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Multiscale Quantile Correlation Coefficient: Measuring Tail Dependence of Financial Time Series

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Abstract: In the context of the frequent occurrence of extreme events, measuring the tail dependence of financial time series is essential for maintaining the sustainable development of financial markets. In this paper, a multiscale quantile correlation coefficient (MQCC) is proposed to measure the tail dependence of financial time series. The new MQCC method consists of two parts: the multiscale analysis and the correlation analysis. In the multiscale analysis, the coarse graining approach is used to study the financial time series on multiple temporal scales. In the correlation analysis, the quantile correlation coefficient is applied to quantify the correlation strength of different data quantiles, especially regarding the difference and the symmetry of tails. One reason to adopt this method is that the conditional distribution of the explanatory variables can be characterized by the quantile regression, rather than simply by the conditional expectation analysis in the traditional regression. By applying the MQCC method in the financial markets of different regions, many interesting results can be obtained. It is worth noting that there are significant differences in tail dependence between different types of financial markets.

Keywords: tail dependence; quantile correlation coefficient; multiscale analysis; financial market

1. Introduction

The developing trend of economic globalization has posed more demanding challenges to the sustainable development of financial markets. Specifically, as economic globalization expands its influence, and the connections between financial markets, for example in terms of capital flow and information dissemination, continue to solidify, the financial markets of different countries and regions are becoming more and more close-knit, and the influence that one market experiences from another is also all the greater [1–3]. When a financial event plays out, risks often tend to spread across various markets, resulting in the appreciable fluctuations in asset prices [4]. If there is a remarkable correlation between financial markets, the likelihood of risk spillover between markets will be heightened, and the probability of price fluctuations in one market causing price fluctuations in other markets will be higher [5–8]. This may even lead to market paralysis, which in turn affects the sustainable development of financial markets. Hence, the study of the correlation between different markets is of great significance for investors of all kinds, as regards avoiding risks, as well as for governmental decision-makers, who must build up their ability to supervise and regulate the marketplace.

It is worth noting that financial crises, which take place frequently throughout history, have always led to huge losses. However, the results of the distribution show that such extreme losses (extreme negative returns) tend to be at the tail of the distribution, and thus the type of risk that threatens investors in this case is often defined as tail risk. When the market fluctuates violently, the tail correlation between financial assets will show certain features that are not normally present. Tail correlation is divided into left tail correlation and right tail correlation, with the former appearing in an extremely pessimistic or a downward market, and the latter appearing in an extremely optimistic or an upward market. In addition, a large amount of the literature indicates that the characteristics of high peaks and fat tails are common in the distribution of financial assets [9–13]. Considering that the extreme loss caused by tail risk is inestimable, while the probability of tail risk occurring is relatively small, it can never be ignored. Therefore, the question that we urgently need to solve regards how to find a precise indicator to measure the correlation between financial markets, especially to unravel the tail correlation between financial markets concerning returns. Accurately quantifying the tail correlation of the financial markets can promote the effective operation of the financial markets in the long term, thereby achieving the effect of maintaining the sustainable development of the financial markets.

Previous studies have focused on the overall correlation of financial markets in the main, and a comparatively small part of them direct attention to the measure of tail correlation. It is even rarer to find considerations of different time scales in studies of tail correlation. In the studies of financial time series, time scale is a non-negligible aspect, since there are often "long-term trends" and "short-term fluctuations" in the analysis of financial time series [14–18]. If the time scale is at a low level, the time series between financial markets that we observe may exhibit short-term fluctuations, but if the time scale is extended, we will have the opportunity to observe the long-term trend of the financial time series.

Hence, the objective of this paper is to delve into the overall picture of the correlation between financial markets at different quantiles and different scales, so as to further grasp differences in tail correlation. Specifically speaking, the coarse graining method is selected to pre-process financial time series in the multiscale analysis. In the measurement of correlation, the quantile regression and regression coefficient are combined together to generate a quantile correlation coefficient, in order to gauge the overall picture of correlation at different quantiles of financial markets. In this paper, we select stock markets, gold markets and foreign exchange markets from financial markets as the primary research objects, and endeavor to observe the tail correlations between financial markets of different regions.

The organizational framework of this paper is as follows. Section 2 gives an overview of the relevant literature in this paper. Section 3 introduces the main research method of this paper: the multiscale quantile correlation coefficient. Section 4 validates the effectiveness of the method through simulation experiments. The data description is shown in Section 5. Section 6 provides the results of the empirical analysis of financial markets. Finally, we offer the main conclusions in Section 7.

2. Literature Review

Recent years have witnessed many scholars' efforts in applying a variety of methods and models to study the correlation between financial markets, among which the traditional linear correlation coefficient is recognized as one of the earliest statistical methods [19–21]. Hilliard [22] applied the traditional correlation coefficient method to obtain the conclusion that there is a positive correlation between the closing prices of stock markets in developed countries. Using the linear correlation coefficient method, Calvo et al. [23] found that the correlation of stock markets in emerging countries has increased significantly after the Mexican crisis. The disadvantage of the traditional correlation coefficient method is that it measures the overall correlation between different markets. However, the correlation direction, the degree of the overall correlation and the tail correlation may not be the same. Focusing only on the overall correlation may lead to an overestimation or underestimation of risk. Moreover, co-integration based on the VAR (Vector Auto-Regressive) model and Granger causality tests was widely applied to study the inter-linkage of financial markets [24,25]. Robert et al. [26] used the VAR model to study the volatility of the stock markets, and found that the stock markets can be infected across markets. Jeon and Chiang [27] found that there was a certain linkage between the stock markets of the US, the UK and France by using the co-integration test. However, in co-integration based on vector auto-regression VAR models and Granger causality tests, only linear effects were considered, which failed to describe the complex causal relationships. Furthermore, it examined the information spillovers of mean and variance, which could not reveal the correlation at a more complex level of the major international financial markets, such as the measurement of extreme risks. Some scholars applied the GARCH (Generalized Auto-Regressive Conditional Heteroscedasticity) model to the study of correlation between financial assets [28–30]. Kanas and Kouretas [31] used the bivariate EGARCH (Exponential GARCH) model, finding that there was an asymmetric volatility spillover between the Greek black market exchange rate and the official exchange rate, and that the volatility spillover effect caused by bad news was greater. Mohamed et al. [32] studied the dynamic correlation between the stock indices of six Latin American countries and the world stock indices via the DCC-GARCH (Dynamic Conditional Correlation GARCH) model, and found that the correlation between the stock indices of the six Latin American countries increased significantly, especially during a crisis. Although time-varying volatility could be described through the GARCH model, the GARCH model is researched around the measurement variance, and the increase of the variance does not necessarily indicate that there is a spillover effect between markets. The GARCH model is mainly used to test the stability of parameters, but financial market data has the characteristic of non-stationarity. Therefore, using the GARCH model may make the empirical results biased. GARCH cannot measure the relevant trend at the tail of the markets. In addition, Copula function is also one of the important tools for financial market correlation modeling at the present time [33–35]. Through studying the correlation between the exchange rates between GBP against USD, and JPY against USD, Andrew [36] found that the degree of correlation and the correlation pattern between the two exchange rates were significantly different before and after the introduction of the EURO system.

All the above studies strongly prove that there are different degrees of correlation between different types of financial markets. However, previous studies have mainly focused on the measurement of overall correlation, and relatively few studies on tail correlation. In addition, the previous forms of correlation analysis were mainly performed on the basis of ordinary regression models, which require that the dependent variable is normally distributed, and which are sensitive to outliers. Such problems as outliers, collinearity and heteroscedasticity may cause deviations in regression results. In addition, through ordinary regression analysis, we cannot understand the changing process of the independent variable's influence on the dependent variable, while the quantile regression is effective in solving this problem. Inspired by the quantile regression model, it is found that the quantile correlation coefficient, derived from the combination of quantile regression and correlation coefficient, can be employed to observe correlation differences in financial time series at different quantile levels [37,38].

In recent years, multiscale analysis has also received greater attention from scholars in the study of time series. The main reason is that the multiscale analysis method can reveal the fluctuation characteristics existing in the sequence at different scales. Such research can help us to more clearly identify fluctuation trends between series. The methods of coarse graining analysis, wavelet analysis and empirical mode decomposition are all popular methods of multiscale analysis [39,40]. The coarse graining method has evolved into one of the most widely used multiscale analysis methods at present, because of its ease of operation and its universality.

3. Multiscale Quantile Correlation Coefficient (MQCC)

The goal of this paper is to combine multiscale analysis and the quantile correlation coefficient, in order to measure the correlation between financial time series via conditional quantiles at multiple time scales. In particular, the quantile correlation coefficient is used to capture the difference between the tail correlation and the symmetry. The new method is called multiscale quantile correlation coefficient (MQCC), the diagram of which is shown in Figure 1.

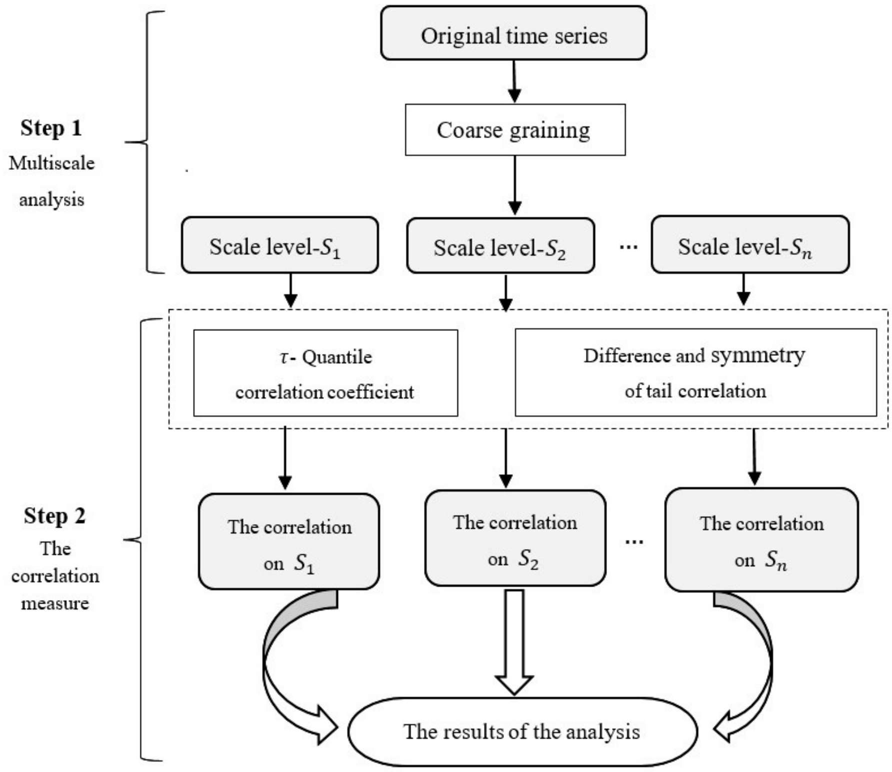


Figure 1. The framework of the MQCC method.

3.1. Step 1: Multiscale Analysis

Multiscale analysis is a pre-processing method for data analysis. Before performing data analysis, the data sequence is subjected to multiscale analysis in advance, and we can observe various relationships between the data on different scales. For example, before analyzing the correlation between variables x and y, we can process the variable x as X and the variable y as Y through multiscale analysis. We then analyze the correlation between X and Y. The multiscale analysis allows us to observe the relationship between data on different scales, and it is then possible to discover rules that were not observed in the original time series.

Coarse graining is a common method in the domain of multiscale analysis methods. Coarse grained data involves the averaging of different numbers of consecutive data points to create data signals of different scales. The coarse graining process is divided into two groups: one is the non-overlapping partitioning method, which jumps n data at a time, and averages the n data to generate new data; the second is an overlapping division method, which jumps m $(m \ll n)$ data every time, taking n data as averaged.

This paper chooses the first non-overlapping method for coarse graining. Given a time series containing N data points, the steps for constructing it with coarse graining are as follows: for scale 1, there is no difference between the coarse grained time series and the original sequence, and the sequence length remains the same; for scale n $(n \geq 2)$, the data sequence is divided into consecutive non-overlapping blocks, and each non-overlapping block contains n data points. Then, we calculate the average value in each block, and construct a new time series, as shown in Figure 2. Because the time series composed of the average data of each block is the time series after coarsening, the time series after coarsening will be shorter than the original time series. The above coarse graining process can be described by mathematical symbols as follows:

$$X_j^n = \frac{1}{n}\sum\nolimits_{(j-1)n+1}^{jn} x_i,\ 1 \leq j \leq \frac{N}{n}, \tag{1}$$

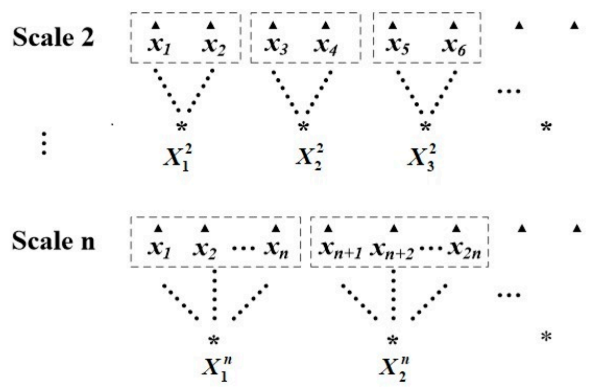


Figure 2. Schematic diagram of coarse graining process.

3.2. Step 2: The Correlation Measure

In traditional correlation analysis, (X, Y) is assumed to be a random variable with a second moment. Let $\sigma_X = Var(X)$, $\sigma_Y = Var(Y)$ and $\sigma_{XY} = Cov(X, Y)$. We found that $\beta_{X.Y} = \frac{\sigma_{XY}}{\sigma_X}$ and $\beta_{Y.X} = \frac{\sigma_{XY}}{\sigma_Y}$, where $\beta_{X.Y}$ and $\beta_{Y.X}$ are obtained by minimizing the expected squared errors $E\Big[(Y - \alpha - \beta X)^2\Big]$ and $E\Big[(X - \alpha - \beta Y)^2\Big]$, respectively. The correlation coefficient $\rho = \frac{\sigma_{XY}}{\sqrt{\sigma_X \sigma_Y}} = sign(\beta_{X.Y})\sqrt{\beta_{X.Y}\beta_{Y.X}}$ is the geometric mean of two linear regression coefficients.

Traditional regression analysis focuses on the mean. Specifically, regression analysis uses the function of the conditional mean of the dependent variable to describe the mean of the dependent variable at each specific value of the independent variable. This type of regression model is actually a study of the conditional expectation of the explanatory variable, and describes the change in the conditional mean of the dependent variable, but this is not feasible in the analysis of financial time series. Of course, people also care about the relationship between the explanatory variables and the median, and other quantiles of the distribution of the explanatory variables.

Quantile-related regression techniques were first proposed completely by Bassett and Koenker [41,42]. The effect of explanatory variables on the range of the explanatory variables can be described by quantile regression. In other words, quantile regression can more comprehensively describe the whole picture of the conditional distribution of the explanatory variables. Benefiting from the advantages of quantile regression, the quantile correlation coefficient can be obtained by combining quantile regression and the correlation coefficient, so that the correlation can be measured at different quantile levels. The tail correlation measure in this paper is mainly based on the quantile correlation coefficient.

For any random variable Y, all its properties regarding data distribution can be characterized by the distribution function $F(y) = Prob(Y \leq y)$. For any $\tau \in (0, 1)$, the τ-quantile function $Q(\tau)$ of the random variable Y is defined as follows:

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

The loss function of general τ-quantile regression is shown below:

$$\rho_\tau(u) = u(\tau - I(u < 0)), \tag{3}$$

where $I(Z)$ denotes illustrative function, and Z denotes indicator relation. When the quantile τ is set to 0.5, this is the median regression.

The estimation of τ-quantile regression is achieved by completing the minimum expected loss, by:

$$L_\tau^{X,Y}(\alpha, \beta) = E[\rho_\tau(Y - \alpha - \beta X)],\ L_\tau^{Y,X}(\alpha, \beta) = E[\rho_\tau(X - \alpha - \beta Y)],\ \tau \in (0, 1), \tag{4}$$

where $\rho_\tau(u)$ denotes the loss function of τ-quantile regression.

Given $\tau \in (0,1)$, then the following formula holds:

$$(\alpha_{X.Y}(\tau), \beta_{X.Y}(\tau)) = argmin_{\alpha,\beta} L_{\tau}^{X,Y}(\alpha,\beta), \tag{5}$$

$$(\alpha_{Y.X}(\tau), \beta_{Y.X}(\tau)) = argmin_{\alpha,\beta} L_{\tau}^{Y,X}(\alpha,\beta), \tag{6}$$

The τ-quantile correlation coefficient is defined as the geometric mean of the two τ-quantile regression coefficients $\beta_{X.Y}(\tau)$ and $\beta_{Y.X}(\tau)$ [38], which are specifically expressed as follows:

$$\rho_{\tau}^{X,Y} = sign(\beta_{X.Y}(\tau)) \sqrt{\beta_{X.Y}(\tau)\beta_{Y.X}(\tau)},\ \tau \in (0,1), \tag{7}$$

For given $\tau \in (0,1)$, the size of $\left|\rho_{\tau}\right|$ represents the sensitivity of the conditional τ-quantile of a random variable to the changes of other variables. Regression coefficient estimates under different quantiles are often different, that is, the explanatory variables have different effects on the explanatory variables at different levels. Therefore, it is necessary to compare the differences in the quantile correlation coefficient ρ_{τ} according to different quantiles τ. For example, $\rho_{0.05} > \rho_{0.95}$ means that, compared to the variable 0.95 quantile of a variable, the condition 0.05 quantile of this variable is more sensitive to changes with other variables. If there is a different correlation between the tail of (X, Y) and the rest of (X, Y), then the correlation between X and Y can be described as heterogeneous. Such heterogeneity can be expressed by ρ_{τ}.

In addition, the tail correlation difference measurement index ρ_{τ}^{D} can measure the correlation difference between the (X, Y) quantiles and the 0.5 quantile, as follows:

$$\rho_{\tau}^{D} = \rho_{\tau} - \rho_{0.5},\ \tau \in (0,1), \tag{8}$$

If $\rho_{\tau}^{D} \neq 0$, it means that the conditional τ-quantile of one variable is not as sensitive to changes in other variables as the conditional median of the variable.

The difference in correlation between the left and right symmetric quantiles can be reflected by ρ_{τ}^{S}. The tail correlation symmetry metric ρ_{τ}^{S} is defined as follows:

$$\rho_{\tau}^{S} = \rho_{\tau} - \rho_{1-\tau},\ \tau \in (0,0.5), \tag{9}$$

4. Simulation

In this section, we generate several artificial time series so as to verify the effectiveness of the MQCC method. First, assume that X and λ satisfy the standard normal distribution, and are independent, and let $Y = X^5 + 2\lambda$. We can observe the correlation between variables X and Y through the MQCC method. Figure 3 shows the correlation between X and Y on different scales and at different quantiles. It is obvious that the tail correlation between X and Y is stronger than the correlation at the median quantiles level. The highest difference between the quantile correlation coefficient at the left tail and the 0.5 quantile correlation coefficient is 0.3. However, the highest difference between the right tail and the 0.5 quantile correlation coefficient is 0.35. The results of the correlation difference show that the right tail correlation of X and Y is stronger than the left tail correlation. On the time scales [1,20], the correlation difference between the left and right tails can be as high as 0.11. The correlation coefficients of X and Y also fluctuate on different time scales. For example, the 0.01 quantile correlation coefficient of X and Y is significantly higher on the time scales [11,19] than on the time scales [3,11]. The correlation coefficient of the right tail 0.99 quantiles of X and Y on the time scales [11,19] is significantly lower than on the time scales [3,11]. With the help of the MQCC method, we can clearly observe the overall picture of the correlation between the variables X and Y in the above example. In particular, differences in tail correlation were also revealed.

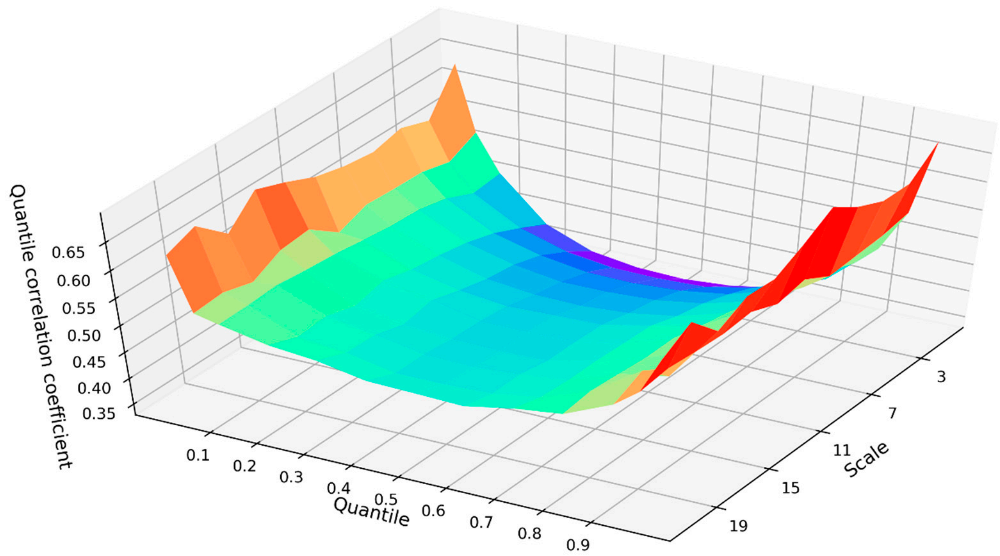


Figure 3. MQCC of linear simulation model.

Next, we use the classic Hénon map to generate data, and study the tail dependence:

$$\begin{cases} x_t = 1 + y_{t-1} - a x_{t-1}^2 \\ y_t = b x_{t-1} \end{cases}, \tag{10}$$

where $a = 1.4$, $b = 0.3$, $t = 1, \cdots, N, N = 10^4$. The correlation of simulated sequences x and y, on different scales and at different quantiles, is shown in Figure 4. The quantile correlation coefficients of x and y change in the same direction as the time scale. In other words, as the time scale increases, the positive correlation between x and y becomes stronger. Similar to the results of the above linear model, the tail correlation of the sequences x and y simulated by Hénon mapping is also stronger than the correlation at other quantiles. Compared with the 0.5 quantile correlation coefficient, the difference between the left tail quantile correlation coefficient of x and y and the 0.5 quantile correlation coefficient can be up to 0.5, and the right tail quantile correlation coefficient has a difference up to 0.17. We can also clearly observe that the correlation between the left and right tails is obviously asymmetric. The correlation between the left and right tails is stronger, and the correlation difference between the left and right tails can be as high as 0.71. With the MQCC method, we can observe the correlation difference between sequences simulated by Hénon mapping. Such results also indirectly confirm the effectiveness of the method in this paper.

It is worth noting that both of the above simulation series show that the tail correlation to be stronger than it is at other quantiles. At the same time, we predict that in real financial markets, the tail correlation between financial assets will display certain characteristics that are not seen normally. This is because, in terms of revenue distribution, extreme returns tend to be distributed at the tail. Investors are inclined to react more strongly to extreme returns than usual. This phenomenon may be explained by the herd effect and risk aversion in behavioral finance. In the face of extreme returns, investors in financial markets often show limited rationality, which may even cause herd behavior. In addition, most investors in financial markets are risk-averse. For example, investors in the stock market are often more sensitive when facing extreme negative returns. This can also be described as overreaction. Furthermore, financial markets are more likely to move together during the crisis.

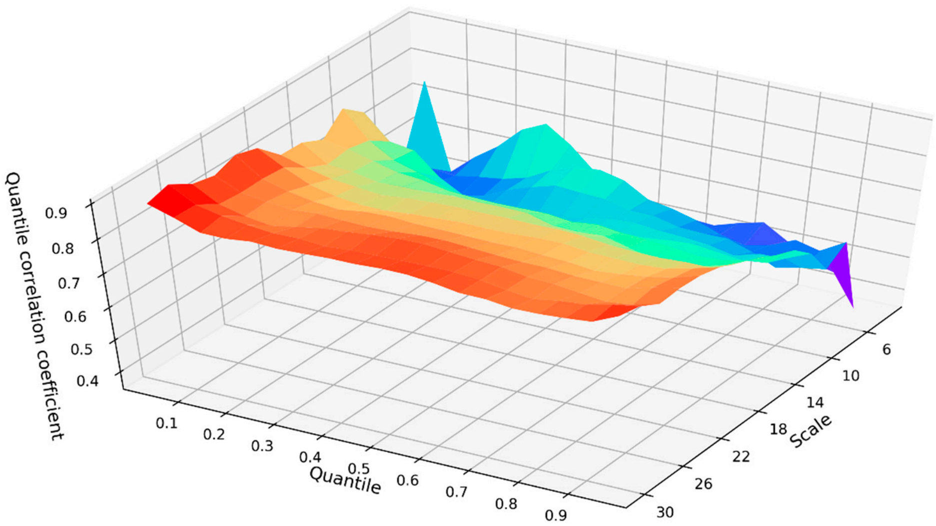


Figure 4. MQCC of the nonlinear simulation model.

5. Data Description of Financial Time Series

The time series set analyzed comes from three types of financial sub-markets, namely the stock market, the gold market and the foreign exchange market (see Supplementary Materials). First, the samples of the stock market are taken from the daily closing prices of major stock indices throughout the world, including the S&P 500 of the US, China's HIS and the UK's FTSE 100. The stock series were collected from January 1, 2000 to December 31, 2019. Secondly, the objects of the research in the gold market include LONDON Gold in the UK, SHFE Gold in China and COMEX Gold in the US. The gold market's daily closing price series were recorded from January 1, 2015 to December 31, 2019. Lastly, the research sample for the foreign exchange market includes the daily closing prices of DINIW (US dollar index), USDCNY (USD/CNY), EURCNY (EUR/CNY) and EURUSD (EUR/USD). The series from the foreign exchange market were recorded from 1 June 2009 to 31 December 2019. It is worth mentioning that the periods from which the daily closing price series of the three types of market were collected are not the same, due to the availability of data. However, the different lengths of the financial time series sets analyzed is indirect evidence of the universality of the MQCC method proposed in this paper. After excluding different markets and different open trading days from the samples of the above financial time series, there are 4534 data remaining in each stock market, 1152 data in each gold market, and 2580 data in each foreign exchange market. Let $\{x_t\}$ denote the daily closing price sequence of the financial markets. For the purpose of eliminating possible heteroscedasticity in financial time series, the logarithmic daily return is defined by

$$r_t = \log x_t - \log x_{t-1}, \tag{11}$$

According to the series of returns of each financial market, we carry on the descriptive statistics to the data, and get the statistical result of returns as shown in Table 1 below. As regards the means of the selected financial markets, the overall mean of the gold markets is greater than the overall mean of the stock markets, but the overall mean of the foreign exchange markets is the lowest. SHFE Gold has the highest mean value in the gold markets, and S&P 500 has the highest mean value in the stock markets. The standard deviation results show that the stock markets are the most volatile, followed by the gold markets, and the foreign exchange markets fluctuate less than the former two. In the analysis results of kurtosis, the overall kurtosis of the stock markets is the largest, while those of the gold markets and the foreign exchange markets are similar. The kurtosis of all three financial markets are far greater than 3, especially that of the USDCNY, which is as high as 14.88703. From the angle of skewness, the stock markets are left-skewed, while the time series of gold markets and foreign exchange markets are mainly right-skewed. Compared with the normal distribution, the stock markets show the characteristics of left deviation and peak, while the gold markets and the foreign exchange markets show the characteristics of right deviation and peak. From Jarque-Bera statistics and corresponding P values, it can be concluded that the time series of the three types of financial markets reject the hypothesis of normal distribution. From the above analysis, it can be seen that the return series of the three kinds of financial markets have all shown the characteristics of peak and fat tail of the financial time series, and we can also see that the three kinds of financial markets have all shown significant volatility clustering.

Table 1. Statistical result of financial time series.

	Mean	Maximum	Minimum	Std.Dev	Kurtosis	Skewness	Jarque-Bera	Probability
HIS	0.00011	0.13407	−0.14695	0.01515	13.05600	−0.29515	19165.45000	0.00000
S&P 500	0.00019	0.10957	−0.13777	0.01243	13.72552	−0.40354	2850.60000	0.00000
FTSE 100	0.00003	0.09384	−0.10327	0.01200	10.08142	−0.20588	9503.43700	0.00000
LONDON GOLD	0.00025	0.05471	−0.03941	0.00775	6.64210	0.36641	666.91850	0.00000
COMEX GOLD	0.00016	0.04639	−0.04450	0.00801	5.31363	0.07267	257.72810	0.00000
SHFE GOLD	0.00026	0.04530	−0.04041	0.00783	6.85354	0.33742	734.01260	0.00000
USDCNY	0.00001	0.01810	−0.01150	0.00174	14.88703	0.54060	15309.65000	0.00000
EURCNY	−0.00008	0.02842	−0.02704	0.00545	5.25942	0.00346	548.57770	0.00000
EURUSD	−0.00009	0.03016	−0.02716	0.00574	4.88805	−0.05407	384.31620	0.00000
DINIW	0.00008	0.02495	−0.02142	0.00468	4.78914	0.03184	344.41240	0.00000

6. Results and Analysis of Financial Time Series

Financial markets are essential in regulating economic development and promoting social progress. Different types of markets have different roles. The stock markets can reflect the development of a region's economy, and are often called "the barometer" of the economy. Gold has scarcity and currency attributes, and it has vital strategic significance in economic development. It is often called "safe haven" for investors. Foreign exchange is not only an important part of a country's international reserves, but is also an indispensable tool for international economic exchanges. Considering that different types of markets have different roles, stock, gold and foreign exchange respectively occupy crucial positions in the financial markets. A phenomenon known as "financial contagion" exists in financial markets. During the financial crisis, we often found that when a market suffered severe turbulence for the first time after the shock, this turbulence could spread to many other markets and countries as quickly as an "infectious disease" [43]. As a result, the correlation between different markets or different assets at this time becomes much stronger than that in the quiet period. In other words, the distribution result of financial assets return show that the correlation is different at the tail of the distribution and at the middle of the distribution. Therefore, this paper analyzes the correlation difference of the three types of financial time series from the two viewpoints of time scale and quantile level, especially regarding the tail correlation.

6.1. Stock Market

It is useful to study the price dependence between stock markets in different regions, because the supply and demand relationship of the stock markets can be quickly reflected in prices. This paper selects the S&P 500 in the US, the HIS in China and the FTSE 100 in the UK as research objects. There are two reasons for choosing these stock indices. One is that these stock indices are important indices in the international stock markets, and the other is that these stock indices belong to different regions, respectively in the Americas, Asia and Europe. In this paper, the time scales are set to [1, 20], and the quantile levels are marked as [0.05, 0.95] (sampling interval is 0.05). Before applying the MQCC method, we first use the traditional correlation coefficient to test the correlation of the stock time series. The measurement results are shown in Figure 5 below. The traditional correlation coefficient measurement results show that the correlation of the stock series is enhanced with the increase of the time scale. The S&P 500 and the FTSE 100 have the highest overall correlation. The correlation between the HIS and the FTSE 100 is stronger on the lower scale than the correlation between the HIS and the

S&P 500. As the time scale increases, the correlation between the HIS and the FTSE 100 is not much different from the correlation between the HIS and the S&P 500. However, the results of the traditional correlation coefficient cannot reveal the strength of the tail correlation, and such a measurement is not accurate enough.

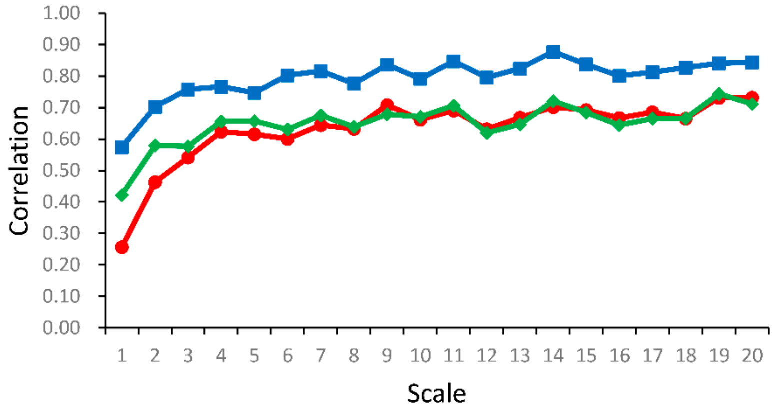
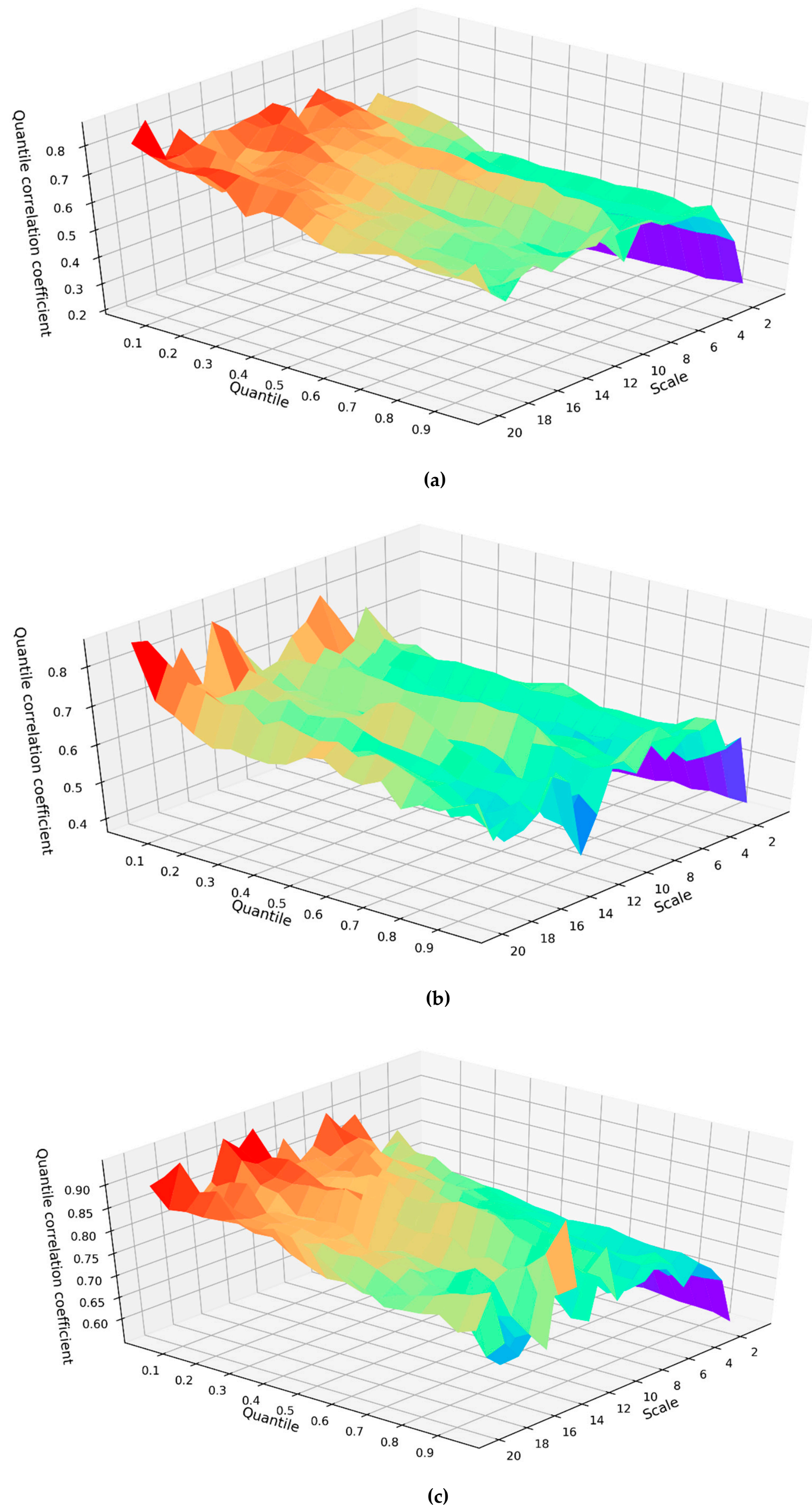


Figure 5. Measurement results of traditional correlation coefficient in stock time series.

The MQCCs of the stock time series are shown in Figure 6 below. From the three-dimensional figure, we can clearly see that the returns between these stock markets show a positive correlation, and the τ-quantile correlation coefficient between the two markets increases with the increase of the time scale. At the level of raw data ($\text{scale} = 1$), the quantile correlation coefficients of the returns of the HIS and the S&P 500 fluctuated between [0.20, 0.28], the quantile correlation coefficients of the HIS and the FTSE 100 fluctuated between [0.38, 0.47], and the quantile correlation coefficients of the S&P 500 and the FTSE 100 fluctuated between [0.55, 0.61]. From the whole trend, the correlation between the returns of the S&P 500 and the FTSE 100 was stronger than the correlation of the returns of the HIS and the FTSE 100. The correlation between the HIS and the S&P 500 was the lowest. On the lower time scales ($2 \leq \text{scale} \leq 7$), the quantile correlation coefficients of the returns of HIS and S&P 500, HIS and FTSE 100, and S&P 500 and FTSE 100 fluctuated respectively in the intervals [0.40, 0.72], [0.51, 0.75] and [0.64, 0.89]. On the medium time scales ($8 \leq \text{scale} \leq 14$), the correlation fluctuation ranges of the returns of the three stock indices changed to [0.50, 0.77], [0.44, 0.81] and [0.68, 0.94]. On the higher time scales ($\text{scale} \geq 15$), there was not much difference from the middle time scales. The quantile correlation coefficients fluctuated within the intervals of [0.53, 0.87], [0.53, 0.86] and [0.68, 0.94]. Among them, the quantile correlation coefficients between two of three stock markets were higher when the time scale was set to around 14.

In addition, the quantile correlation coefficients of the time series of the two markets also differ significantly at different quantile levels. The positive correlation of the left tail is stronger than that of the right tail. In the left tail ($\tau \leq 0.1$), the quantile correlation coefficients of the returns of the HIS and the S&P 500, the HIS and the FTSE 100, and the S&P 500 and FTSE 100 respectively fluctuated within the intervals of [0.26, 0.87], [0.45, 0.84] and [0.61, 0.94]. However, in the right tail ($\tau \geq 0.9$), the quantile correlation coefficients of the corresponding stock markets fluctuated in the ranges [0.22, 0.71], [0.39, 0.70] and [0.55, 0.94], respectively. The strong correlation of the left tail may be explained by risk aversion in behavioral finance research. The attitude of most investors towards extreme returns is often unusual.



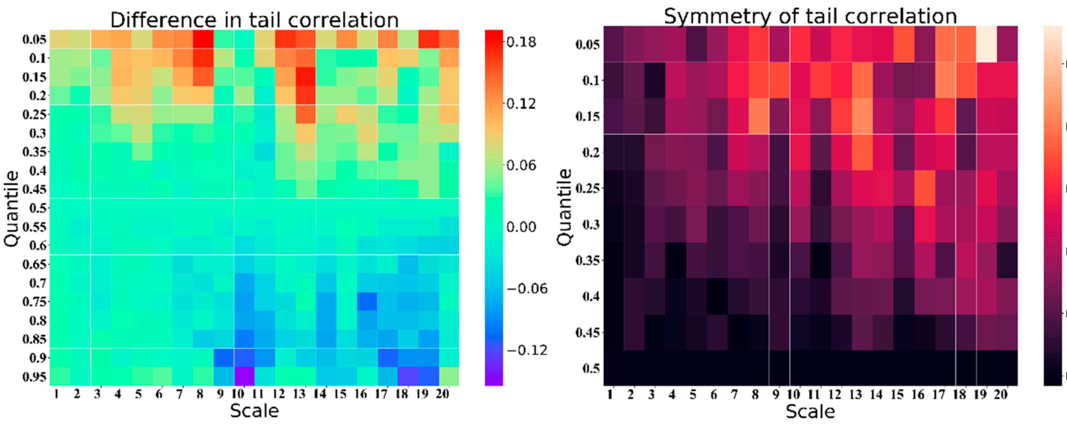
(a)

(b)

(c)

Figure 6. The MQCC of stock time series: (**a**) HIS and S&P 500; (**b**) HIS and FTSE 100; (**c**) S&P 500 and FTSE 100.

The difference and symmetry analysis results of the tail correlation among the returns of the stock markets are shown in Figure 7 below. Judging from the tail correlation metric difference index ρ_τ^D, compared with the 0.5 quantile correlation coefficient, the correlation difference between the left tail and the 0.5 quantile was greater than that of the right tail. Among the correlations between the HIS and the S&P 500, the HIS and the FTSE 100 and the S&P 500 and the FTSE 100, the correlation differences between the left tail and 0.5 quantiles fluctuated by [0.00, 0.19], [−0.02, 0.23] and [0.01, 0.17], respectively. However, the differences between the right tail and 0.5 quantiles fluctuated within [−0.16, 0.05], [−0.18, 0.12] and [−0.18, 0.10], respectively. The tail correlation symmetry measure ρ_τ^S also reflects the obvious difference between the left and right tails' correlation, and the tail correlations were asymmetric. Among them, the maximum difference between the left tail correlation and right tail correlation of the HIS and the S&P 500, the HIS and the FTSE 100 and the S&P 500 and the FTSE 100 were up to 0.28, 0.29 and 0.27, respectively.



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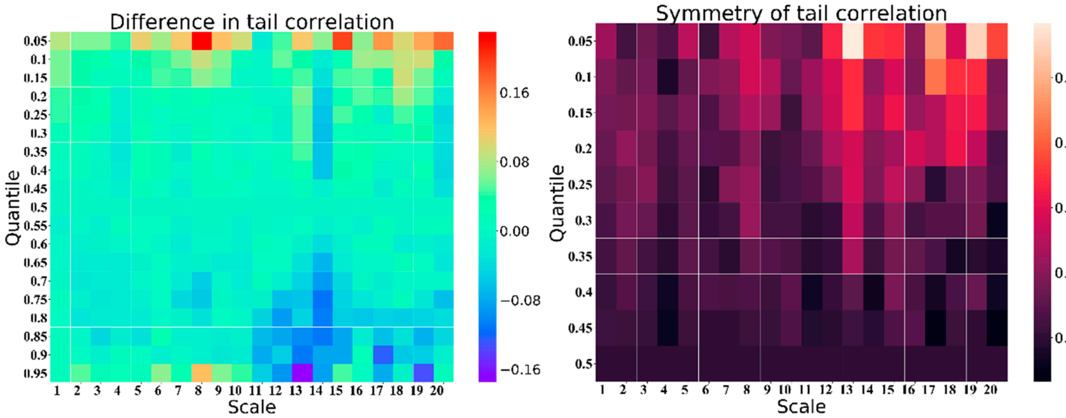

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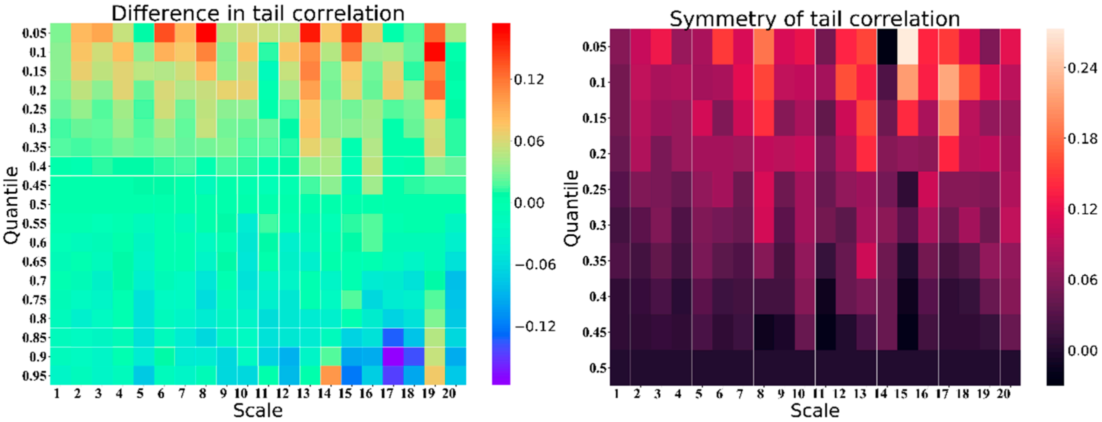

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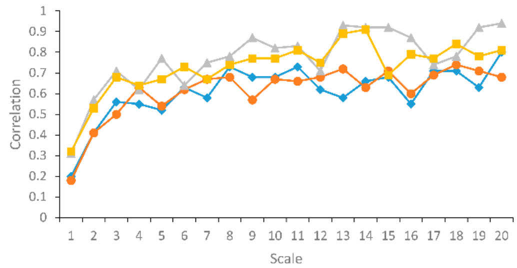
Figure 7. Difference and symmetry of tail correlation of stock time series: (**a**) HIS and S&P 500; (**b**) HIS and FTSE 100; (**c**) S&P 500 and FTSE 100.

In particular, we expect that the returns of financial assets will fluctuate sharply during the financial crisis, and the tail correlation between financial markets will be different from before. Our expectations are based on the theoretical and empirical financial literature, focusing on various findings [23,32,44]. Using the 2008 financial crisis as the time node, this paper divides the original financial time series into two parts, before and after the financial crisis, and uses the quantile correlation coefficient to observe the correlation differences between the stock markets. Figures 8 and 9 provide the tail correlation before and after the financial crisis.



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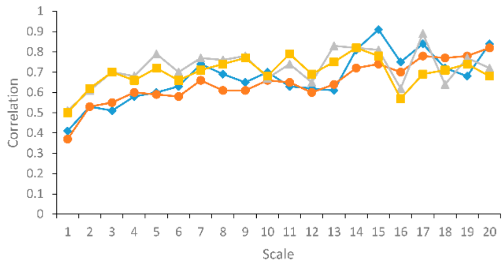

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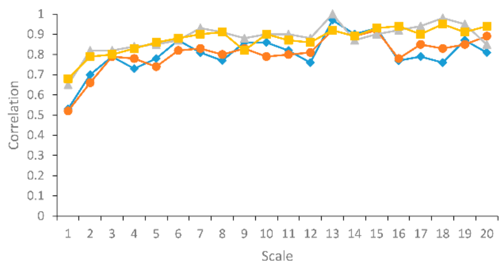

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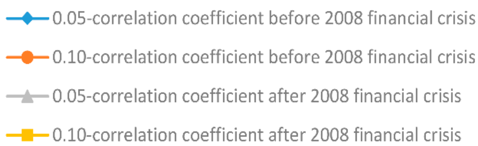
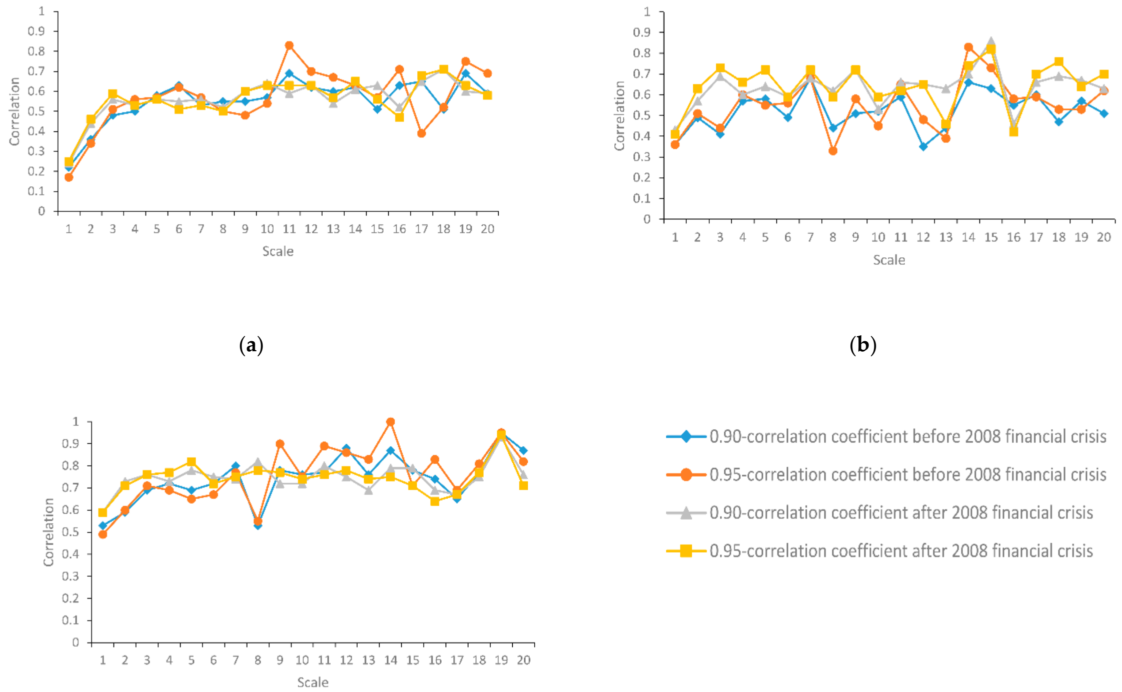


(**d**)

Figure 8. The MQCC of the left tail of stock time series before and after the 2008 financial crisis: (**a**) HIS and S&P 500; (**b**) HIS and FTSE 100; (**c**) S&P 500 and FTSE 100; (**d**) Explanation of different types of lines.



(**a**) (**b**)

(**c**) (**d**)

Figure 9. The MQCC of the right tail of stock time series before and after the 2008 financial crisis: (**a**) HIS and S&P 500; (**b**) HIS and FTSE 100; (**c**) S&P 500 and FTSE 100; (**d**) Explanation of different types of lines.

On the whole, whether before the 2008 financial crisis or after the financial crisis, the returns of the S&P 500 and FTSE 100 showed the strongest positive correlation. The left tail correlation after the financial crisis is significantly higher than the left tail correlation before the financial crisis on different time scales, and the correlation of the left tail becomes stronger with the increase of the time scale. The right tail correlation after the financial crisis is also different. However, the correlation difference between the right tail before and after the financial crisis is not as obvious as the correlation difference between the left tail before and after. This shows that when facing extremely negative returns, the stock markets' linkages in different regions are relatively strong. Tail symmetry was also found to be different. Before the financial crisis, the maximum differences between the left and right tails of the HIS and the S&P 500, the HIS and the FTSE 100 and the S&P 500 and the FTSE 100 were up to 0.31, 0.36 and 0.27, respectively. However, after the financial crisis, the maximum differences between the left and right tails of the three stock markets were larger than before the financial crisis, reaching 0.39, 0.37 and 0.30, respectively. The asymmetry between the left and right tails has increased since the financial crisis.

The empirical results of the MQCC method in the stock markets have brought some inspiration to investors. The MQCC method accurately detects the tail correlation in the stock markets more strongly than it does the correlation in other quantiles. Such results may be explained by the herd effect in behavioral finance. Investors often have a herd mentality, and their reactions to extreme returns are usually strong. More specifically, the MQCC method also reveals that the left tail correlation in the stock market is stronger than the right tail correlation. Such phenomena may be related to risk aversion in behavioral finance. Most investors in the stock markets are risk-averse. Investors are often more sensitive when facing extreme negative returns (left tail), that is, they overreact. However, when they face extreme positive returns (right tail), the response is often not as strong as when they face negative returns, which is called underreaction. In addition, the results of the MQCC method indicate that the correlation of the time series of stocks increases as the time scale increases. The implication for investors is that, when judging the price dependence of two markets based on historical price information, they should not be limited to the original daily sequence's information. Appropriately pulling the time scale will allow investors to observe clearer long-term trends. Investors in the stock market should be more cautious when facing extreme returns, and reduce herd behavior. In this way, investors are more likely to make investment decisions rationally.

6.2. Gold Market

The development of the gold markets has increased the number of investment channels for investors, which can largely diversify investment risks and play a role in preserving and increasing value. In addition, the gold markets have provided countries with new tools for monetary policy operations. In other words, countries can adjust the composition and quantity of international reserves by buying and selling gold in the gold markets, and thus further control the money supply. This paper mainly analyzes the correlation between returns in the LONDON Gold market in the UK, the COMEX Gold market in the US, and the SHFE Gold market in China. These three gold markets are also distributed across different continents, and occupy an indispensable position in the international gold markets. Similarly, the traditional correlation coefficient method is used to test the correlation of the gold markets, as shown in the Figure 10. LONDON Gold and COMEX Gold have always maintained a high positive correlation, and the correlation coefficient between them has been greater than 0.9. Although the correlation between LONDON Gold and SHFE Gold, and COMEX Gold and SHFE Gold, is not as strong as that between LONDON Gold and COMEX Gold, they have all maintained a relatively high level of positive correlation. Compared with stock series, the correlation between gold series tends to be stable when the time scale is at a medium level or above. More subtle measurement results should also be expressed through the MQCC method.

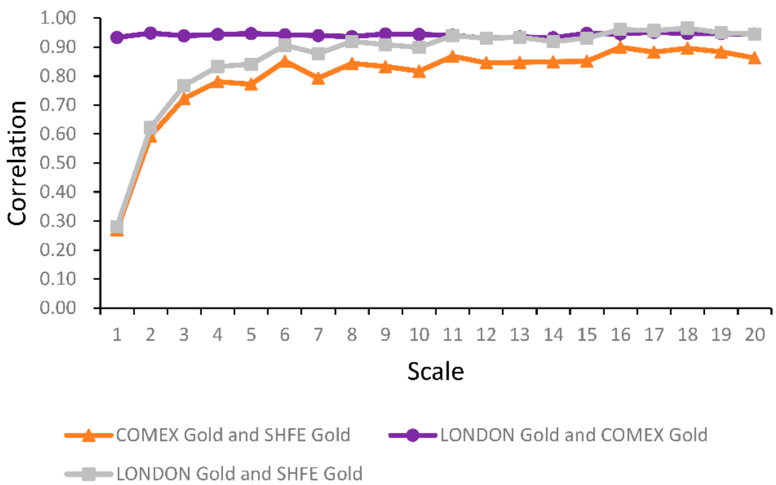


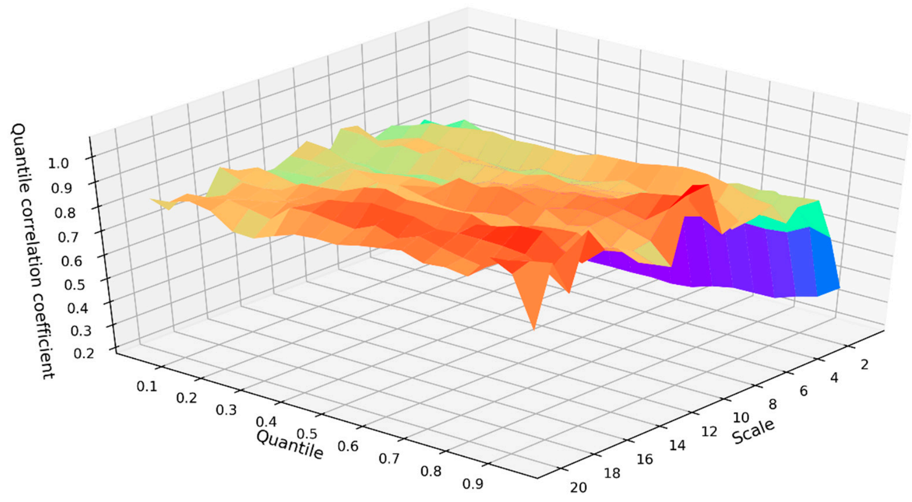
Figure 10. Measurement results of traditional correlation coefficient in gold time series.

Figure 11 provides the results of the correlation between gold time series measured by the MQCC method. Overall, the correlation between the returns of the gold markets is stronger than that of the stock markets, and it also shows a clear positive correlation. With the increase of time scale, the correlations between COMEX Gold and SHFE Gold, and LONDON Gold and SHFE Gold, get stronger. At the level of raw data, the quantile correlation coefficients between COMEX Gold and SHFE Gold, and LONDON Gold and SHFE Gold, fluctuated within the ranges of [0.19, 0.37] and [0.19, 0.39], respectively. When the observed time scales were lower ($2 \leq$ scale ≤ 7), the corresponding quantile correlation coefficients changed, to fluctuate within the ranges of [0.58, 0.91] and [0.60, 0.95]. However, with medium and high time scales (scale ≥ 8), the returns of COMEX Gold and SHFE

Gold, and LONDON Gold and SHFE Gold, showed strong correlation, and the quantile correlation coefficients were in the intervals [0.78, 1] and [0.88, 1]. In contrast, the quantile correlation coefficients of returns between LONDON Gold and COMEX Gold have not changed significantly over time. The returns of these two markets have maintained a high correlation for a long time, with correlation coefficients greater than 0.83. From different quantile levels, the results of the gold markets and the stock markets are exactly the opposite. The correlation between each pair in the three gold markets was higher in the right tail $(\tau \geq 0.9)$ than the left tail $(\tau \leq 0.1)$. In the left tail, the quantile correlation coefficients of the returns of COMEX Gold and SHFE Gold, LONDON Gold and SHFE Gold, and LONDON Gold and COMEX Gold fluctuated in the [0.27, 0.84], [0.22, 0.99] and [0.83, 0.95]. In the right tail, the corresponding quantile correlation coefficients fluctuated in the ranges [0.31, 1], [0.31, 1] and [0.90, 1] respectively. When the quantile was around 0.95 and the time scale around 10, two of the three gold markets had the strongest correlation.

The tail correlation difference and tail symmetry of the returns between the gold markets are shown in Figure 12 below. Compared with the 0.5 quantile correlation coefficient, the correlation difference between the right tail and the 0.5 quantile is greater than the left tail. The difference between the left tail correlation coefficients and the 0.5 quantile correlation coefficient of the returns of COMEX Gold and SHFE Gold, LONDON Gold and SHFE Gold, and LONDON Gold and COMEX Gold fluctuated within the ranges of [−0.17, 0.08], [−0.09, 0.07] and [−0.14, −0.03]. In particular, the left tail correlation coefficients of LONDON Gold and COMEX Gold were always lower than the 0.5 quantile correlation coefficient. The difference between the right tail and the 0.5 quantile correlation coefficient fluctuated within the ranges of [−0.15, 0.21], [−0.08, 0.20] and [−0.08, 0.12]. The result of the tail correlation symmetry metric ρ_τ^S show that there was also asymmetry in the tail correlation of the returns between gold markets, and the right tail was significantly stronger than the left tail. The maximum difference between the right tail and the left tail of COMEX Gold and SHFE Gold was up to 0.31. Such difference could be as high as 0.19 in LONDON Gold and SHFE Gold, and as high as 0.24 in LONDON Gold and COMEX Gold.

Overall, there is a long-term positive correlation between the gold price series, which may be related to the precious metal characteristics of gold. Gold has a certain degree of value preservation function, and the price fluctuations in the gold market are less affected by human factors. If investors in the financial market tend to maintain their value, then gold products will be a good choice. Unlike in the stock market, the MQCC revealed that the right tail correlation in the gold price series is stronger than the left tail. This shows that the gold market is more likely to move together during the bull market. In the face of extreme positive returns on gold assets, investors' reactions are relatively strong, and investors' risk aversion is more pronounced. Although gold has a certain degree of value preservation function, investors should also remain rational and avoid tail risks as much as possible.



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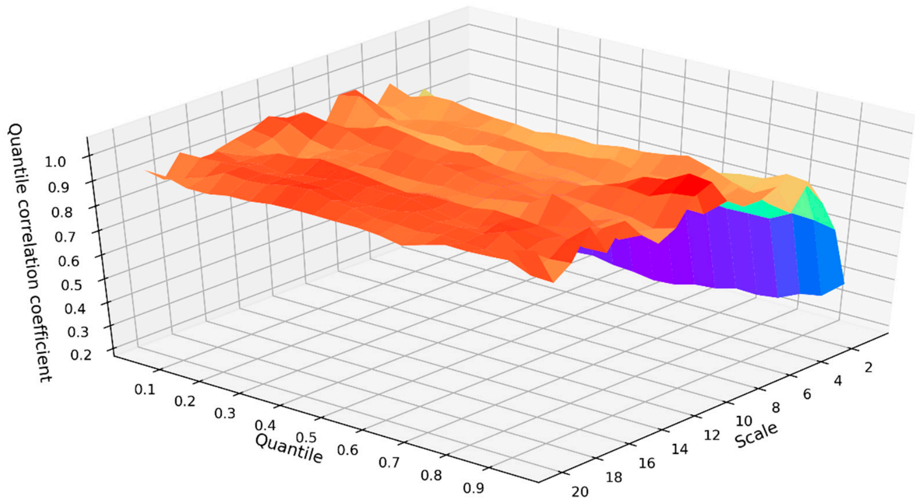

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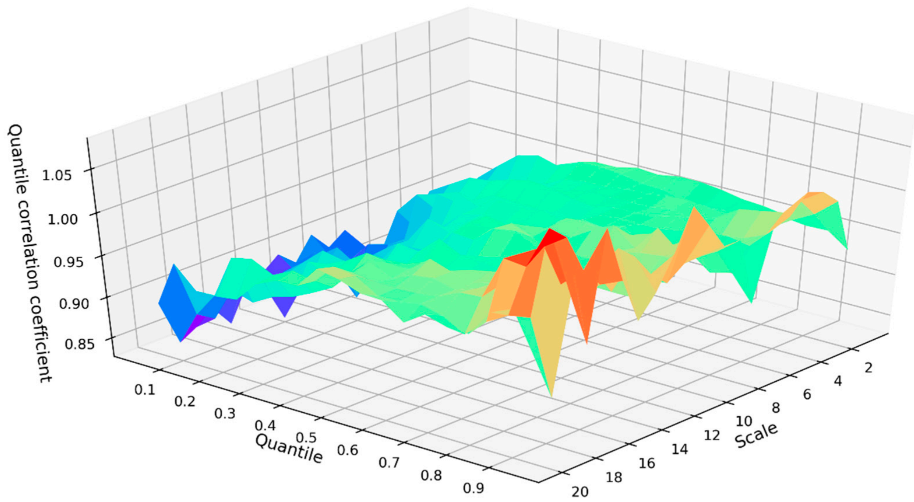

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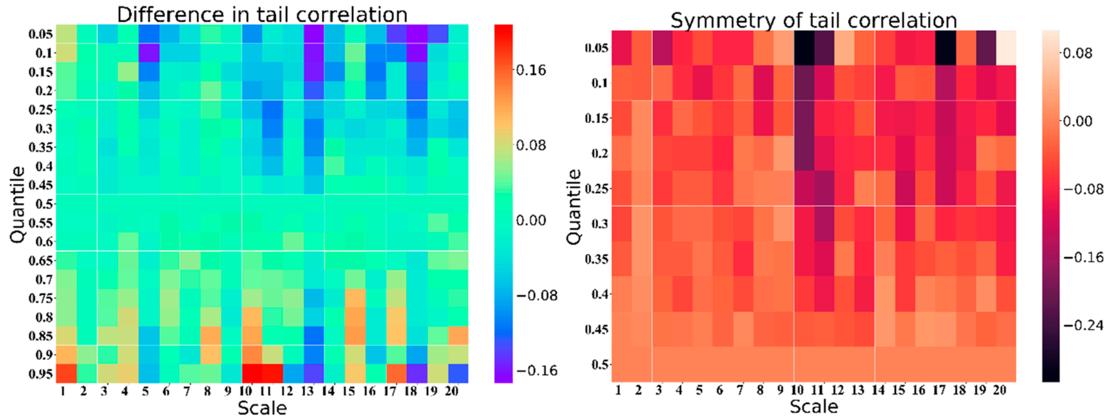
Figure 11. The MQCC of gold time series: (**a**) COMEX Gold and SHFE Gold; (**b**) LONDON Gold and SHFE Gold; (**c**) LONDON Gold and COMEX Gold.



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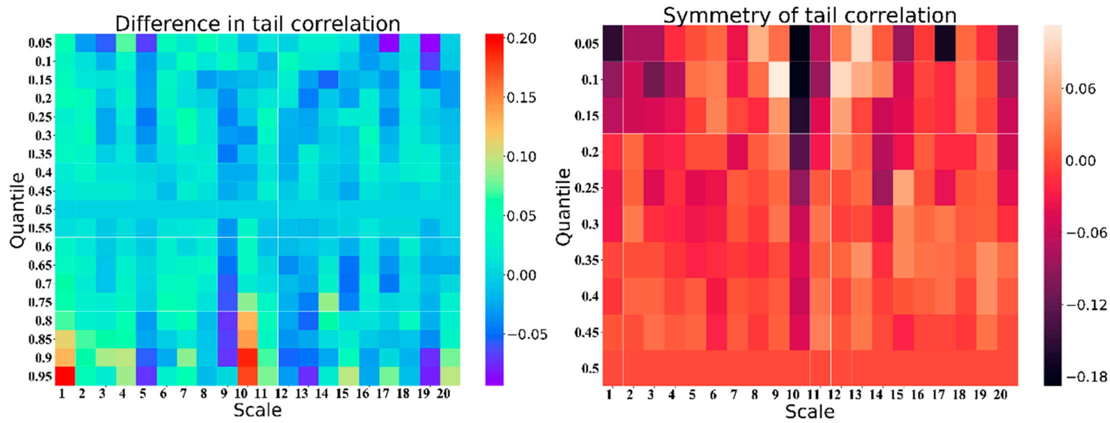

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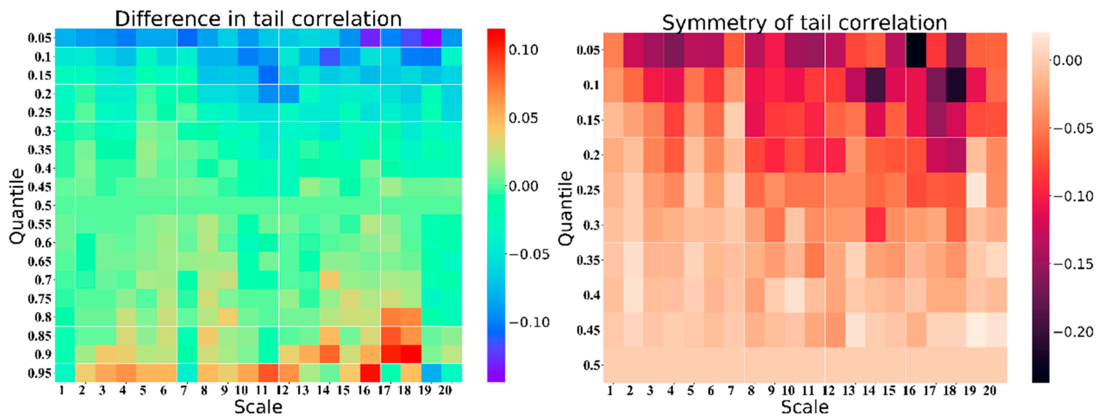


(c)

Figure 12. Difference and symmetry of tail correlation of gold time series: (**a**) COMEX Gold and SHFE Gold; (**b**) LONDON Gold and SHFE Gold; (**c**) LONDON Gold and COMEX Gold.

6.3. Foreign Exchange Market

The US dollar index is an indicator that reflects changes in the exchange rate of the US dollar in international foreign exchange markets, and is a standard for changes in the exchange rate of the US dollar. The public can judge the current value of the US dollar from the US dollar index, and infer possible changes in the market situations of the foreign exchange markets. Therefore, the US dollar index can be used as a tool to measure the value of the US dollar, from which people can judge the flow of capital and capital output in the US. Therefore, this paper selects the US dollar index as the main research object, and studies the correlation between the US dollar index (DINIW) and internationally important exchange rates (EURUSD, USDCNY and EURCNY). The results of measuring the correlations between foreign exchange markets through traditional correlation coefficients are shown in the Figure 13 below. Unlike the stock market and the gold market, the overall correlation in the foreign exchange market shows a positive correlation, while some aspects show a negative correlation. Obviously, this type of measurement is still a bit rough.

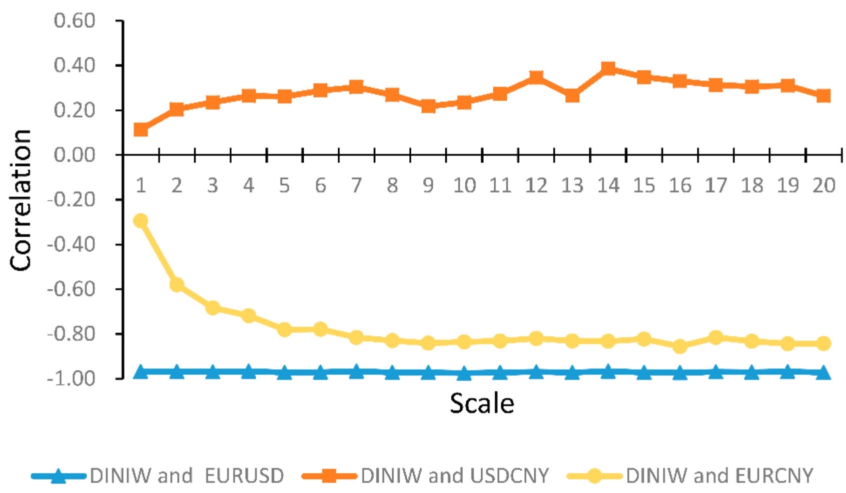
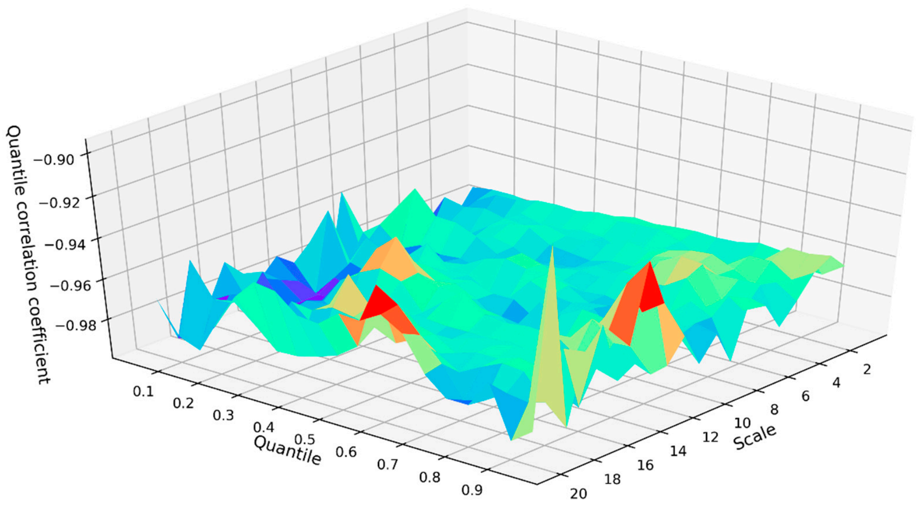


Figure 13. Measurement results of traditional correlation coefficients in foreign exchange time series.

The precise measurement results of the MQCC method in the foreign exchange markets are shown in Figure 14. On the whole, DINIW has the strongest correlation with EURUSD, followed by the DINIW and EURCNY, and the weakest correlation between returns was found in the DINIW and USDCNY. Among them, the DINIW and EURUSD, and the DINIW and EURCNY, showed negative correlation, while the DINIW and USDCNY showed a positive correlation. The quantile correlation coefficients between the DINIW and EURUSD did not change significantly on different time scales, and the quantile correlation coefficients were all less than –0.90, which means that the two markets have always maintained high negative correlation. The reason for this result may be related to the composition of the DINIW. The DINIW is calculated based on the geometric average weighted value of changes in the exchange rates of the six currencies against the dollar; the Euro is one of these six currencies, and accounts for 57.6%. With the increase of the time scale, the positive correlation between the DINIW and USDCNY has gradually increased. At the original data level ($scale = 1$), the quantile correlation coefficients between the DINIW and USDCNY were between [0.04, 0.21]. On the lower time scales ($2 \leq scale \leq 7$) and on the higher time scales ($scale \geq 15$), the quantile correlation coefficients between the two foreign exchange indices were between [0.15, 0.41] and [0.17, 0.57], respectively. With the increase of scale, the negative correlation between the DINIW and EURCNY strengthens.



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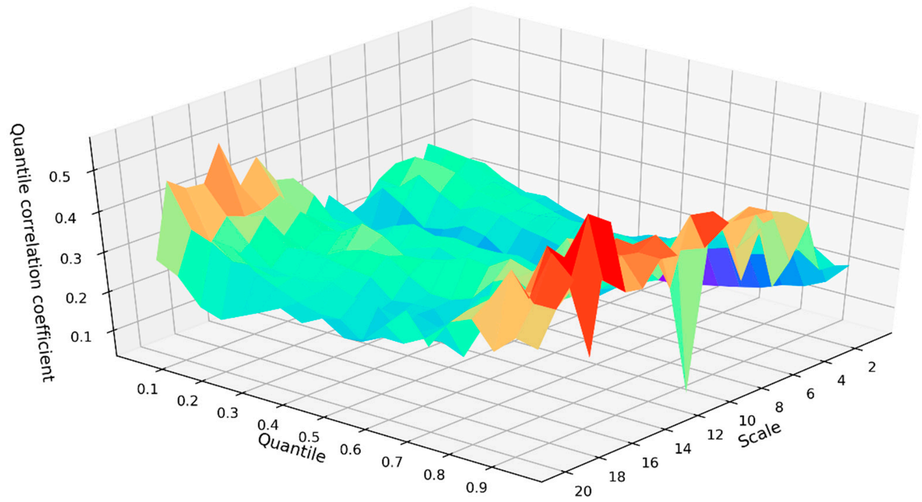

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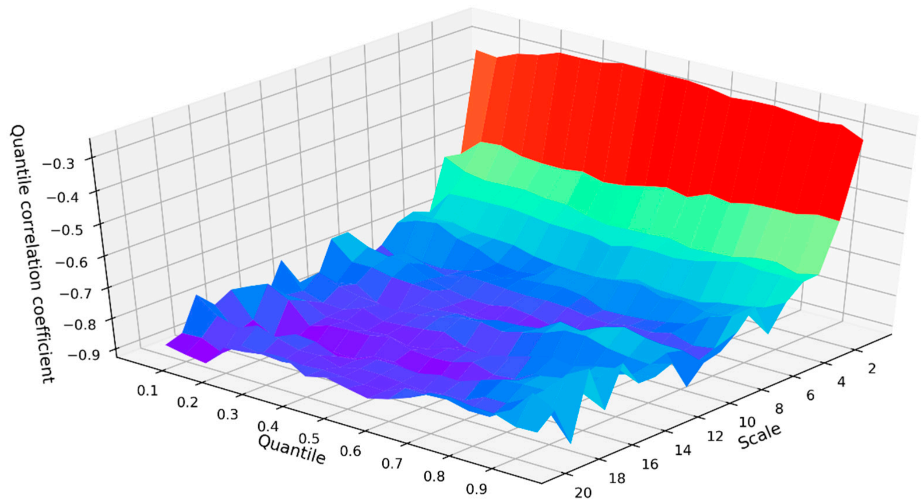

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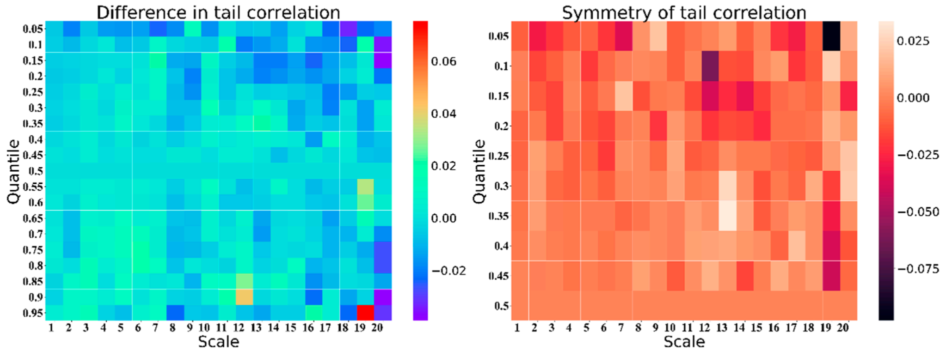
Figure 14. The MQCC of foreign exchange time series: (**a**) DINIW and EURUSD; (**b**) DINIW and USDCNY; (**c**) DINIW and EURCNY. Among them, DINIW means the US dollar index, EURUSD means the euro against the dollar, USDCNY means the dollar against the Chinese yuan, EURCNY means the euro against the Chinese yuan.

The difference and symmetry analysis results for the tail correlation between the foreign exchange markets are shown in Figure 15. Compared with the 0.5 quantile correlation coefficient, the tail correlation difference between the DINIW and EURUSD is not obvious. The left and right tails of the DINIW and USDCNY, and the right tail of the DINIW and EURCNY, are significantly different from the 0.5 quantile correlation coefficient. Among them, the difference between the left tail and the 0.5 quantile correlation coefficient of the DINIW and USDCNY was up to 0.27, and the difference between the right tail and the 0.5 quantile was up to 0.33. In addition, ρ_{τ}^{S} shows that there was significant asymmetry in the tail correlation between the DINIW and USDCNY, and DINIW and EURCNY, in these three foreign exchange markets. The positive correlation between the right tails of the DINIW and USDCNY was significantly stronger than that for the left tails, with a difference of up to 0.24. For the DINIW and the EURCNY, the negative correlation at the left tail was stronger than the negative correlation at the right tail. This tail difference could be as high as 0.17.



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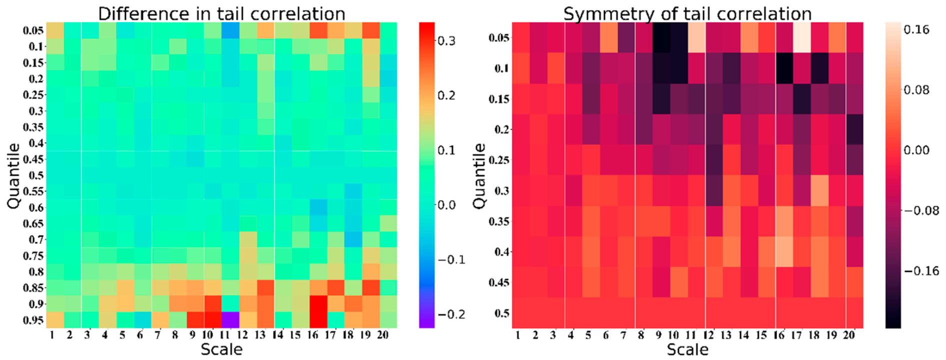

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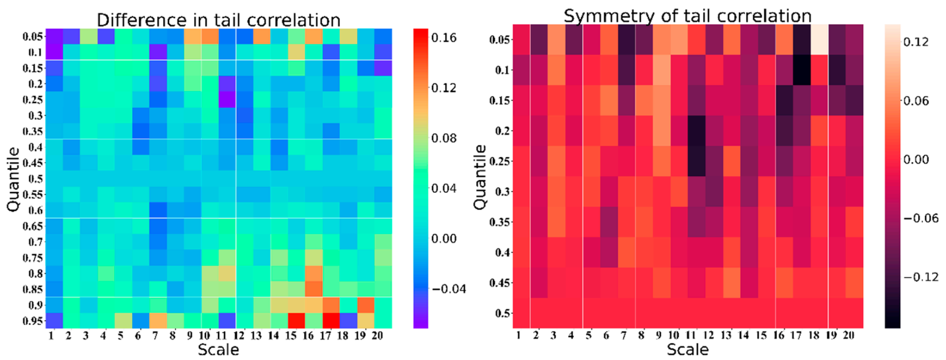

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Figure 15. Difference and symmetry of tail correlation of foreign exchange time series: (**a**) DINIW and EURUSD; (**b**) DINIW and USDCNY; (**c**) DINIW and EURCNY.

In contrast, the results of the MQCC method for the foreign exchange markets are significantly different from those in the stock and gold markets. With the change of time scale, the correlations between foreign exchange price series have no consistent rules. Among them, the change in the correlation between DINIW and EURCNY was most obvious as the time scale increased. In addition, the tail correlation revealed by MQCC also has no consistent rules. For example, the right tail correlation of DINIW and USDCNY was stronger than the left tail correlation, while the left tail negative correlation of DINIW and EURCNY was stronger than the right tail negative correlation. Such results may be related to the special status of the foreign exchange markets. As a tool of payment and settlement, foreign exchange is an important international reserve of every country. The price changes between foreign exchanges are not only affected by market information, but also by the foreign exchange adjustment policies of governments. Investors in the foreign exchange market should not only pay attention to the information of the historical price of foreign exchange, but also always pay attention to the current political information regarding the governments of various countries.

7. Conclusions

The paper conceives an innovative method of MQCC and applies it to the study of financial time series. Two advantages can be noted for this method, including its ability to achieve the effect of multiscale analysis by means of coarse-grained methods, and to accurately quantify the characteristics of tail correlation between financial time series through the agency of the quantile correlation coefficients. The empirical results of the MQCC method for financial markets demonstrate that, at different time scales, there are obvious differences in correlation, and visible differences are also noted between tail correlation and the correlations of other quantiles. In addition, there are remarkable differences between the tail correlations in different types of financial markets. In the stock market, there tends to be a stronger correlation at the left tail than at the right tail, while in the gold market the contrary holds true, demonstrating a stronger correlation at the right tail than at the left tail. In the foreign exchange market, the difference in tail correlation is not as pronounced as in the aforementioned two types of markets. The results of strong tail correlation may be related to the concepts of herd effect and risk aversion in behavioral finance. Investors in the marketplace tend to have a certain degree of herd mentality, and react intensely to extreme returns. It is hoped that this measurement can help investors adjust their investment plans to some degree, and reasonably avoid risks, thereby further safeguarding the sustainable development of financial markets.

A flaw of this study is that we chose for research the daily closing price series of financial assets, rather than the closing price series of higher frequencies, such as five-minute and ten-minute price series; perhaps the multiscale analysis could discern more obvious regularities in the higher-frequency time series. In recent years, the methods for multiscale analysis, such as wavelet analysis, empirical modal decomposition (EMD) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), are popular in the studies of time series. For example, CEEMDAN can precisely reconstruct the financial time series, and divide the price series into high-frequency and low-frequency components. Besides, the price series of different frequencies each have different economic significance. In the future, these advanced multiscale analysis methods can be combined with quantile correlation coefficients, so as to more accurately measure the multiscale and tail characteristics of correlations in the price series. In turn, it can help to more accurately detect the tail risks in price series, thus promoting the long-term effective operation and sound development of the financial markets. It is certain that the MQCC method proposed in this paper can also be employed in other fields, in order to uncover a greater abundance of information.

Supplementary Materials: The following are available online at http://www.mdpi.com/2071-1050/12/12/4908/s1.

Author Contributions: Conceptualization, C.X., X.Z., J.K; methodology, C.X.; X.Z.; software, C.X.; X.Z.; validation, C.X., X.Z. J.K.; formal analysis, C.X.; investigation, X.Z.; resources, X.Z.; data curation, X.Z.; writing—original draft preparation, C.X.; writing—review and editing, C.X., X.Z.; visualization, J.K.; supervision, J.K.; project administration, J.K. All authors have read and agreed to the published version of the manuscript.

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