85)	(0.26)	(0.25)	

Note: (1) ***, ** and * represent that the coefficients reject the null hypothesis at the 1%, 5% and 10% significance levels, respectively, and the standard errors corresponding to the nonlinear cointegration test coefficients are in brackets; (2) The null hypothesis H_0 in the linear cointegration test indicates that there is no cointegration vector, and the alternative hypothesis H_1 indicates that at least one cointegration vector exists; (3) The test statistic in linear cointegration is the maximal eigenvalue statistic and the trace statistic respectively; (4) All the nonlinear cointegration tests based on LSTAR passed the significance test of the equation; (5) 'OPPO-*' in Panel A represents the stock market index (including the total index and sector index) of the other market, and Panel B indicates that the CSI sector index corresponds to the S&P sector index.

4.3 Dynamic Interdependent Structure Analysis

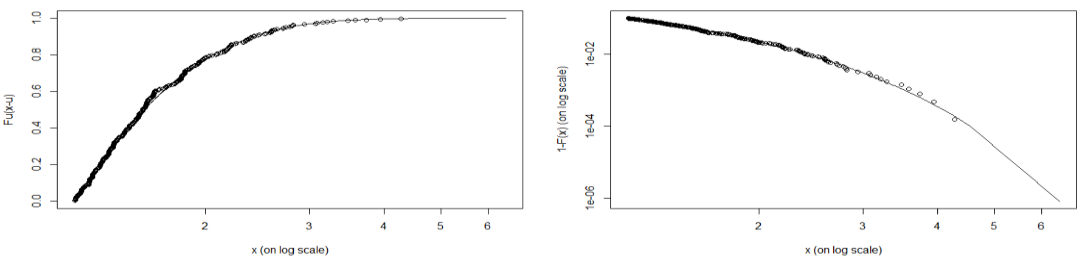
When studying the linkage relationship between Chinese and the US stock markets, we cannot only use the cointegration test analysis, because the cointegration test seeks mutual commonality in a certain time dimension (Evans and McMillan, 2006), and cannot describe the time-varying relationship between the stock markets. The results of the cointegration testing methods are only economically meaningful and not practical when testing over longer time horizons. In this paper, the copula function method, which can better handle the nonlinear relationship of random variables, is used to investigate the total and sub-sectors interdependence and interaction structure of the two stock markets.

4.3.1 Full Sample Results

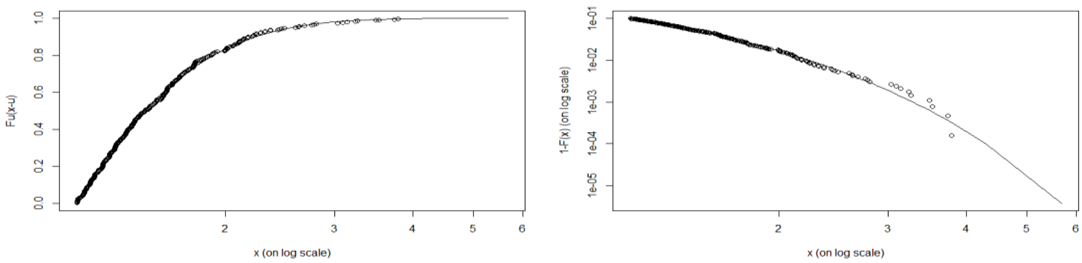
The ARMA(1,1)-EGARCH(1,1) model is used to fit the sequence of each sector, and the residual sequence is extracted to study the interdependence between the sample indices. The residual sequence distribution is used as the marginal distribution modeled by the copula function, the part of each residual sequence that exceeds the threshold is fitted with GPD, and the part within the threshold is fitted with empirical distribution, which can better convert the residual sequence to a uniform distribution on the [0,1] interval. This paper draws on previous research experience[①] and according to the 10% principle proposed by DuMouche, that is, the 10% quantile in the residual sequence is determined as the lower tail threshold, and the 90% quantile is the upper tail threshold. The maximum likelihood estimation method is used to estimate scale parameter $\sigma(u)$ and shape parameter ξ of GPD function. Taking the CSI 300 and S&P 500 index return residuals as examples, by observing the excess function distribution and tail estimation of their GPD, as shown in Figure 1, each point is basically located on the distribution curve, indicating the effect of GPD fitting the sample residual series better. The quantile and parameter estimation results are obtained by fitting each residual sequence based on the GPD, as shown in Table 3, and then substituting the estimated parameters back into the GPD definition formula (9) to obtain the GPD function of each group of residual sequences, which is used as the marginal distribution form for constructing the copula function model. Furthermore, since there are few parameters in GPD estimation, there may be some limitations in describing higher-order information of specific distributions. This paper also uses skewed generalized error distribution (SGED) to fit the series of return residuals. From the parameter results in Table 4, it can be seen that the parameter θ representing the skewness index is not equal to 1 (except for the CSI Consumer Staples index and CSI Financials index, where θ is less than 1), and the parameter λ representing the shape index is less than 2. It can be seen that the sequence basically exhibits the

[①] The selection of the threshold value in GPD is very important. If the selected value is too high, it may lead to a small excess value and cause a large variance in the parameter estimation. If the selected value is too low, it is difficult to ensure the convergence of the super-threshold distribution, which is prone to bias estimate. At present, there is no unified standard for threshold selection methods. There are two commonly used methods: graphical method and computational method. The graphical method mainly includes the mean excess function method, and the computational method mainly includes the Hill estimation method, the kurtosis method and the De Haan moment estimation method.

characteristics of “left-biased and fat-tailed”, indicating that the estimated results have certain robust characteristics.



(a) CSI 300 index



(b) S&P 500 index

Figure 1 CSI 300 and S&P 500 excess distribution function fitting and tail estimation

Table 3 Threshold and parameter estimation results of residual sequence under GPD

Index	Chinese Stock Market				The US Stock Market			
	Tail Type	Threshold	ξ	σ(u)	Tail Type	Threshold	ξ	σ(u)
Total Index	Upper Tail	1.20	-0.04	0.55	Upper Tail	1.15	-0.01	0.48
	Lower Tail	-1.15	-0.03	0.54	Lower Tail	-1.24	-0.01	0.47
Energy	Upper Tail	1.17	0.01	0.62	Upper Tail	1.18	0.06	0.45
	Lower Tail	-1.18	0.04	0.62	Lower Tail	-1.26	0.08	0.43
Materials	Upper Tail	1.19	-0.07	0.55	Upper Tail	1.15	0.08	0.45
	Lower Tail	-1.21	-0.07	0.56	Lower Tail	-1.27	0.11	0.43
Industrials	Upper Tail	1.20	0.07	0.49	Upper Tail	1.17	0.01	0.49
	Lower Tail	-1.19	0.06	0.45	Lower Tail	-1.23	-0.01	0.51
Consumer Discretionary	Upper Tail	1.19	-0.03	0.51	Upper Tail	1.15	-0.02	0.51
	Lower Tail	-1.20	-0.02	0.50	Lower Tail	-1.25	0.03	0.46
Consumer Staples	Upper Tail	1.21	-0.16	0.70	Upper Tail	1.18	-0.08	0.56
	Lower Tail	-1.15	-0.05	0.60	Lower Tail	-1.26	-0.09	0.57
Health Care	Upper Tail	1.22	-0.01	0.54	Upper Tail	1.19	-0.07	0.54
	Lower Tail	-1.21	0.02	0.53	Lower Tail	-1.24	-0.05	0.51
Financials	Upper Tail	1.19	-0.01	0.67	Upper Tail	1.15	-0.03	0.57
	Lower Tail	-1.10	0.03	0.65	Lower Tail	-1.22	-0.01	0.57
Information Technology	Upper Tail	1.18	-0.13	0.54	Upper Tail	1.16	--0.05	0.51
	Lower Tail	-1.22	-0.12	0.52	Lower Tail	-1.24	0.01	0.46
Communication Services	Upper Tail	1.16	0.04	0.62	Upper Tail	1.17	-0.05	0.56
	Lower Tail	-1.11	0.05	0.58	Lower Tail	-1.19	-0.04	0.55
Utilities	Upper Tail	1.17	-0.03	0.59	Upper Tail	1.16	0.03	0.47
	Lower Tail	-1.22	-0.01	0.56	Lower Tail	-1.23	0.03	0.47
Real Estate	Upper Tail	1.21	-0.04	0.65	Upper Tail	1.16	-0.02	0.50
	Lower Tail	-1.12	-0.02	0.61	Lower Tail	-1.24	-0.06	0.55

Table 4 Parameter estimation results of residual series under SGED distribution

Index	Chinese Stock Market					The US Stock Market				
	α	β	γ	θ	λ	α	β	γ	θ	λ

Total Index	-0.01	0.99	0.12	0.95	1.20	-0.17	0.97	0.16	0.87	1.26
Energy	0.01	0.99	0.13	0.98	1.22	-0.07	0.98	0.13	0.90	1.48
Materials	0.01	0.98	0.15	0.90	1.41	-0.09	0.98	0.13	0.86	1.42
Industrials	-0.01	0.99	0.15	0.92	1.26	-0.11	0.98	0.13	0.88	1.33
Consumer Discretionary	0.02	0.98	0.16	0.89	1.39	-0.10	0.98	0.17	0.86	1.38
Consumer Staples	0.01	0.98	0.15	1.02	1.38	-0.12	0.97	0.17	0.90	1.42
Health Care	0.02	0.99	0.13	0.95	1.40	-0.12	0.96	0.17	0.89	1.38
Financials	0.01	0.99	0.12	1.03	1.17	-0.09	0.99	0.18	0.93	1.28
Information Technology	0.01	0.99	0.14	0.84	1.45	-0.14	0.97	0.13	0.87	1.31
Communication Services	0.01	0.98	0.15	0.98	1.22	-0.06	0.98	0.11	0.90	1.32
Utilities	0.02	0.99	0.14	0.94	1.29	-0.04	0.98	0.14	0.86	1.44
Real Estate	0.01	0.99	0.13	0.98	1.22	-0.06	0.99	0.16	0.86	1.41

According to the marginal distribution function, the R-vine copula function is used to describe the interdependence structure of Chinese and the US stock markets. In the R-vine copula modeling process, the maximum spanning tree algorithm is used, that is, strong interdependencies are first reflected in higher-level trees. In this paper, the structure of the nth layer tree is described on the basis of the n-1th layer tree. The total number of interdependent structure trees is 23, and there is a nonlinear Kendall τ coefficient between the nodes of each layer of tree to describe the size of the interdependent relationship. As shown in Table 5, the Kendall τ interdependence coefficient between the stock market indices of the two countries is relatively large, and the tree level to which they belong is also relatively high. Combining the Kendall τ interdependence coefficient and the tree level to which it belongs, first of all, from the perspective of the interdependence relationship between the total index and the sector index, the S&P 500 and CSI Energy have the largest interdependence coefficient, and their tree level is also the highest. The S&P 500 is highly interdependent on the Materials, Financials, Consumer Discretionary, and Industrials of CSI, but less interdependent on the Real Estate, Utilities, and Communication Services of CSI. The CSI 300 is more interdependent on the Energy, Materials, Consumer Discretionary, and Financials of S&P, and less interdependent on the Real Estate, Utilities, and Communication Services of S&P. Secondly, from the perspective of the interdependence between sector stock prices, the Kendall τ interdependence coefficient of the Energy sector of the two countries is the largest, and the tree level to which it belongs is also the highest, followed by Materials, Financials, Consumer Discretionary, and Industrials, and the interdependence between Real Estate, Utilities, and Communication Services is weaker.

It can be seen that within the full sample range, the interaction between the financial markets of China and the United States is relatively close, and the linkage effect of Energy, Materials, Financials, Consumer Discretionary, and Industrials indices is obvious. Where the linkage between the Energy indices is the largest linkage in the interdependent structure of the stock markets of the two countries. The possible reason is that the two countries have frequent exchanges in crude oil, natural gas exploration, new energy development, materials, industrials product trade and cross-border consumption. In addition, capital flows between the two countries are huge and financial transactions are close. Specifically, if the international crude oil price is represented by West Texas Intermediate (WTI), the R-vine copula model is also used to examine its linkage with the Energy sectors of China and the United States. The empirical results show that the Energy indices of both countries have a strong correlation with world crude oil prices①, so the performance of international crude oil prices may be the external factor with the strongest interdependence on Energy indices. Moreover, from the perspective of bilateral trade and capital flows, according to statistics, in recent years, the proportion of goods belonging to the field of Industrials and Materials in Sino-US bilateral trade ranked the top two respectively. For example, from 2007 to 2018, the average middle-aged proportion of industrial products in China's total exports to the United States was 73.6%, and the average middle-aged proportion in the total exports of the United States to China was 63.8%. In the same period, the average middle-aged proportion of materials in China's total exports to the United States was 21.1%, and the average middle-aged proportion in the total exports of the United States to China was 26.0%, while the proportion of commodity trade in other fields was relatively small, which can explain the strong interdependence of the stock prices of Industrials and Materials of the two countries to a certain extent. At the same time, from the perspective of financial exchanges and capital flows between China and the United States, as of the end of 2018, the top three sectors of the US direct investment (FDI) in China were Industrials (20.7%), Financials (18.1%), and Consumer Discretionary (8.6%), and the top three sectors for China's direct investment in the United States are Industrials (23.5%), Financials (14.9%), and Consumer Discretionary (13.2%)②. The above data can further explain the strong interdependence of Financials and Consumer Discretionary in the interdependent structure of Chinese and the US stock markets. Within the full sample range, the Real Estate, Utilities, and Communication Services indices have relatively weak interdependencies. The possible reason is that the related sectors are more affected by the supply and demand or policies of the domestic market, so the degree of interdependence is relatively low.

Table 5 Analysis results of Chinese and the US stock markets interdependence based on R-vine copula model

Model	Fitting results of R-vine Copula Model					
Panel A: Total Index – Sector Index						
Index	CSI 300			S&P 500		
	Optimal Copula	Tree Level	Kendall τ	Optimal Copula	Tree Level	Kendall τ
OPPO-Total Index	Student t	4	0.06	Student t	4	0.06
OPPO-Energy	Student t	2	-0.03	Student t	3	0.06
OPPO-Materials	Student t	3	0.04	Student t	5	-0.04
OPPO-Industrials	Student t	9	0.01	rotated Gumbel 180°	9	0.03
OPPO-Consumer Discretionary	Student t	5	-0.01	rotated Clayton 180°	7	0.01

① In order to avoid the endogenous influence of WTI current price on S&P 500 and Energy index, this study also attempts to replace WTI current price with Brent crude oil current price, Dubai crude oil current price and a package of crude oil current price formulated by OECD, and then test the interdependence of these crude oil prices on S&P Energy, CSI Energy, S&P 500 and CSI 300. The results show that no matter what kind of world crude oil price is selected, the interdependence results are consistent, and the conclusion is robust. The relevant data comes from the WIND information system.

② The data comes from the composition (category) data of major bilateral exports between China and the United States on the website of the Ministry of Commerce of China, the US Bureau of Economic Analysis (BEA) database and *the 2018 China Foreign Direct Investment Statistical Bulletin*. All the proportions are calculated by the author and the proportions in parentheses are the proportion of FDI stock by sector as of the end of 2018. In addition, the data in 2006 is partially missing, so it is not included.

OPPO-Consumer Staples	Frank	7	0.01	Gaussian	8	0.02
OPPO-Health Care	Student t	9	0.01	Clayton	9	0.01
OPPO-Financials	Student t	6	0.03	Student t	6	0.04
OPPO-Information Technology	Student t	8	0.01	rotated Clayton 180°	10	0.03
OPPO-Communication Services	rotated Joe 90°	11	-0.02	rotated Joe 180°	14	0.02
OPPO-Utilities	Student t	10	0.01	Frank	13	0.02
OPPO-Real Estate	Student t	12	-0.00	rotated Joe 270°	11	-0.01

Panel B: Sector Index – Sector Index

Index	S&P Sector		
	Optimal Copula	Tree Level	Kendall τ
CSI Energy	Student t	1	0.26
CSI Materials	Student t	4	0.04
CSI Industrials	Student t	9	0.02
CSI Consumer Discretionary	Joe	8	0.01
CSI Consumer Staples	Gaussian	11	0.02
CSI Health Care	Gaussian	11	0.02
CSI Financials	rotated Joe 180°	5	0.04
CSI Information Technology	Gumbel	14	0.02
CSI Communication Services	Clayton	22	0.01
CSI Utilities	rotated Clayton 90°	20	-0.01
CSI Real Estate	rotated Gumbel 180°	20	0.02

Note: 'OPPO-*' in Panel A represents the stock market index (including the total index and sector index) of the other market, and Panel B indicates that the CSI sector index corresponds to the S&P sector index.

The R-vine copula function constructed in this paper has a total of 23 tree layers, and the farther the tree is from the root, the weaker the degree of interdependence. In order to more intuitively present the interdependence between the stock markets of China and the United States, we select the index nodes whose Kendall τ interdependence coefficient is greater than or equal to 0.01 in the tree structure of the first 10 layers, and use the complex network analysis method to obtain the interdependence structure of the stock markets of the two countries, as shown in Figure 2[①]. The main findings are as follows: First, according to the interdependence structure diagram and the results of network centrality analysis, it can be seen that the Energy, Materials, Financials and Consumer Discretionary play leading roles in the interaction structure of Chinese and the US stock markets. The sector indices with the highest degree of interdependence and highest network centrality are CSI Energy and S&P Energy, which indicates that the Energy is the most dominant sector in the interdependence structure and plays the most important role in the overall linkage of the stock markets of the two countries. Industrials, Information Technology, Consumer Staples, Health Care and other sectors play secondary roles, while Utilities, Real Estate, and Communication Services are in marginal areas and play a relatively small role. Second, according to the results in Table 6, from the perspective of the correlation characteristics of sector centrality in different countries, the average sector centrality of Chinese and the US stock markets are 4.82 and 5.27, respectively, indicating that the US stocks are slightly higher than China in terms of comprehensive influence, mainly reflected in Health Care, Information Technology and other sectors. In addition, the centrality variances of Chinese and the US stock markets are 9.97 and

① The size of the node in the figure represents the position of the corresponding stock price index in the interdependent structure of the stock markets of the two countries, the same below.

8.38, respectively, indicating that the centrality of the Chinese stock market sector has greater dispersion, and the influence of different sectors in the entire interdependent structural system is more different. Third, the short-term interdependence of the stock markets will have an impact on the long-term equilibrium relationship, which is consistent with the analysis results of the R-vine copula function. For example, there is almost no long-term equilibrium relationship between Utilities and Real Estate sectors in the two countries with weak interdependencies, including linear and nonlinear equilibrium relationships. However, sectors such as Energy, Materials, and Financials that are strongly interdependent also generally have relatively significant long-term equilibrium relationships, which are mainly non-linear. This shows that the short-term interdependence structure of Chinese and the US stock markets is inherently consistent with the long-term equilibrium relationship between the two stock markets, and the relationship between the two shows obvious nonlinear characteristics.

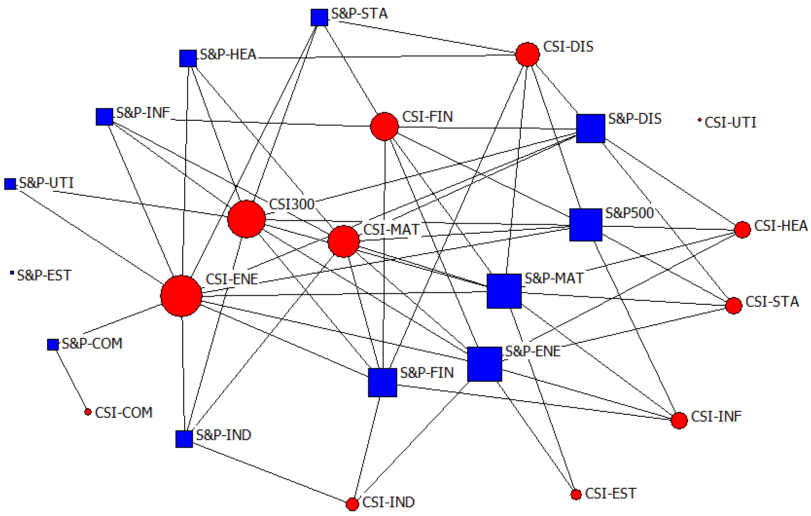


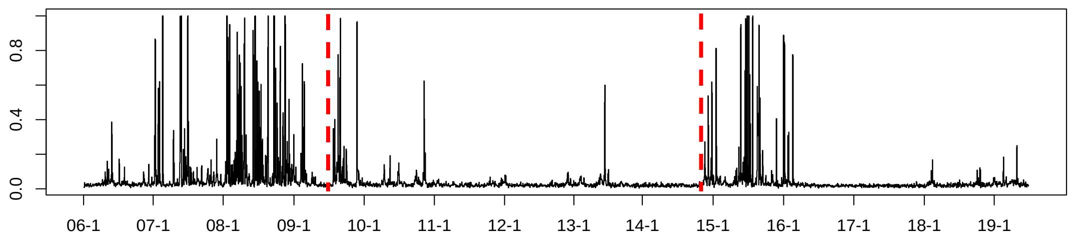
Figure 2 Interdependent structure of Chinese and the US stock markets in the full sample range

Table 6 Analysis of the network centrality of the sector interdependent structure of Chinese and the US stock markets

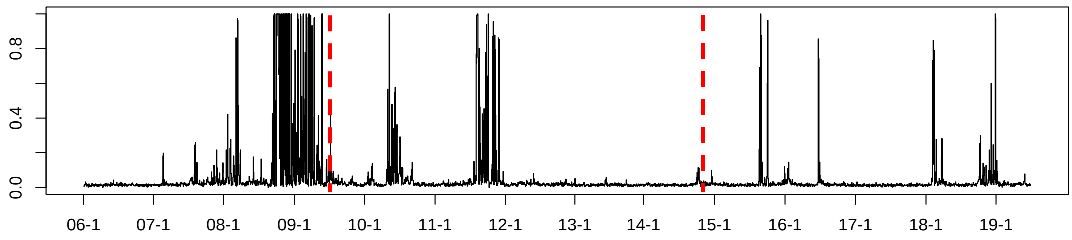
Period / Sector	Full Sample				S1				S2				S3			
	CSI	S&P	Absolute Difference	Sum	CSI	S&P	Absolute Difference	Sum	CSI	S&P	Absolute Difference	Sum	CSI	S&P	Absolute Difference	Sum
Energy	11	10	1	21	11	9	2	20	7	7	0	14	12	11	1	23
Materials	9	9	0	18	5	7	2	12	10	12	2	22	10	9	1	19
Industrials	4	5	1	9	8	4	4	12	3	8	5	11	7	7	0	14
Consumer Discretionary	6	7	1	13	6	4	2	10	7	3	4	10	6	7	1	13
Consumer Staples	5	5	0	10	1	3	2	4	3	4	1	7	4	5	1	9
Health Care	4	6	2	10	1	4	3	5	4	3	1	7	2	8	6	10
Financials	7	7	0	14	9	10	1	19	8	5	3	13	10	7	3	17
Information Technology	4	5	1	9	3	6	3	9	5	6	1	11	6	6	0	12
Communication Services	1	2	1	3	2	2	0	4	3	3	2	6	4	5	1	9
Utilities	0	2	2	2	2	2	0	4	1	1	0	2	3	1	2	4
Real Estate	2	0	2	2	4	12	8	16	1	0	1	1	3	3	0	6
Mean	4.82	5.27	1.00	10.09	4.73	5.73	2.45	10.45	4.73	4.73	1.82	9.45	6.09	6.27	1.45	12.36
Variance	9.97	8.38	0.55	35.36	10.56	10.38	4.43	32.43	7.83	10.56	2.33	31.52	10.08	6.93	2.79	29.14

4.3.2 Sub-sample results

In order to comprehensively examine the dynamic characteristics of the interdependent structure of Chinese and the US stock markets, the following subsection sample research is carried out. In order to avoid subjectivity bias, this paper adopts the structural change point estimation method based on the Bayesian prior distribution of Erdman and Emerson (2007) to analyze the return series of Chinese and the US stock markets. Figure 3 shows the posterior probability estimation results of the stock market returns in China and the United States. The point with p-value greater than 0.05 is a structural change point. When a structural change point occurs continuously, it can be considered that the stock market has experienced structural fluctuations. Combined with NBER's determination of the end time of the global financial crisis in 2008, the full sample interval can be roughly divided into three sub-periods: (1) from January 3, 2006 to June 30, 2009, it was the period of financial crisis (referred to as the S1 period); (2) from July 1, 2009 to December 4, 2014, it was the post-financial crisis economic recovery period (referred to as the S2 period); (3) from December 5, 2014 to July 3, 2019, it was the period of financial market volatility (referred to as the S3 period). It should be noted that the changes in the stock markets of China and the United States were comprehensively considered when dividing the sub-sample intervals. For example, due to the impact of the European debt crisis, the US stock market experienced structural fluctuations around May 2010, and the US sovereign rating was downgraded by Standard & Poor's. Influenced by the continuous fermentation of the European debt crisis, the US stock market experienced structural volatility again from the second half of 2011 to the beginning of 2012. However, since these two periods of structural fluctuations do not directly affect the interaction between Chinese and the US stock markets, this paper does not consider them separately when dividing the subsamples.



(a) CSI 300



(b) S&P 500

Figure 3 Posterior probability estimation of mean returns of S&P 500 and CSI 300 index

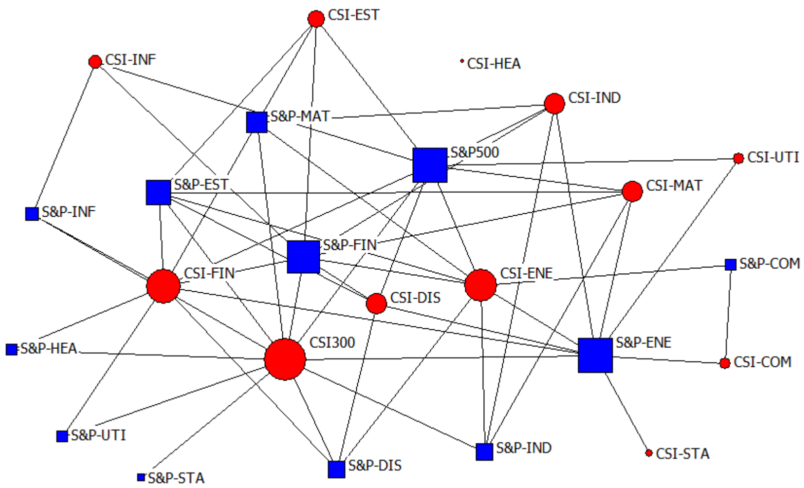
According to the results of the R-vine copula function, the sample nodes with interdependent coefficients greater than or equal to 0.01 in the first 10 tree structures are also selected to obtain the interdependent structures of Chinese and the US stock markets in three periods, as shown in Figure 4(a), (b) and (c). Combined with the network centrality measurement results of the segmented samples (see Table 6), the brief analysis is as follows:

(1) S1 period. First, according to the interdependence structure diagram and the analysis results of network centrality, it can be seen that the Energy, Real Estate, and Financials sectors played leading roles in the interaction structure of Chinese and the US stock markets in the S1 period, followed by the Materials, Industrials and other sectors, while the Consumer Staples, Communication Services and Utilities sectors are the least important in the interdependent structure. In general, the distribution of the stock market interdependence structure in the S1 period is consistent with the full sample range, but the Real Estate sector made a greater contribution to the stock market interdependence between the two countries during this period. The possible reason is that the root cause of the US subprime mortgage crisis and the international financial crisis began in the Real Estate sector and then hit the Financials sector. Affected by the stock market contagion effect and information spillover, the Financials and Real Estate sectors in Chinese stock market have also been affected, and further spread to other sectors. At the same time, China and the United States are both major energy consumers in the world, and the large fluctuations in international oil prices have a huge impact on the economic development and business operations of the two countries. Therefore, CSI Energy and S&P Energy are still the sectors with the most interdependence between the two stock markets. Second, from the perspective of the correlation characteristics of sector centrality in different countries, the average sector centrality of Chinese and the US stock markets is 4.73 and 5.73, indicating that the influence of the US stocks in the S1 period was significantly higher than that of China, which is directly related to the origin of the financial crisis center in the United States. In addition, the variances of the centrality of Chinese and the US stock markets are 10.56 and 10.38, respectively, indicating that the influence of different sectors in Chinese stock market is more different in the interdependent structure system.

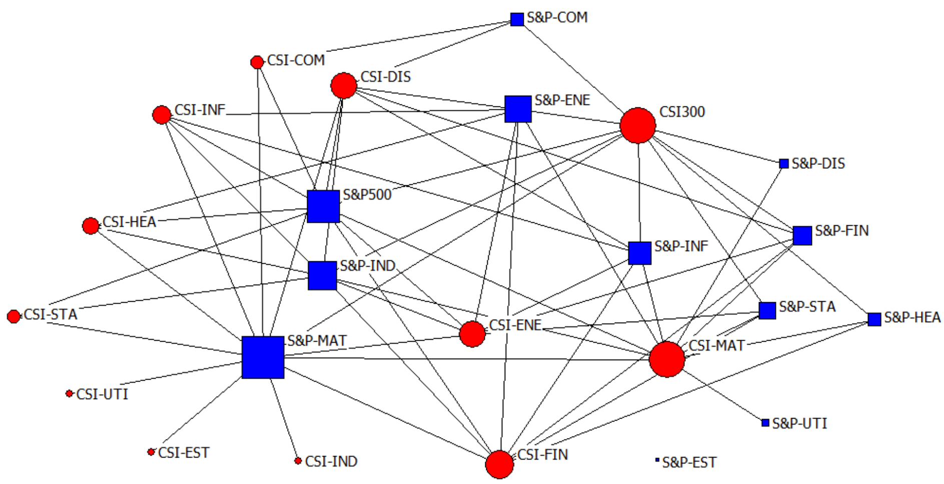
(2) S2 period. First, according to the interdependence structure diagram and the analysis results of network centrality, it can be seen that the Materials, Energy, and Financials sectors play leading roles in the interaction structure of Chinese and the US stock markets in the S2 period, followed by Information Technology, Industrials, Consumer Discretionary and other sectors, while the Utilities and Real Estate sectors are in the least important positions. During this period, the sector influence of the Real Estate index decreased significantly, but the role of the Material sector increased significantly, even surpassing the Energy sector, and was in the most dominant position in S2 period. The possible reasons are as follows: ①the world crude oil price fluctuated greatly in S1 and S3 period, while it fluctuated less in S2 period. International oil prices continued to decline from mid-June 2014, and almost "halved" by December 2014. Therefore, the impact of the Energy sector on the interdependent structure of the two stock markets naturally decreases; ② the S2 period is at an important stage of economic recovery between China and the United States. The production, investment and bilateral trade of the two countries have developed steadily and rapidly. The demand for Materials by production and consumption behavior is increasing, and the stock prices of Material sectors in the two stock markets are also closely interactive. In addition, the influence of the Consumer Staples sector in the two countries has also increased significantly, and the interaction with other sectors has increased significantly compared with the previous period. The possible reason is that the two countries implemented a series of economic stimulus plans during the 2008 international financial crisis, including increasing investment in infrastructure and public facilities, and adopting fiscal and monetary expansion policies to stimulate household consumption. Second, from the perspective of the correlation characteristics of sector centrality in different countries, the average sector centrality of China and the United States is 4.73 and 4.73 respectively, and the two countries are basically the same, indicating that the influence of Chinese stock market sector index in the interdependent structure system has increased significantly. In addition, the variances of the centrality of Chinese and the US stock markets are 7.83 and 10.56, respectively, indicating that the influence of different sectors in the US stock market in the S2 period is more different in the interdependent structure system.

(3) S3 period. First, according to the interdependence structure diagram and the analysis results of network centrality, it can be seen that the Energy, Materials, and Financials sectors played leading roles in the interaction structure of Chinese and the US stock markets in the S3 period, followed by the Industrials, Consumer Discretionary, and Information Technology sectors, while the Real Estate and Utilities sectors are in the least important positions. In the S3 period, the sector with the greatest degree of interdependence on the stock markets of the two countries changed from Materials to Energy again, and the summed average centrality of the sector indices of the two countries became 12.36, which was much larger than 10.45 in the S1 period and 9.45 in the S2 period, indicating that in the S3 period, the stock markets of the two countries have the greatest degree of interaction. From S1, S2 to S3, the network centrality of the Information Technology, Communication Services, and Consumer Staples sectors of CSI showed an

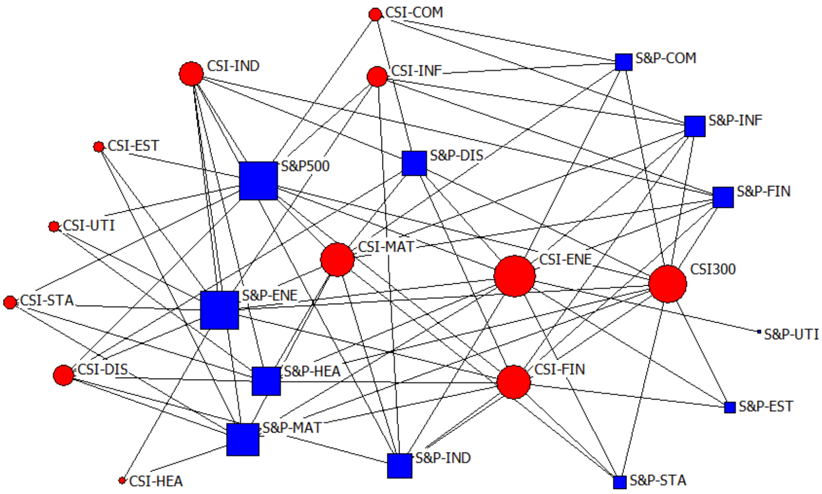
increasing trend, and gradually moved closer to the center from the more peripheral parts of the interdependent structure. This shows that China's digital economy has flourished in recent years, its information and communication technology capabilities have been continuously enhanced, and certain progress has been made in promoting consumption and adjusting the structure. In addition, the residents' consumption has grown steadily, and the external impact of the corresponding sector index has also continued to increase. Second, from the perspective of the correlation characteristics of sector centrality in different countries, the average sector centrality of China and the United States is 6.09 and 6.27, respectively, indicating that the influence of the US stock market sector index in the interdependent structure system is still slightly greater than that of China during the S3 period. In addition, the variances of the centrality of Chinese and the US stock markets are 10.08 and 6.93, respectively, indicating that the influence of different sectors within the Chinese stock market in the interdependent structure system is more different in the S3 period.



(a) The interdependence structure of Chinese and the US stock markets in the S1 period



(b) The interdependence structure of Chinese and the US stock markets in the S2 period



(c) The interdependence structure of Chinese and the US stock markets in the S3 period

Figure 4 Analysis of the interdependent structure of Chinese and the US stock markets in samples by time period

Throughout the three periods, the sectors in which the interdependent structure of the Chinese and the US stock markets played leading roles were Energy, Materials and Financials. The pattern of changes in the interdependent structure is concentrated in the sectors in the secondary and marginal positions. The influence of some sectors has gradually increased over time, such as Information Technology, Communication Services, Health Care, and Consumer sectors, while the influence of other sectors is generally fluctuating. In addition, judging from the decreasing trend of the average change of the absolute difference of sector centrality between the two countries, over time, the sector status of China and the United States tends to be more equal, and the contribution of the same sector to the stock market interdependence structure gradually converges. Judging from the trend of the average change of the summation of the sector centrality of the two countries to first decrease and then increase, during periods of financial market volatility, China and the US interact more closely, while during periods of relatively stable financial markets, the degree of interaction between the stock markets of the two countries decreases. But overall, the degree of interaction between the stock markets of the two countries has increased over time. Judging from the variance changes of the summation of sector centrality between the two countries, the influence distribution of sector indices in the interdependent structure of the stock markets of the two countries is different in different periods. With the passage of time, the degree of dispersion of sector influence shows a decreasing trend, and the status of different sectors tends to be equalized.

4.4 Robustness Study

In this paper, the robustness test of the empirical part is carried out from the two aspects of the model and the results:

(1) Model Robustness

In the process of constructing the R-vine copula function, each layer of pair copula function is selected according to the principle of the largest likelyhood statistic or the smallest AIC value. However, this method only considers the corresponding parameter adjustment to maximize the likelihood function of the copula function, while less attention is paid to the distance between the copula function fitted by the actual data and the empirical copula function. To this end, this paper adopts the CvM test method proposed by Genest et al. (2009) for robustness analysis. Under the null hypothesis of $H_0 : C \in \mathcal{C}_0$, the empirical copula function of n-dimensional simulated observations $U_1, \ldots, U_n$ can be expressed as:

$$C_n(u) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(U_{i1} \leq u_1, \ldots, U_{id} \leq u_d), u = (u_1, \ldots, u_d) \in [0,1]^d \tag{26}$$

According to formula (26), regardless of whether the null hypothesis H_0 is accepted or not, C_n is a consistent estimator of the true copula function in the case of large samples based on different assumptions (Fermanian and Wegkamp, 2004). Since the form of C_n is completely nonparametric and can be used as a substitute for the true copula function in the CvM test, the CvM test statistic can be expressed as:

$$S_n = \int_{[0,1]^d} n\left(C_n(u) - C_{\theta_n}(u)\right)^2 dC_n(u) \tag{27}$$

where n is the number of observations, d is the dimension of the model, and θ_n is the estimated parameter to fit the copula function. Since the asymptotic distribution of the CvM statistic is unknown, its p-value is solved by the Bootstrap method. The CvM test results of the pair copula function in R-vine are shown in Table 7. The values in the table are the p-values corresponding to the CVM test. The larger the p-value, the smaller the distance between the estimated pair copula and the real copula function, and the more unable to reject the original hypothesis, which indicates that the probability of the wrong setting of the copula function is smaller. The results in the table tested the fitting degree of 144 groups of pair copula functions. Under the CvM criterion, except that the copula functions fitted between the five groups of indices are not ideal, most of the pair copula functions determined by the AIC criterion in R-vine passed the CvM test, and the error probability is only 3.5%. Therefore, it can be considered that the pair copula function selected in the R-vine construction process is robust.

Table 7 Robustness test result matrix of R-vine copula model based on CvM method

Index	CSI 300	CSI Energy	CSI Materials	CSI Industrials	CSI Consumer Discretionary	CSI Consumer Staples	CSI Health Care	CSI Financials	CSI Information Technology	CSI Communication Services	CSI Utilities	CSI Real Estate
S&P 500	0.72	0.84	0.59	0.71	0.22	0.22	0.62	0.49	0.61	0.13	0.38	0.77
S&P Energy	0.70	0.91	0.08	0.23	0.43	0.72	0.27	0.89	0.04*	0.56	0.51	0.24
S&P Materials	0.46	0.45	0.73	0.82	0.94	0.89	0.16	0.23	0.10	0.48	0.45	0.53
S&P Industrials	0.63	0.33	0.34	0.20	0.25	0.29	0.45	0.72	0.45	0.23	0.34	0.24
S&P Consumer Discretionary	0.85	0.15	0.63	0.29	0.83	0.28	0.72	0.18	0.23	0.02*	0.32	0.09
S&P Consumer Staples	0.43	0.35	0.09	0.47	0.32	0.81	0.13	0.02*	0.75	0.22	0.04*	0.45
S&P Health Care	0.31	0.94	0.41	0.14	0.08	0.55	0.42	0.20	0.62	0.82	0.33	0.82
S&P Financials	0.57	0.29	0.11	0.44	0.23	0.25	0.59	0.34	0.70	0.39	0.49	0.93
S&P Information Technology	0.66	0.13	0.07	0.06	0.45	0.47	0.82	0.29	0.23	0.57	0.35	0.43
S&P Communication Services	0.84	0.49	0.04*	0.72	0.66	0.89	0.45	0.98	0.53	0.24	0.45	0.29
S&P Utilities	0.66	0.25	0.48	0.11	0.21	0.29	0.58	0.75	0.61	0.23	0.56	0.41
S&P Real Estate	0.15	0.39	0.66	0.34	0.14	0.34	0.38	0.44	0.53	0.88	0.38	0.60

Note: * represents that the pair copula function rejects the null hypothesis at the 5% significance level.

(2) Results Robustness

Based on the consideration of robustness, this paper also uses the traditional binary copula function to re-examine the degree of interdependence between Chinese and the US stock markets. Although the traditional copula function cannot describe the complex interdependence structure between stock indices, and it is assumed that the stock index as an independent variable is independent of other stock indices, which may overestimate the Kendall τ interdependent coefficient to a certain extent. However, using the traditional copula function to obtain the relative magnitude of the interdependence coefficient between stock indices also has certain reference significance. By investigating the interdependence relationship between the total index and the total index, between the total index and the sector index, and within the sector index (Table 8), it is found that the sectors with high interdependence and strong interaction are the Energy, Financials and Materials, followed by Industrials, Consumer Discretionary and Information Technology, then the Consumer Staples, Health Care and Communication Services, and the Utilities and Real Estate with the least interdependence. This is basically consistent with the results of using R-vine copula function, which shows that the empirical results of this paper are robust.

Table 8 Analysis results of Chinese and the US stock markets interdependence based on binary copula model

Model	Binary Copula Model Fitting Results			
Panel A: Total Index – Sector Index				
Index	CSI 300		S&P 500	
	Optimal Coupla	Kendall τ	Optimal Copula	Kendall τ
OPPO-Total Index	Student t	0.15	Student t	0.15
OPPO-Energy	BB7	0.13	Student t	0.16
OPPO-Materials	BB7	0.14	BB7	0.17
OPPO-Industrials	BB7	0.16	BB7	0.17
OPPO-Consumer Discretionary	Student t	0.14	BB7	0.15
OPPO-Consumer Staples	Student t	0.10	Student t	0.09
OPPO-Health Care	Student t	0.12	Student t	0.07
OPPO-Financials	BB7	0.15	Student t	0.14
OPPO-Information Technology	Student t	0.14	BB7	0.14
OPPO-Communication Services	Student t	0.11	Student t	0.11
OPPO-Utilities	Student t	0.07	Student t	0.10
OPPO-Real Estate	BB7	0.14	Student t	0.08
Panel B: Sector Index – Sector Index				
Index	S&P Sector			
	Optimal Copula	Kendall τ		
CSI Energy	Student t	0.17		
CSI Materials	BB7	0.15		
CSI Industrials	BB7	0.14		
CSI Consumer Discretionary	BB7	0.13		
CSI Consumer Staples	Student t	0.07		
CSI Health Care	Student t	0.07		
CSI Financials	rotated Joe 180°	0.17		
CSI Information Technology	BB7	0.13		
CSI Communication Services	Student t	0.07		
CSI Utilities	Student t	0.04		
CSI Real Estate	Student t	0.06		

Note: 'OPPO-*' in Panel A represents the stock market index (including the total index and sector index) of the other market, and Panel B indicates that the CSI sector index corresponds to the S&P sector index.

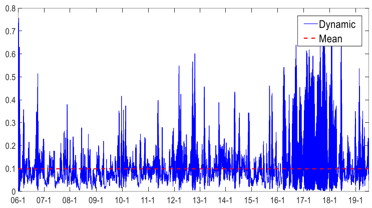
5. Risk Spillover Effect Analysis

In view of the complex interdependent structure of Chinese and the US stock markets, this paper further studies the risk spillover effect between the two stock markets, investigates the infection mechanism of one country's market to the other country's market when there is extreme rise or fall risk, and further provides support for monitoring, preventing, and resolving systemic financial risks. For the stock market, the risk is mainly reflected in the downside risk, and the upside risk will show the irrational behavior of investors and the accumulation of market risks. Whether it is down or up, the risk factors can be classified as extreme conditions of stock returns. Risk correlation refers to the interdependence of the lower tail and upper tail of the stock index return distribution. The lower tail and the upper tail interdependent coefficient correspond to the probability of simultaneous downside and upside risk in the financial market, respectively. If the tail interdependence coefficient is large, the risk correlation between the two stock markets is strong. The risk spillover is based on conditional probability, examining the size of the risk change in the other market when one market is in extreme conditions. If the risk changes greatly, it indicates that one market is subject to the greater risk spillover from the other market. The investigation of risk correlation is the basis for the study of risk spillover. If the risk correlation between the two stock markets is relatively large, the degree of risk spillover may also be large. In this paper, we first use the Archimedes-type copula function to examine whether the two stock markets have the correlation of extreme risks, and then use the generalized CoVaR model based on the R-vine copula function to examine the mutual spillover of extreme risks.

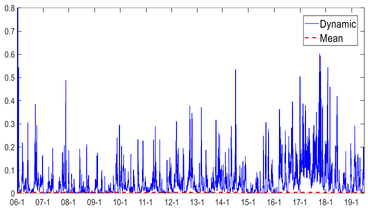
5.1 Risk Correlation

The copula function of Archimedes-type can describe the correlation between extreme values of random variables through the tail interdependence coefficient. The SJC copula function in Archimedes-type copula is used to measure the upper and lower tail interdependence coefficients of the two stock markets.

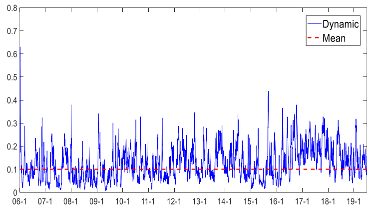
The results show that the fluctuations in the sample interval have obvious "clustering" characteristics, regardless of the upper tail or the lower tail interdependence coefficient, but there are differences in the dynamic change trends of the coefficients of different indices. As shown in Figure 5, due to space limitations, this paper only shows the tail interdependence coefficients of the total stock market indices and representative sectors of the two countries, including five major sectors: Energy, Financials, Materials, Utilities and Real Estate. First, for the composite index, the lower tail interdependent coefficient is significantly larger than the upper tail interdependent coefficient, indicating that the probability of simultaneous crash risk in the stock markets of the two countries is generally greater than the probability of skyrocket risk. Since the beginning of 2017, both the upper and lower tail interdependence coefficients have increased, and the lower tail interdependence coefficient has increased more obviously and has obvious clustering characteristics. It can be seen that the overall risk linkage between Chinese and the US stock markets has increased significantly in recent years. Second, for the Sino-US Energy index, the lower tail interdependence coefficient is greater than the upper tail interdependence coefficient, but the difference between the two is not large. Similarly, the risk linkage between Energy indices has also increased since the beginning of 2017. Third, for the Sino-US Financials index, the lower tail interdependent coefficient is also significantly larger than the upper tail interdependent coefficient, and the lower tail interdependent coefficient increases gradually during the sample period, indicating that the linkage between the financial markets of the two countries continues to increase. Fourth, for the Sino-US Materials index, the change of the upper and lower tail interdependence coefficients is similar to that of the Energy index, but the increasing trend of the lower tail interdependence coefficient is more obvious. Fifth, for the Sino-US Utilities and Real Estate index, compared with the first three sector indices, the tail interdependence coefficient is significantly smaller, and the volatility clustering is weaker. The reason may be that the Energy, Materials and Financials sectors are in dominant positions in the interdependent structure of Chinese and the US stock markets, while the Utilities and Real Estate sectors are in marginal positions, and the risk linkage between the two is also weak.



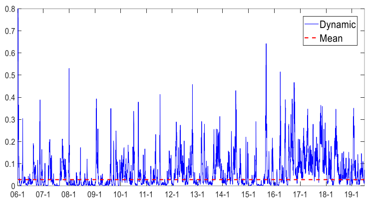
(a) the Sino-US total index lower tail



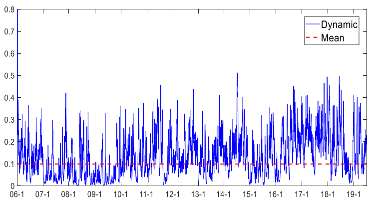
(b) the Sino-US total index upper tail



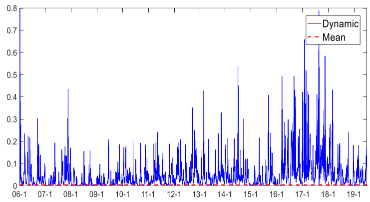
(c) the Sino-US Energy index lower tail



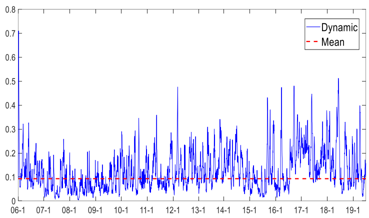
(d) the Sino-US Energy index upper tail



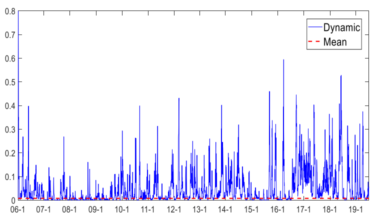
(e) the Sino-US Financials index lower tail



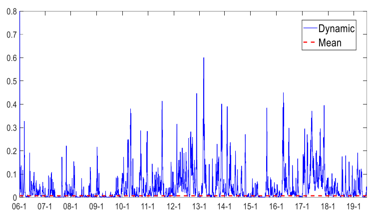
(f) the Sino-US Financials index upper tail



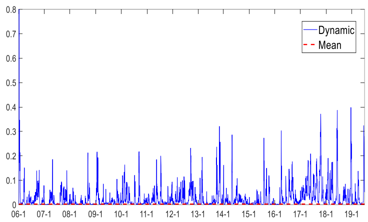
(g) the Sino-US Materials index lower tail



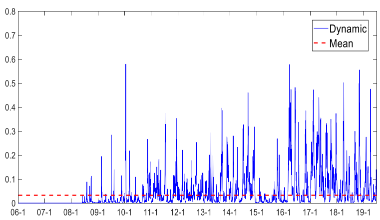
(h) the Sino-US Materials index upper tail



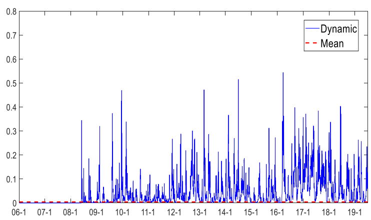
(i) the Sino-US Utilities index lower tail



(j) the Sino-US Utilities index upper tail



(k) the Sino-US Real Estate index lower tail



(l) the Sino-US Real Estate index upper tail

Figure 5 The tail dynamic interdependent coefficient of Chinese and the US stock markets

What deserves special attention is that most of the lower tail risk interdependence coefficients among various sectors have shown an increasing trend since the beginning of 2017, indicating that the risk linkage between the two countries' stock markets has been continuously improved in recent years, and the level of internationalization of Chinese stock market has been continuously improved. In fact, from April to November 2017, China and the United States held three "Xi-Trump meetings" to jointly conduct Sino-US economic and trade consultations. At this time, Sino-US relations were once for the better. As a barometer of the economic situation, this positive sentiment was first reflected in the stock market, which led to the continuous enhancement of the linkage between Chinese and the US stock markets at this stage. However, in January 2018, the linkage between the stock markets of the two countries showed an inflection point, and the interdependence coefficient began to decline, and even fell below the average level in April 2018. The reasons for the above stock market fluctuations are mainly affected by the Sino-US trade friction. For a long time, China and the United States have had close economic exchanges, frequent bilateral trade and capital flows, and the stock market linkage caused by economic fundamentals and emotional contagion has been increasing. However, on August 19, 2017, President Trump authorized the Office of the US Trade Representative to open a Section 301 investigation into China. At the end of 2017, the United States released the "Report on China's Non-Market Economy Status". In January 2018, the United States announced to impose tariffs ranging from 20% to 50% on some products such as solar panels and washing machines. This series of events has led to the escalation of the Sino-US trade dispute, which has a profound impact on the global economic situation and also brought huge potential risks to the international financial market. The stock markets of China and the United States bear the brunt of this, resulting in a decrease in the overall interdependence of the stock markets of the two countries and a weakening of the risk correlation. But on the whole, the correlation between the downside risk of China and the United States stock market is large, while the correlation between the upside risk is small, that is to say, the probability of falling of two stock markets at the same time is large and the probability of rising at the same time is small. In particular, sectors that are on the fringes of the interdependent structure of the two stock markets, such as Health care, Consumer Staples, Utilities and Real Estate, have almost zero probability of skyrocketing.

5.2 Risk Spillover

Due to the extreme risk correlation between the Sino-US sector indices, this paper further uses the generalized CoVaR method based on R-vine copula to measure the risk spillover effect of the two stock markets. According to formula (20), the conditional risk spillover %CoVaR can be calculated. The traditional extreme risk measurement mainly focuses on the downside risk spillover, so we first measure the downside risk spillover effect of Chinese and the US stock markets.

This paper firstly measures the directed network structure of extreme risk spillovers in Chinese and the US stock markets, as shown in Table 9 and Figure 6[①]. The main findings are as follows: first, the risk spillover of the S&P 500 index to the CSI 300 index is 71.74%, which is almost twice the risk spillover of the CSI 300 index to the S&P 500 index. This shows that although the Chinese stock market had a certain spillover effect on the US stocks during the inspection period, the impact was relatively weak, far less than the spillover effect of accepting the US stocks. Second, the risk spillover effects of the two countries are consistent with the market

① In order to display the results more clearly and intuitively, this paper assigns the spillover risk greater than the mean value of the spillover to 1, otherwise it assigns it to 0, and constructs the extreme risk spillover network of the two stock markets.

interdependent structure. Whether it is accepting risk spillovers or generating risk spillovers, the sectors in the dominant position in the interdependent structure have large average values, such as Energy, Materials, and Financials sectors, while the average values of the marginal sectors in the interdependent structure are relatively small, such as Utilities and Real Estate sectors. The relative risk spillover values of Energy, Materials, and Financials indices are all relatively large, which indicates that the financial and commodity industries of the two countries are closely interacting with each other, and the risk spillover effect of each other is relatively large. Third, it can be seen from the directed network structure diagram of extreme risk spillovers that relatively speaking, the US stocks play more of the role of extreme risk issuers in the interdependent structure, such as the Materials, Consumer Discretionary, and Health care of S&P, while the Chinese stock market plays more of an extreme risk taker role, such as the Energy, Financials, Materials, Consumer Discretionary, and Industrials of CSI.

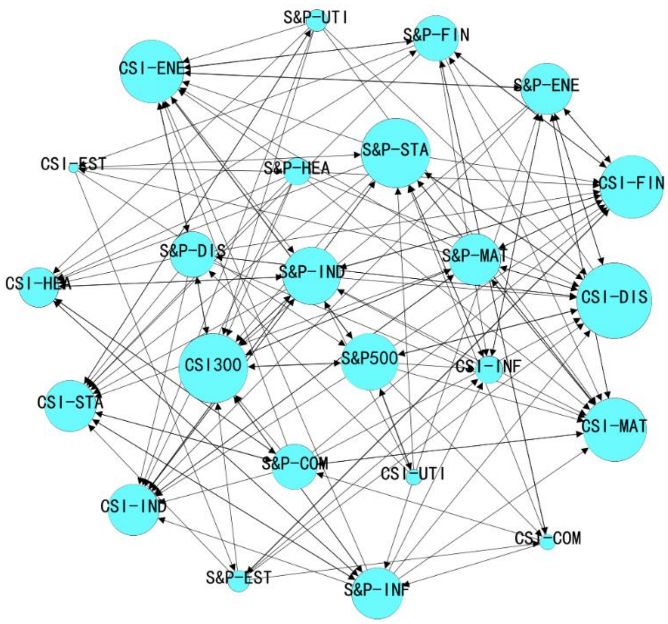


Figure 6 Directed network structure of Chinese and the US stock markets risk spillovers

Table 9 Relative conditional risk spillover (%CoVaR) analysis results

From / To	OPPO-total index	OPPO-Energy	OPPO-Materials	OPPO-Industrials	OPPO-Consumer Discretionary	OPPO-Consumer Staples	OPPO-Health Care	OPPO-Financials	OPPO-Information Technology	OPPO-Communication Services	OPPO-Utilities	OPPO-Real Estate	Accept Spillover Mean
Chinese Stock Market													
CSI 300	71.74	72.25	78.27	76.36	69.33	43.06	56.82	65.77	74.38	68.52	49.44	59.18	65.43
CSI Energy	65.93	83.07	74.01	59.07	61.86	41.28	50.09	86.29	68.57	61.78	45.29	44.14	61.78
CSI Materials	61.26	76.47	70.18	70.23	64.58	39.18	54.74	78.17	74.22	68.07	47.15	53.73	63.17
CSI Industrials	62.31	75.22	66.34	66.30	70.28	46.20	56.23	69.62	78.48	65.50	44.47	51.35	62.69
CSI Consumer Discretionary	59.19	69.06	79.83	70.82	63.47	44.76	58.88	69.40	68.19	63.36	50.62	34.39	61.00
CSI Consumer Staples	49.48	55.32	71.76	65.49	61.93	39.96	55.14	72.21	73.37	62.77	48.84	47.10	58.61
CSI Health Care	41.04	57.20	56.64	65.83	60.88	40.82	50.64	67.61	69.34	61.25	45.91	41.77	54.91
CSI Financials	68.01	81.83	72.08	73.28	67.58	44.29	52.73	90.39	65.74	61.96	41.48	57.43	64.73
CSI Information Technology	60.87	68.11	50.13	62.94	57.46	39.82	47.51	86.56	68.51	51.81	33.22	39.26	55.52
CSI Communication Services	59.66	59.36	51.52	54.02	56.34	32.29	46.99	75.24	60.72	49.56	42.98	25.59	51.19
CSI Utilities	58.38	47.66	48.44	58.32	43.15	36.87	25.26	22.49	52.44	39.29	42.01	24.26	41.55
CSI Real Estate	35.07	56.93	65.51	48.76	47.89	20.47	38.37	76.72	47.55	49.65	26.29	54.39	47.30
Produce Spillover Mean	57.75	66.87	65.39	64.29	60.40	39.08	49.45	71.71	66.79	58.63	43.14	44.38	—
the US Stock Market													
S&P 500	37.21	26.08	17.46	14.53	25.83	18.34	17.66	21.44	15.57	21.42	26.88	23.05	22.12
S&P Energy	26.38	47.23	26.39	20.34	22.49	19.70	18.21	53.71	26.21	14.72	16.23	15.23	25.57
S&P Materials	33.26	22.51	34.17	35.84	26.32	19.23	16.34	72.58	15.43	17.23	13.42	16.62	26.91
S&P Industrials	41.39	27.56	19.47	46.34	15.67	11.12	27.43	58.30	18.13	16.95	18.84	20.68	26.82
S&P Consumer Discretionary	46.50	28.36	17.56	13.85	23.34	14.32	14.53	15.34	16.47	17.63	19.09	18.73	20.48
S&P Consumer Staples	13.19	20.62	25.88	29.03	34.76	20.69	14.03	26.66	25.62	25.33	15.84	29.31	23.41
S&P Health Care	21.22	21.29	17.45	18.39	17.42	16.22	16.77	24.85	16.23	21.19	15.24	24.52	19.23
S&P Financials	26.84	33.55	17.65	19.32	30.33	19.34	29.78	46.34	16.16	36.31	8.85	19.15	25.30
S&P Information Technology	39.20	14.28	14.73	14.29	19.15	27.34	19.03	18.75	15.23	43.74	17.77	19.80	21.94
S&P Communication Services	27.81	15.64	25.48	15.30	16.43	47.24	22.57	21.35	16.79	50.07	12.52	18.63	24.15
S&P Utilities	15.63	13.95	17.45	18.55	18.43	33.28	16.38	25.58	13.88	19.22	14.34	19.15	18.82
S&P Real Estate	14.27	9.66	20.06	22.04	11.68	13.54	15.35	48.77	11.39	15.66	7.26	36.27	18.83
Produce Spillover Mean	28.58	23.39	21.15	22.32	21.82	21.70	19.01	36.14	17.26	24.96	15.52	21.76	—

Note: ‘OPPO-*’ represents the stock market index (including the total index and sector index) of the other market.

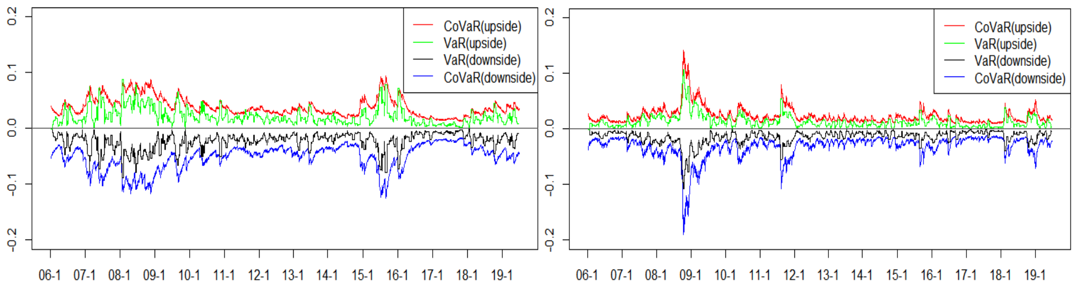
Considering both the downside and the upside risk spillover, the generalized CoVaR method is used to examine the extent of the stock market risk spillover effect of the two countries from a dynamic perspective. The VaR of the stock market is measured by the method of "Rolling Window Estimation". In order to simultaneously examine the volatility and trend of VaR in different time periods, the rolling window should not be too large or too small[①]. In view of the significant partial autocorrelation of stock price returns at most k=14 order, the rolling analysis window width is set to 14 days, and the method based on historical data is selected for rolling analysis to obtain the dynamic analysis results of VaR. On the basis of VaR value, combined with the parameters of R-vine copula, iterative solution is carried out. Based on the easy-to-observability principle of mapping, the results of VaR and CoVaR are numerically standardized, so the difference between CoVaR and VaR (ΔCoVaR) can be used to directly express the size of the spillover risk.

Looking at the CSI 300 and S&P 500 first, see Figure 7(a) and (b), the overall risk of Chinese stock market is higher than that of the US stock market. The upside and downside risks of the two countries have similar trends, but they are not completely symmetrical, and the downside risks are greater than the upside risks. During the 2008 international financial crisis, the stock market risk spillover effect of the two countries increased significantly. The CoVaR started to expand from January 2007, reached a maximum value around October 2008, and began to decline until it returned to the pre-expansion level in January 2010, which lasted for about three years. In contrast, the US stock market's CoVaR changes more widely and shows abruptness, while the Chinese stock market's CoVaR changes smaller and shows persistence. From January 2010 to January 2015, the CoVaR of the stock markets of the two countries remained stable. Since then, affected by the downgrade of the US sovereign rating and the European debt crisis, the S&P 500's CoVaR expanded significantly from the second half of 2011 to the beginning of 2012, but the Chinese stock market's CoVaR on average is larger than that of the US stock market. From January 2015 to June 2016, the CoVaR of the stock markets of the two countries expanded again, the risk of the Chinese stock market expanded more obviously, and then entered a short period of stability of about a year. Affected by the Sino-US trade dispute, there has been a new round of expansion in the stock market risks of the two countries since the beginning of 2018, and the performance of the Chinese stock market has also become more obvious.

Judging from the value of the ΔCoVaR, the risk spillover effects of the stock markets of the two countries are mainly concentrated in the S1 and S3 periods, which indicates that the spillover risk effect is greater when the stock market volatility is more severe. Where the spillover risk of the US stock market is mainly concentrated in the S1 financial crisis period, while the spillover risk of the Chinese stock market in both the S1 period and the S3 period is relatively large. From the results, the value of the ΔCoVaR in the down period is greater than that in the up period, that

[①] If the window is too large, the volatility of VaR may not be obvious, and if it is too small, it may be difficult to observe the trend of VaR over time.

is to say, the downside spillover risk is greater than the upside spillover risk. Moreover, in comparison, both the upside and the downside risk, the ΔCoVaR value of the Chinese stock market is larger, indicating that the US stock market has a more significant impact on the spillover risk of the Chinese stock market during the sample period. It is worth noting that since the outbreak of the Sino-US trade dispute, although the CoVaR has increased significantly, the risk transmission of the stock markets of the two countries has weakened, and the spillover risk from the stock market of the other side has not significantly increased, and the ΔCoVaR has almost remained at the original level. It can be seen that the Sino-US trade dispute has increased the overall risk level of the stock markets of the two countries, but the risk spillover effect between them has not increased significantly, and the volatility characteristics of the two stock markets have diverged.

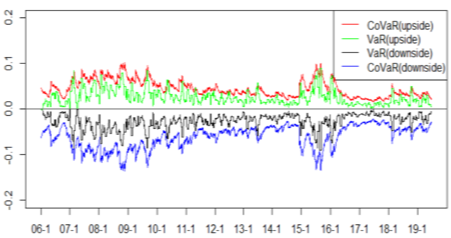


(a) CSI 300 dynamic VaR and CoVaR (b) S&P 500 dynamic VaR and CoVaR

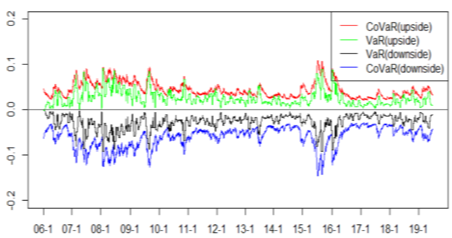
Figure 7 Analysis on the Risk Spillover Effect of Chinese and the US stock markets

The dynamic risk spillover effect between stock prices of various sectors is similar to that of the total index, but different sectors also show some differences, as shown in Figures 8 and 9. Generally, from the perspective of Chinese stock market, the Energy, Materials, Consumer Discretionary and Health Care sectors of CSI have similar trends, and are the most similar to the total market index risk situation. While the Financials, Information Technology and Communication Services sectors of CSI have similar trends, and the trends in the rest of the sectors show more obvious uniqueness. Generally, from the perspective of the US stock market, the Industrials, Consumer Discretionary, Health Care and Information Technology sectors of S&P have similar trends, and are the most similar to the risk profile of the total market index. While the Energy and Materials sectors of S&P have similar trends, the rest of the sectors show more obvious uniqueness. From the value of the ΔCoVaR, the spillover risk of Chinese stock market sector indices is significantly greater than that of the US stock market sector indices. That is to say, the risk spillover effect of the US stock market on the stock prices of various sectors in the Chinese stock market is relatively more significant, while the risk spillover effect of Chinese stock market on the stock prices of various sectors in the US stock market is weaker.

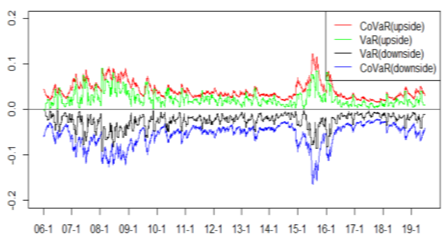
Specifically, from the perspective of the Chinese stock market, Chinese sector stock prices are generally far more affected by the downside risk spillover from the US stock market than the upside risk spillover, which also shows obvious asymmetry. That is to say, the downside risk spillover in the traditional sense dominates the risk contagion between the two stock markets. In general, when the own CoVaR fluctuates greatly, the risk spillover from the other party is also relatively large. This was especially evident during the 2008 international financial crisis. It can be seen that the degree of stock market price volatility is positively correlated with the degree of risk spillover. The average values of the CoVaR in the Energy, Materials and Information Technology sectors of CSI are larger in the S1 and S2 periods, but the changes are relatively gentle, and it is also greatly affected by the risk spillover of the US stock market, especially in the S1 period. The CoVaR in the Industrials, Consumer Staples, Consumer Discretionary, Health Care and Communication Services sectors of CSI has similar trends, but the difference is that the rise in risk around July 2015 was different for different sectors. Where the CoVaR of the Industrials and Communication Services sectors of CSI increased more, indicating that the “stock market crash” in China in 2015 had a greater impact on the two sectors than the other three sectors, and the risk spillover effect of the US stocks on Chinese Industrials sector stock prices was relatively large. However, the stock price spillover risk of the Consumer Staples sector is relatively small in the S1 and S3 periods when the stock market is more volatile. The reason is that the United States is one of Chinese major exporters of industrial products, but the domestic and foreign consumer staples markets are relatively stable and less volatile. What is different is that the stock price risk in the Financials sector experienced an obvious fluctuation cycle in 2013, which was mainly affected by the “money shortage” event of that year, but other fields were not affected much. The risk spillover of the US stocks to Chinese Financials sector was more obvious in the S1 period. The Utilities stock prices are less risky and are least exposed to the US risk spillovers. During the sample period, the stock price of the Real Estate sector has always maintained a relatively large average risk, indicating that the risk of Chinese Real Estate sector agglomeration is relatively large, but it is only greatly affected by the upside and downside risk spillovers of the US stocks during the S1 period. Finally, except for the Utilities, affected by the Sino-US trade dispute, the CoVaR of all sectors of the Chinese stock market has expanded again since the beginning of 2018, and the risk spillover effect of the US stocks on the stock prices of Chinese sectors has also risen, but the magnitude is smaller than the previous two periods.



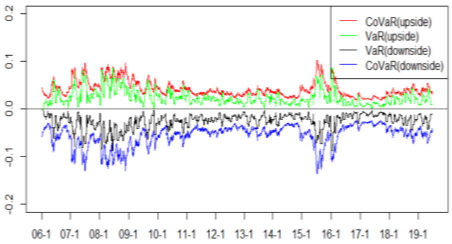
(a) Energy Dynamic VaR and CoVaR



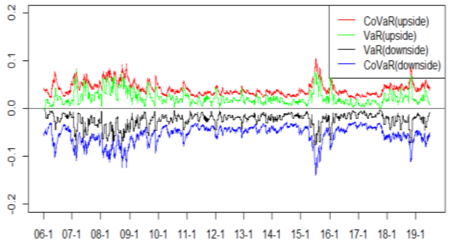
(b) Materials Dynamic VaR and CoVaR



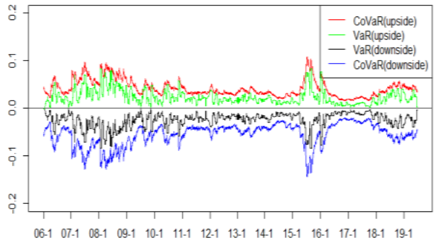
(c) Industrials Dynamic VaR and CoVaR



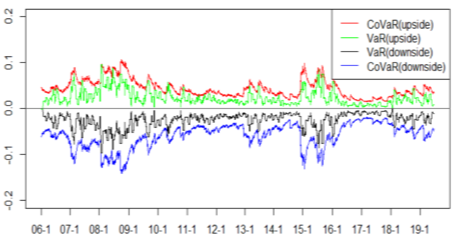
(d) Consumer Discretionary Dynamic VaR and CoVaR



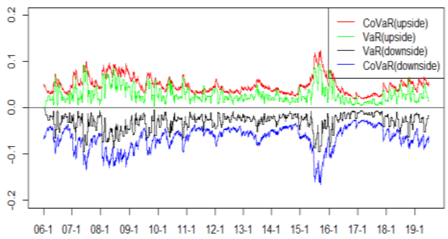
(e) Consumer Staples Dynamic VaR and CoVaR



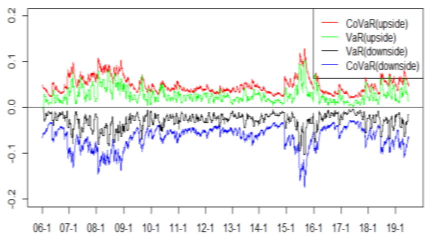
(f) Health Care Dynamic VaR and CoVaR



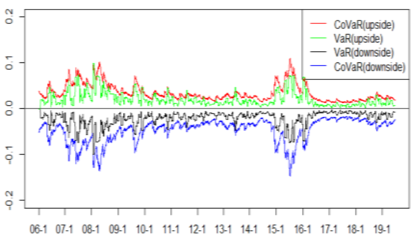
(g) Financials Dynamic VaR and CoVaR



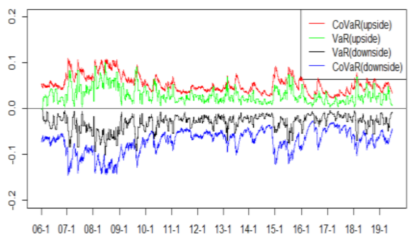
(h) Information Technology Dynamic VaR and CoVaR



(i) Communication Services Dynamic VaR and CoVaR



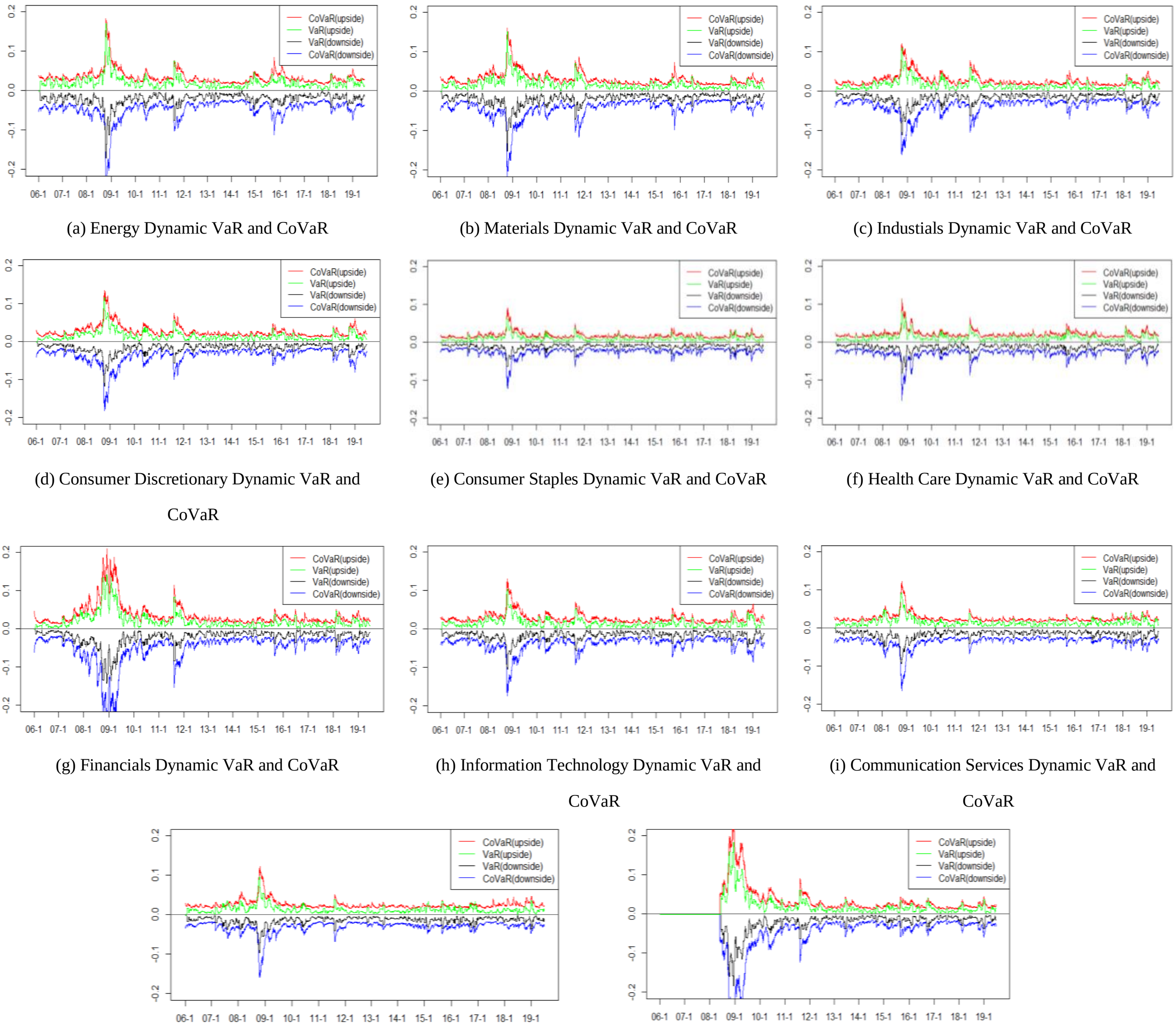
(j) Utilities Dynamic VaR and CoVaR



(k) Real Estate Dynamic VaR and CoVaR

Figure 8 Analysis of risk spillover effect of Chinese stock market sector index

Specifically, from the perspective of the US stock market, in the impact of the risk spillover from the Chinese stock market in the stock price of the US sector, the downside risk spillover is also much larger than the upside risk spillover. However, in contrast, the spillover effect of Chinese stock market on the downside risk of the US stock market is generally small, indicating that the external impact of Chinese stock market is still relatively limited. Where Energy and Materials sectors of S&P have been relatively affected by the risk spillover of the Chinese stock market, and both have large risk accumulation in the S1 and S3 periods. In fact, these two sectors themselves are highly interdependent on Chinese companies, markets or products. The Industrials, Information Technology, Utilities, and Consumer Discretionary sectors of S&P have similar risk profiles. The main manifestations are: the risk in the S1 period is relatively large, the risk in the S2 period is stable, the risk in the S3 period expands slightly, and the S1 and S3 periods are greatly affected by the downside risk spillover of the Chinese stock market. In addition, during the S1 period, the CoVaR of the Financials and Real Estate sectors of S&P was relatively large and fluctuated sharply. The risks of both the S2 and S3 periods decreased significantly. Except for the S1 period, which was greatly affected by the risk spillover of the Chinese stock market, other periods were affected by the Chinese stock market smoothly. Finally, the CoVaR of the Consumer Staples, Communication Services and Health Care sectors of S&P during the inspection period is small and the volatility is small, and the three are also less affected by the risk spillover of the Chinese stock market. It is worth noting that since the outbreak of the Sino-US trade dispute in 2018, although the CoVaR of stock prices in various sectors in the United States has risen, it has not increased significantly, and there has been basically no significant increase due to the impact of risk spillovers from the Chinese stock market. This is completely different from the risk change characteristics of Chinese sector stock prices, which shows that the US stock market is limited by the Sino-US trade dispute.



(a) Energy Dynamic VaR and CoVaR

(b) Materials Dynamic VaR and CoVaR

(c) Industials Dynamic VaR and CoVaR

(d) Consumer Discretionary Dynamic VaR and CoVaR

(e) Consumer Staples Dynamic VaR and CoVaR

(f) Health Care Dynamic VaR and CoVaR

(g) Financials Dynamic VaR and CoVaR

(h) Information Technology Dynamic VaR and CoVaR

(i) Communication Services Dynamic VaR and CoVaR

(j) Utilities Dynamic VaR and CoVaR

(k) Real Estate Dynamic VaR and CoVaR

Figure 9 Analysis of risk spillover effect of the US stock market sector index

6. Conclusion

This paper selects the daily closing prices of CSI 300, S&P 500 and their sector indices from January 3, 2006 to July 3, 2019 as samples, and mainly uses the multivariate R-vine copula-complex network analysis and R-vine copula-CoVaR model to investigate the dynamic interdependent structure and risk spillover effect of Chinese and the US stock markets from a nonlinear perspective. Cointegration analysis shows that there is no linear cointegration relationship between Chinese and the US stock markets, but there is a significant nonlinear cointegration relationship, which means that there is a long-term nonlinear equilibrium between the stock markets of the two countries. The results of the R-vine copula function show that the Energy, Materials and Financials sectors play leading roles in the interdependent structure of Chinese and the US stock markets, while the Utilities and Real Estate sectors are marginal and play the least important roles, and the rest of the sectors play secondary roles in the interdependent structure. The analysis of network centrality shows that the Chinese stock market is relatively close to the US stock market in terms of comprehensive influence, but the difference in the influence of different sectors in the US stock market in the entire interdependent structural system is smaller.

The subsection sample study shows that the interdependent structure of the stock markets of the two countries will change dynamically in different periods, and the status of each sector will be different, especially in the Energy, Materials, Consumer Staples, Health Care, Information Technology, Communication Services, and Real Estate. The influence of some sectors has increased significantly over time, such as the Information Technology, Communication Services, Health Care, and Consumer sectors. With the passage of time, the status of sectors in China and the United States has become more equal, the contribution of the same sector in different countries to the interdependent structure of the stock market has gradually converged, and the degree of dispersion of influence between different sectors in the same country has also shown a decreasing trend. There is a positive correlation between the degree of interaction between the two stock markets and the degree of market volatility, which is mainly reflected in the greater the degree of market volatility, the higher the degree of interdependence of the two stock markets. In addition, the dynamic interdependence structure of the two stock markets has a significant impact on the long-term equilibrium relationship between the two, and the Utilities and Real Estate sectors, which are marginal in the interdependence structure, are not significant in the long-term equilibrium relationship. It can be seen that the interdependent structure and changes of Chinese and the US stock markets are highly endogenous, closely related to the bilateral economic and trade exchanges between the two countries, and are especially deeply affected by the factors of trade, investment and energy between the two countries.

Further research shows that the lower tail interdependent coefficient between Chinese and the US stock markets is large, while the upper tail interdependent coefficient is very small, and it exhibits an obvious fluctuation clustering effect, and the probability of simultaneous crash risk is higher in extreme cases. The periods of relatively large CoVaR in the stock markets of the two countries are concentrated in the S1 and S3 periods, and the risk spillover effect generated by the stock price fluctuations in the two stock markets will increase the risk of the other side’s market. But in comparison, the US stock market plays more of an extreme risk sender role in the interdependent structure, while the Chinese stock market plays more of an extreme risk taker role, and the Chinese stock market is more vulnerable to the fall of the US stock market. However, the upside risks arising from the interaction between the two markets are relatively small, indicating that the probability of irrational behavior by investors of the two countries only by tracking each other's stock market trends is small. Through the investigation of the risk interdependence coefficient, it is found that the downside tail interdependence coefficient of Chinese and the US stock markets has been increasing since January 2017, but dropped below the mean line in early 2018, indicating that the Sino-US trade dispute has reduced the risk correlation between the two stock markets. Although the stock market risk of both countries has generally increased, and the risk of Chinese stock market has risen more significantly, the spillover effect of both the total indices and their sector stock prices risk has not increased significantly between the stock markets of the two countries. That is to say, the stock market risk of the two countries has increased but the interaction between the two sides has decreased.

This paper examines the dynamic interdependence structure and risk spillover effects of Chinese and the US stock markets, which has important policy implications. First, the opening of Chinese stock market should pay close attention to the input of external risks. With the continuous improvement of the internationalization of Chinese stock market, the relationship between Chinese and the US stock markets has been continuously strengthened, showing a nonlinear long-term equilibrium relationship and dynamic interdependence. But in general, the Chinese stock market is more significantly affected by the US stock market, while the impact on the external market is still relatively weak. Second, regulators and investors should pay attention to the risk transmission mechanism of different sectors when paying attention to external risks flowing into the Chinese stock market. Due to the differences in internal economic relations and sector characteristics, different sectors have different mechanisms and performances of external risk spillovers, and the Financials, Energy, Materials and other sectors are more significantly affected by the risk spillover effect of the US stock market. Third, in response to the Sino-US trade frictions in recent years, China should pay more attention to the prevention of internal risks in its own stock market. The trade friction has increased the price volatility of Chinese and the US stock markets, but the interaction between the stock markets of the two countries has weakened, and the risk spillover effect of both the overall and the sectors has not increased significantly.

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