Return Correlation Between Chinese and US Stock Markets Based on Bivariate Tail Asymmetry Model

Xinmeng Hou*, Linping Kong
School of Economics, Guangzhou College of Commerce, Guangzhou, Guangdong, China
**Corresponding Author*

Abstract: This study selects closing prices of Chinese and US stock market indices as research subjects and constructs a bivariate Gumbel Copula model to investigate the return relation between this two markets. This paper reveals that the closing prices of Chinese and US stock market indices do not follow a normal distribution. By plotting bivariate frequency distribution histograms, the study identifies asymmetric tail risks between the two markets, with sample data primarily concentrated in the upper tail. The bivariate Gumbel Copula model demonstrates superior performance in capturing upper-tail correlations compared to the bivariate normal Copula model. Parameter estimations from the Gumbel Copula model consistently indicate robust positive correlations, whether analyzing the correlation between CSI 300 and S&P 500 indices or the CSI 300 and NASDAQ indices. Tail risk measurements across two sample groups show no significant differences in tail correlation coefficients.

Keywords: Bivariate Gumbel Copula; Chinese Stock Markets; US Stock Market; Return Correlation; Empirical Study

1. Introduction

As the main and important economies in this world, the United States and China have stock markets that hold significant positions globally and offer investors a wide range of financial products. Against this backdrop, international investors often allocate funds among global stock markets to optimize their asset portfolios. There are certain differences between the US and Chinese financial markets in terms of product design, trading systems, and regulatory frameworks. These differences provide investors with a rich array of financial risk management methods. Investors can conduct various operations across different markets to mitigate risks associated with single-market investments, such as country and policy risks. This cross-market investment approach is of great strategic significance to investors.

Based on the above background, the interlinkage effect between the Chinese and US financial markets has always been a focal point in the global financial system. This interlinkage effect reflects, to a certain extent, the depth and breadth of global economic integration. Therefore, in-depth research and understanding of this interlinkage effect are of great significance for investors in formulating investment strategies, financial institutions in managing risks, and regulatory authorities in maintaining financial market stability.

Domestic and international scholars have achieved certain research results on the relation between the Chinese and US finance markets, providing plenty of theoretical bases for subsequent empirical studies.

Gong and Huang [1] used a time-varying t-Copula model to enquire the effect of the subprime crisis on China's stock market. The results showed that the strong fluctuations in the US stock market triggered by the subprime crisis would be transmitted to the stock market through the other stock market, with phased changes. Zhang et al.[2] estimated the Copula model function using the rank correlation coefficient between the SCI and the S&P 500 Index to explore the correlation between the Chinese and US stock markets during the financial crisis. The results indicated that the tail correlation between the two markets was close to symmetric independence. Cao and Lei [3] analyzed whether the tail risk contagion effect in reference to the Chinese and US stock markets had changed against the backdrop of the Sino-US trade war using a time-varying twisted mixed Copula model. The study found that the likelihood of risk contagion between the two countries' stock markets increased because of the Sino-US trade war. Zheng et al. [4] used a block-mixed Copula model to analyze the daily closing prices of the Shanghai Composite Index and the S&P 500 Index from 2001 to 2020, identifying the correlation structure and the direction of risk contagion between the US and Chinese stock markets. The research found that the two markets exhibited asymmetry under extreme market conditions. He et al. [5] combined traditional models with Copula theory models to explore the risk dependency structure between the US and Chinese bond markets and stock markets. The results showed that the US and Chinese bond markets had a certain negative impact on the stock markets and revealed the dependency of risks. Between the US and Chinese stock markets, Chen and Zhou [6] looked into the dynamic interdependency structure and risk spillover effects in accordance with the R-vine Copula complex network analysis method. The study found that the interdependence structure of the two markets varied across different sectors, and the market fluctuations of the US and Chinese stock markets were positively correlated.

In addition to using Copula models, scholars have also attempted to use other models to examine the correlation between the two markets. Based on the time-varying parameter generalized autoregressive conditional heteroskedasticity model (TVP-GARCH-M), He and Dong [7] analyzed the risk preferences of investors using the stock markets trading data of US and Chinese and employed the Granger causality test in order to understand the relationship between the risk preferences of investors in the two noteworthy markets. The study found that changes in the risk preferences of US stock market investors would lead to changes in the risk preferences of Chinese stock market investors, thereby affecting the return changes in the US and Chinese stock markets to a certain extent. Wang and Zhou [8] used wavelet coherence spectrum and GARCH-Copula methods to study the time-varying correlation mechanism of stock market volatility between the US and China. The study found that there were extreme co-upward movements in the US and Chinese stock indices. Du et al. [9] used an ARJI-GARCH model to investigate the risk contagion particular attribute between the US and Chinese security market during the COVID-19 pandemic. The results showed that the dependency between the two countries' stock markets increased during the pandemic, with a certain degree of risk contagion. Chen et al. [10] used the MF-DCCA model to clarify the multiple fractal characteristics of the CSI 300 Index and the S&P 500 Index, revealing that there were different correlations at different stages, further indicating the diverse correlations between the US and Chinese security trading markets.

Some scholars have used certain factors in the market to study the disturbance of these factors on external markets. Li and Fang [11] explored the correlation between the US and Chinese stock markets from the perspective of investor sentiment in the market. Through empirical research, they found that US investor sentiment did have an impact on Chinese stock returns. This sentiment first had a negative impact on Chinese stock returns and then turned to a positive impact, indicating to a certain extent that there was a return correlation between the US and Chinese stock markets. Wang et al. [12] studied the impact of US tariff policies on the volatility of China's stock market in the context of the Sino-US trade war. The results showed that the volatility of stocks of products subject to tariffs would significantly increase.

Based on the above background, this paper selects the daily closing prices of the CSI 300 Index from China's stock market and the S&P 500 Index and the NASDAQ Index from the US stock market as representatives of the two markets. Using the theory of bivariate Copula functions as a framework, this paper constructs a bivariate Gumbel Copula function model to study the return correlation between the US and Chinese stock markets.

The article has certain research significance both in theory and practice. At the theoretical level, traditional methods for depicting stock market correlation are mostly linear, and linear models struggle to capture the true non-linear relationships between different assets. There are differences in tail risks between different assets, especially under extreme risk conditions, where traditional models exhibit measurement biases. By taking the correlation between the US and Chinese stock markets as the research object, and using the bivariate frequency distribution as the basis to select the bivariate Gumbel Copula model, this study characterizes the asymmetric risks of the left and right tails. This not only supplements the existing financial market theories but also provides a new perspective for the study of correlations between different markets. At the practical level, understanding the tail asymmetric correlation of returns between the US and Chinese stock markets can help investors more accurately assess the risk and return characteristics of assets across different markets, thereby effectively hedging risks. It also offers new ideas for regulatory authorities to effectively predict and guard against systemic financial risks.

The structure of the article is as follows: Chapter 1, Introduction. Chapter 2, Related Theoretical Introduction. Chapter 3, Empirical Research. Chapter 4, Conclusions.

2. Related Theories

2.1 Bivariate Copula Model

As a "linking function", the Copula function connects the joint distribution attribute of random variables with their marginal distributions characteristics. Suppose there exists a bivariate joint distribution function H(x, y) with marginal distributions F(x) and G(y). Let u = F(x) and v = G(y). Then we have a Copula function formation C(u, v) which satisfies

$$H(x,y) = C(u,v) \tag{1}$$

In the empirical study of this paper, to clarify the difference on the assumption of distribution pattern, the bivariate Gumbel Copula function and the bivariate normal Copula function are used. The bivariate Gumbel Copula function has upper tail dependence and is mainly used for situations where the correlation of data is concentrated in the upper tail. It can analyze the upper tail dependency relationship between random variables.

The expressions for the cumulative distribution function (CDF) of the bivariate Gumbel Copula function is listed on formula (2) and probability density function (PDF) is followed on (3):

$$C_G\left(u,v;\frac{1}{\theta}\right) = exp\left(-\left[(-lnu)^{\theta} + (-lnv)^{\theta}\right]^{\frac{1}{\theta}}\right) \tag{2}$$

$$c_G\left(u,v;\frac{1}{\theta}\right) = \frac{C_G\left(u,v;\frac{1}{\theta}\right)(lnu \times lnv)^{\theta-1}}{uv\left[(-lnu)^{\theta}+(-lnv)^{\theta}\right]^{2-\frac{1}{\theta}}}\left\{\left[(-lnu)^{\theta} + (-lnv)^{\theta}\right]^{-\frac{1}{\theta}} + \theta - 1\right\} \tag{3}$$

In the bivariate Gumbel Copula function, the parameter θ ranges from [1, +∞) and reflects the strength of the correlation between random variables. We could judge the strength of the correlation between the variables according to the final value of θ. When the parameter θ = 1, the bivariate Gumbel Copula function degenerates into an independent Copula function, indicating no significant correlation between the variables. As the value of θ approaches positive infinity, the random variables under study will show a completely correlated relationship. If one variable experiences an extreme event, the other variable will also certainly experience a similar extreme event.

The expression for the cumulative distribution function (CDF) of the bivariate normal Copula function is as follows:

$$C_{Ga}(u,v;\rho) = \int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left\{-\frac{s^2-2\rho st+t^2}{2(1-\rho^2)}\right\} dsdt \tag{4}$$

here, ρ is the correlation parameter of the bivariate normal Copula function. The bivariate normal Copula function has symmetric tails with a tail dependence coefficient of 0, making it suitable for analyzing situations where there is no tail dependence (either upper or lower) between random variables. However, it is not capable of capturing asymmetric tail dependence relationships between random variables.

2.2 Squared Euclidean Distance and Tail Dependence Coefficient

The squared Euclidean distance is a method for measuring the difference between two functions. In the context of Copula functions, the calculation of the squared Euclidean distance involves the empirical Copula. By comparing the squared Euclidean distances between different bivariate Copula functions and the empirical Copula, we can select the bivariate Copula function model that better fits the sample data. The smaller the squared Euclidean distance, the better the bivariate Copula function model fits the data sample.

The expression for the squared Euclidean distance between the bivariate Gumbel Copula function and the empirical Copula function

$\widehat{C}_n(\mathrm{u}, \mathrm{v})$ is as follows:

$$d_G^2 = \sum_{i=1}^{n} \left|\widehat{C}_n(u_i, v_i) - \widehat{C}^G(u_i, v_i)\right|^2 \quad (5)$$

The expression for the squared Euclidean distance between the bivariate normal Copula function and the empirical Copula function $\widehat{C}_n(\mathrm{u}, \mathrm{v})$ is as follows:

$$d_{Ga}^2 = \sum_{i=1}^{n} \left|\widehat{C}_n(u_i, v_i) - \widehat{C}^{Ga}(u_i, v_i)\right|^2 \quad (6)$$

Here, $\mathrm{u}_i = F_n(x_i), v_i = G_n(y_i)(i = 1,2, \cdots, n)$. The squared Euclidean distance d_G^2 reflects the fit of the bivariate normal Copula function to the sample data, while d_{Ga}^2 reflects the fit of the bivariate Gumbel Copula function to the sample data.

The tail dependence coefficient is a deputy of the correlation between two random variables when extreme events occur in the tails (upper or lower) of their distributions. When the tail dependence coefficient is 0, it indicates that there is no tail dependence between the two random variables. When the tail dependence coefficient is greater than 0, it indicates that there is tail dependence between the two random variables, and the closer the value is to 1, the stronger the tail dependence. The bivariate Gumbel Copula function primarily focuses on the correlation between random variables in the upper tail, while there is no correlation in the lower tail. Therefore, this paper uses the tail dependence coefficient to analyze the possibility of simultaneous surges in the US and Chinese stock markets. The larger the tail dependence coefficient, the higher the possibility of simultaneous surges. The upper tail dependence coefficient is denoted as λ^{up}, and the lower tail dependence coefficient is denoted as λ^{lo}. The calculation formula for the tail dependence coefficient of the bivariate Gumbel Copula function is as follows:

$$\lambda^{up} = 2 - 2^{1/\theta}, \lambda^{lo} = 0 \quad (7)$$

3. Empirical Research

3.1 Data Processing and Descriptive Statistics

Compared to returns, closing prices intuitively reflect the impact of daily market information on the fundamental value of stocks. Therefore, this paper selects the daily closing prices of the CSI 300 Index from China's stock market and the S&P 500 and NASDAQ indices from the US stock market as proxies for changes in the market conditions of the Chinese and US stock markets, respectively. The data are sourced from the CSMAR. The sample period is from January 2005 to June 2024.

The CSI 300 Index includes the 300 largest market-capitalization and most liquid companies listed on the Shanghai and Shenzhen stock exchanges, providing a more accurate reflection of China's economic development. The S&P 500 Index comprises 500 representative US-listed companies, and its trend reflects the overall performance of the US economy. The NASDAQ Index mainly covers high-tech and innovative companies listed on the NASDAQ Stock Exchange, representing the cutting-edge trends in global technological development. For robustness testing, this paper also conducted a correlation study between the CSI 300 Index and the NASDAQ Index.

Due to the differences in trading days and trading hours between the Chinese and US stock markets, after collecting the data for the three indices, data from different trading days were removed, retaining only data from the same trading days. Ultimately, 4,577 valid daily closing prices were retained for the three indices between January 2005 and June 2024.

Table 1. Descriptive Statistics of Daily Closing Prices of Indices

Var	Mean	Std	Min	25%	50%	75%	Max	Skew	Kurt	N
HC	3235.20	1088.60	818.03	2498.10	3336.50	3908.20	5877.20	-0.25	2.78	4577
SC	2265.30	1167.00	676.53	1305.40	1958.00	2906.00	5487.00	0.87	2.62	4577
NC	5952.40	4268.10	1268.60	2465.60	4508.30	8015.50	17862.00	0.99	2.73	4577

Note: Table 1 presents the descriptive statistics of the daily trading data (closing prices) of the CSI 300 Index, S&P 500 Index, and NASDAQ Index (HC, SC, NC) over the sample period beginning from January 2005 to June 2024. The variables are defined as follows: Mean represents the average number, Std represents the standard deviation, Min represents the minimum value, 25% represents the first quartile (25th percentile), 50% represents the median (50th percentile), 75% represents the quarter quartile (75th percentile), Max represents the maximum value, Skew represents skewness, Kurt represents kurtosis, and N represents the number of observations.

Skewness and kurtosis are important parameters for characterizing distribution features. The skewness of the daily closing price of the CSI 300 Index is -0.25, which is less than 0, indicating a left-skewed distribution. The kurtosis is 2.78 (less than 3), indicating a relatively flat and light-tailed distribution. This suggests that the data distribution does not follow a normal distribution but rather exhibits a left-skewed and light-tailed characteristic. The skewness of the daily closing price of the S&P 500 Index is 0.87, which is greater than 0, indicating a right-skewed distribution. The kurtosis is 2.61 (less than 3), indicating a relatively flat and light-tailed distribution. This suggests that the data distribution of the daily closing price of the S&P 500 Index does not follow a normal distribution. The skewness of the daily closing price of the NASDAQ Index is 0.99, which is greater than 0, indicating a right-skewed distribution. The kurtosis is 2.73 (less than 3), indicating a relatively flat and light-tailed distribution. This suggests that the data distribution of the daily closing price of the NASDAQ Index does not follow a normal distribution but rather exhibits a right-skewed, flat, and light-tailed characteristic. Combining the skewness and kurtosis indicators, we can basically conclude that none of the three indices follow a normal distribution.

In addition to these simple indicators such as skewness and kurtosis, the JB test and Lillie test are also used to examine the distribution characteristics of the sample data, specifically whether the sample data follows a normal distribution. The results show that the P-values are all less than 0.01. This indicates that at the 5% significance level, the null hypothesis that the daily closing prices of the three indices follow a normal distribution is rejected. In other words, the data distributions of the daily closing prices of the three indices do not follow a normal distribution.

Figure 1 illustrates the bivariate frequency and relative frequency histograms of the marginal distributions of the daily closing prices of the CSI 300 Index and the S&P 500 Index. The sample data are primarily concentrated in the upper-right region (upper tail), while the data in the lower-left region (lower tail) are sparse. This indicates that the sample data are more sensitive to changes in the upper tail, suggesting strong upper tail dependence. Therefore, the bivariate Gumbel Copula function, which captures upper tail dependence, is selected for the analysis of the sample data. For comparison purposes, the bivariate normal Copula model is also employed in the empirical analysis below.

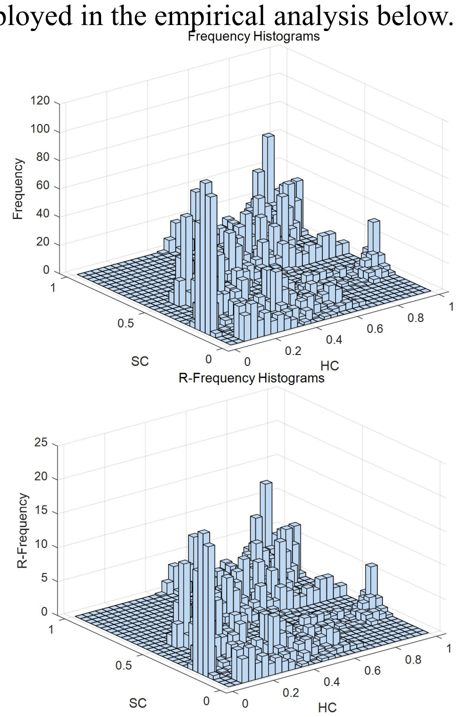

Figure 1. Bivariate Frequency and Relative Frequency Histograms of the Marginal Distributions of Daily Closing Prices of the CSI 300 Index and the S&P 500 Index

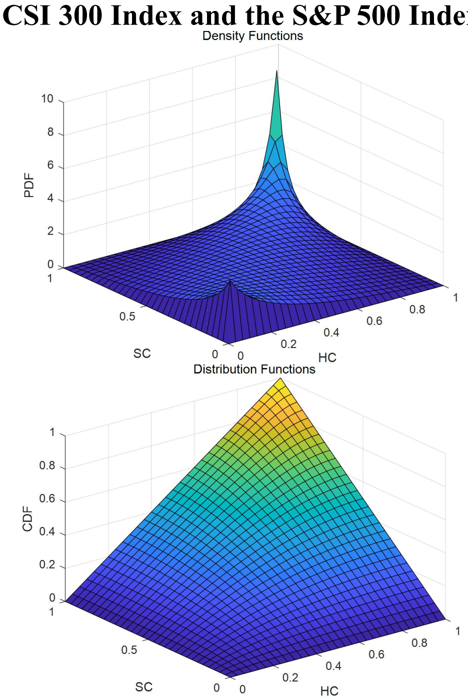

Figure 2. Density and Distribution Functions of the Bivariate Gumbel Copula Function

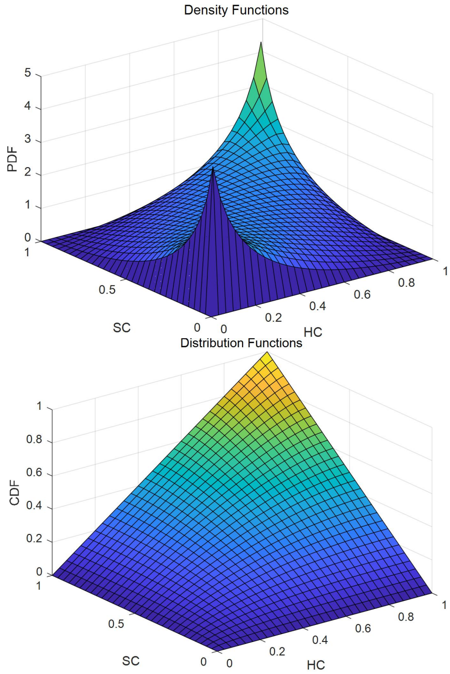

Figure 3. Density and Distribution Functions of the Bivariate Normal Copula Function

Figure 2 and Figure 3 describe the density and distribution functions of the bivariate Gumbel Copula and the bivariate normal Copula for the daily closing prices of the CSI 300 Index and the S&P 500 Index, with the sample period from January 2005 to June 2024. The higher the tail of the density function, the thicker the tail, which better reflects the strength of the correlation between the sample data and indicates stronger dependence in the tail (either upper or lower). The bivariate frequency histograms and bivariate relative frequency histograms drawn in Figure 2 show that the sample data have the characteristic of being higher in the upper tail and lower in the lower tail, which is similar to the results obtained from the bivariate frequency (R-frequency) distribution histograms. Figure 3 assumes that the bivariate joint distribution function follows a normal distribution. From the perspective of the bivariate function probability density diagram, the correlation in the upper tail is slightly higher than that in the lower tail. The assumption of the bivariate Gumbel Copula is more in line with the actual distribution characteristics indicated by the bivariate (Relative) frequency histograms. This paper uses the Euclidean distance to make judgments and provides a robustness test.

In the Copula function, the squared Euclidean distance is used to determine the fit between the theoretical Copula model and the empirical Copula. That is, the smaller the squared Euclidean distance between a theoretical Copula model and the empirical Copula, the better the fit of the theoretical Copula model to the sample data. D^2 is the squared Euclidean distance between the bivariate normal Copula function model and the empirical Copula, and d^2 is the squared Euclidean distance between the bivariate Gumbel Copula function model and the empirical Copula. Since d^2 (the value is 3.08) is less than D^2 (the value is 3.38), it indicates that, compared to the bivariate normal Copula model, the bivariate Gumbel Copula function model can better fit the correlation of the sample data of the daily closing prices of the CSI 300 Index and the S&P 500 Index.

3.2 Parameter Estimation

Bivariate frequency histograms and bivariate relative frequency histograms can provide a more intuitive visualization of the sample data distribution, aiding in the selection of an appropriate Copula model. Additionally, by examining the distribution characteristics in the tail regions of the bivariate histograms, one can identify tail dependence (upper or lower) and thus choose a suitable Copula model. Both the bivariate Gumbel Copula function and the bivariate Clayton Copula function can describe asymmetric tail dependence scenarios. The key difference lies in their focus on upper tail dependence versus lower tail dependence.

As a robustness test, this paper analyzes the sample data of the daily closing prices of the CSI 300 Index and the NASDAQ Index using the bivariate Gumbel Copula function to derive the parameter θ, and calculates the correlation results of the joint distribution between multiple indices of the Chinese and US stock markets to verify whether there is a strong association between the Chinese and US stock markets and to test the stability of this correlation.

From Table 2, the parameter θ value derived from the analysis of the sample data of the daily closing prices of the CSI 300 Index and the NASDAQ Index using the bivariate Gumbel Copula function model is 1.84, which is close to the 1.72 of HC-SC. The similarity in the values of the parameter θ for the two indicates a similar degree of positive correlation during extreme events, meaning that under the influence of some quantifiable extreme factors, there is a strong right-tail risk contagion between the two stock markets, and the likelihood of both markets experiencing extreme conditions simultaneously is relatively high.

Table 2. Estimation of Parameter θ for HC-SC and HC-NC

Index	θ
HC-SC	1.72
HC-NC	1.84

Note: In Table 2, HC-SC represents the sample of daily closing prices of the CSI 300 Index and the S&P 500 Index, while HC-NC represents the sample of daily closing prices of the CSI 300 Index and the NASDAQ Index. θ is the parameter of the bivariate Gumbel Copula function.

The Kendall rank correlation coefficient is a commonly used method for measuring the correlation between two variables. It does not require consideration of the distribution shape of the data and is applicable to any type of variable, making it quite flexible. Under extreme risk conditions, the Kendall rank correlation coefficient can still effectively capture the correlation between assets, thus holding significant importance in risk management.

This section compares the Kendall rank correlation coefficient, the Kendall rank correlation coefficient of the bivariate normal Copula model, and the Kendall rank correlation coefficient of the bivariate t-Copula model. In Table 3, HC-SC represents the sample of daily closing prices of the CSI 300 Index and the S&P 500 Index. Kendall_N is the Kendall rank correlation coefficient of the bivariate normal Copula, Kendall_G is the Kendall rank correlation coefficient of the bivariate Gumbel Copula, and Kendall is the Kendall rank correlation coefficient.

Table 3. Comparison of Rank Correlation Coefficients for Different Models

Index	Kendall	Kendall_G	Kendall_N
HC-SC	0.48	0.42	0.41

Note: In Table 3, HC-SC represents the sample of daily closing prices of the CSI 300 Index and the S&P 500 Index. Kendall_N is the Kendall rank correlation coefficient for the bivariate normal Copula, Kendall_G is the Kendall rank correlation coefficient for the bivariate Gumbel Copula, and Kendall is the Kendall rank correlation coefficient.

As can be seen from Table 3, the Kendall rank relation coefficient, short for Kendall_N, for the bivariate normal Copula function is 0.41, the Kendall rank relation coefficient Kendall_G for the bivariate Gumbel Copula function is 0.42, and the Kendall rank relation coefficient directly calculated from the raw data of the daily closing prices of the CSI 300 Index and the S&P 500 Index is 0.48. The bivariate Gumbel Copula model with a Kendall rank relation coefficient of 0.42 can better reflect the rank relation between the CSI 300 Index and the S&P 500 Index, which is consistent with the results of the Euclidean distance, indicating that the bivariate Gumbel Copula model has a better fit.

3.3 Tail Dependence Coefficient

The tail dependence coefficient presents an effective measure of the correlation between two financial assets in the extreme value regions (i.e., the tails of the distribution). It indicates the likelihood that one asset will experience extreme risk given that the other asset has already experienced extreme risk. The coefficient typically ranges from 0 to 1. When the tail dependence coefficient is 0, the extreme risks of the two assets are independent and uncorrelated. When the coefficient is 1, if one asset experiences an extreme event, the other asset is also likely to experience a corresponding extreme event, indicating a perfectly correlated tail risk. However, this scenario is relatively rare in real life.

The bivariate Gumbel Copula function model was used to analyze the tail dependence coefficients for the sample data of the daily closing prices of the CSI 300 Index and the S&P 500 Index. The article also conducted a tail dependence coefficient analysis for the CSI 300 Index and the NASDAQ Index as a robustness test. The tail dependence coefficients derived from the analysis of the daily closing prices of the CSI 300 Index and the S&P 500 Index, and the CSI 300 Index and the NASDAQ Index, using the bivariate Gumbel Copula function model, were 0.50 and 0.54, respectively.

On the one hand, these results indicate that there is a strong upper tail dependence between the Chinese and US stock markets.

This suggests that when the daily closing prices of the Chinese stock market surge, the US stock market is also likely to experience a surge, and vice versa. In other words, there is a positive co-movement in extreme high values between the Chinese and US stock markets, meaning that when one market experiences a significant upsurge, the other is likely to follow suit.

4. Conclusions

This paper employs bivariate frequency histograms and selects the bivariate Gumbel Copula function model, which characterizes upper tail dependence, to study the correlation of returns between the Chinese and US stock markets. The daily closing prices of the CSI 300 Index from January 2005 to June 2024 are used as a proxy for the Chinese stock market, the S&P 500 Index as a proxy for the US stock market, and the NASDAQ Index as an alternative indicator for robustness testing. The empirical analysis yields the following results:

Firstly, the sample distribution is determined. Descriptive statistics of the sample data reveal that the marginal distributions do not conform to a normal distribution. The shapes of the bivariate frequency and relative frequency histograms of the Chinese and US stock markets show a clear asymmetry, with higher correlation data concentrated in the upper tail. In other words, there is a significant difference in tail dependence between the Chinese and US stock markets during extreme events (strong upper tail dependence and weaker lower tail dependence).

Secondly, an appropriate correlation model is selected. Modeling with the sample data and comparing bivariate Copula functions reveal that the density function of the bivariate Gumbel Copula has a higher upper tail than that of the bivariate normal Copula, indicating that the Gumbel Copula better captures upper tail dependence in the sample data. Further analysis through parameter estimation, rank correlation coefficients, squared Euclidean distance, and robustness tests confirms that the bivariate Gumbel Copula function provides a better fit for the upper tail dependence of the sample data.

Finally, robustness analysis using the daily closing prices of the CSI 300 Index and the NASDAQ Index yields model parameters θ and tail risk dependence results similar to those obtained from the CSI 300–S&P 500 Index, indicating a robust upper tail dependence between the Chinese and US stock markets.

In summary, there is a correlation between the Chinese and US stock markets, with significant differences in tail dependence and a stronger upper tail dependence. This suggests that when one of the two stock markets experiences a surge, the other is also likely to surge; however, when one market experiences a plunge, the likelihood of the other market experiencing a similar plunge is relatively low.

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