

Article

Revisiting the Valuable Roles of Global Financial Assets for International Stock Markets: Quantile Coherence and Causality-in-Quantiles Approaches

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Abstract: We employ the quantile-coherency approach and causality-in-quantile method to revisit the roles of Bitcoin, U.S. dollar, crude oil and gold for USA, Chinese, UK, and Japanese stock markets. The main results show that the impact of global financial assets varies across different investment horizons and quantiles. We find that in most cases, the correlation between global financial assets and stock indexes is not significant or is weakly positive. From the perspective of investment horizons (frequency domain), the correlation in the short term is mostly manifested in Bitcoin, while in the medium and long term it is shifted to dollar assets. At the same time, the relationships are significantly higher in the medium and long term than in the short term. From the point of view of quantiles, it shows a weak positive correlation at the lower quantile. However, the correlation between the two is not significant at the median quantile. At the high quantiles, there is a weak negative linkage. According to the causality-in-quantiles approach results, in most cases global financial assets have different degrees of predictive capacity for the selected stock markets. Especially around the median quantile, the predictive ability was strongest.

Keywords: quantile coherence; causality-in-quantile; global financial assets; stock markets

1. Introduction

Portfolio construction is a hot topic among investors and economists. Asset price fluctuations have become more frequent and the stock market is more volatile due to economic and financial globalization. In this case, the examination of the dynamic role of global financial assets for stock markets is virtual for both investors and policymakers. As for investors, it is needed to consider portfolio construction, appropriate hedging tools, and safe-haven assets when making investment decisions in the stock market. As for policymakers, it is necessary to keep the stock market steady and monitor the development of the whole economy. It is widely accepted that new Bitcoin, traditional gold, crude oil and the U.S. dollar are important global financial asset series which have been attracting attention among investors and economists [1–5]. It follows that analyzing the impact of these financial assets on the investment portfolio from the perspective of spillover effects is also a hot topic [6–8], while previous works mainly discuss this issue from the time domain [6–9]. This motivated us to reassess the role of Bitcoin, traditional gold, crude oil and the U.S. dollar for stock markets from a new quantile perspective to provide fresh evidence for policymakers and investors.

Bitcoin, as an important kind of cryptocurrency, is a new electronic currency that differs from traditional assets, but shares many similarities with gold and the U.S. dollar in portfolio management and risk analysis [10,11]. Some papers point to the idea that not only Bitcoin but other major cryptocurrencies can serve as effective diversification or hedging tools [12]. Besides, Bitcoin can be used as a hedge against the stock exchange index [13,14].

To some extent, Bitcoin has the same hedging capacity as gold regarding specific market risks [15] and outperforms gold in terms of liquidity and hedging capabilities due to its volatility, low transaction costs and low time costs [16].

The U.S. dollar, which still plays an important role in international trade, is still the preferred asset for many investors, especially in a crisis period [17]. As gold, oil and other financial assets are priced by U.S. dollars, there is a negative correlation between the dollar and various assets [18]. Therefore, the strength of the U.S. dollar may suppress the stock markets of other countries including emerging markets, resulting in a negative correlation between U.S. dollar assets and the stock markets, and the stock markets will have a great dependence on the dollar and the United States [19,20]. In this paper, we will re-examine the role of the U.S. dollar in portfolios and whether the trend of U.S. dollar assets can play a role in predicting the market for market monitors.

Gold has always been regarded as a good safe haven, especially in extreme market conditions [21]. Adding gold to a portfolio may yield more diversification benefits than a portfolio without gold, making the portfolio more reasonable and superior [22]. As the stock markets will be slightly affected by gold and other precious metal markets, gold and other precious metals can play a protective role in the stock market turmoil [23]. Especially for the risk-averse investors, adding more gold to their portfolio can maximize the expected benefits of the portfolio [24].

The role of crude oil in the stock markets is generally considered to have some similarities with that of gold, but in fact, the role of crude oil in the stock market is more complicated. The specific role it plays needs to consider different time horizons [25], such as in a special period such as a financial crisis [26], as well as the characteristics of the country where the stock market is located, such as an oil-importing country or oil-exporting country [27]. At the same time, risks in the crude oil market may be transmitted to the stock markets, and the spillover of this risk is different in various periods [28]. This means that the specific role of global financial assets in the stock markets can be considered from different perspectives.

We contribute to the previous literature in the following ways. First, we use a novel quantile framework to conduct an empirical study. To be more specific, we use a new quantile cross-spectral method [29] to investigate and analyze the role of four conventional global financial assets in the stock market. Compared with the traditional wavelet method, dynamic conditional correlation model and copula-based approach [7,30,31], the quantile-coherency (QC) method can help us analyze the specific role of four kinds of financial assets from different time horizons (i.e., short term, medium term and long term) and market conditions with quantiles simultaneously, i.e., the normal markets (intermediate quantiles), bullish markets (higher quantiles) and bearish markets (lower quantiles), which makes our empirical results more accurate, reasonable and diversified [12]. Taking into account the three time horizons of short, medium and long term, we can have a complete picture of the hedging role of global financial assets for international stock markets from different time horizons (frequency domain). Compared with the conventional causality method [25], the Granger causality-in-quantile (CIQ) method employed in this paper excels at tracing the dynamic causality in mean and variance simultaneously from different quantiles to show more comprehensive and accurate results. Second, we use different global financial assets to have a comprehensive study compared with some previous work examining only one or two types of assets [32–34]. In addition, we choose the representative national stock market indexes [9] of the United States, Japan, Britain and China. Third, our results highlight some interesting insights. We found that the role played by global financial assets varies over quantiles. It is worth thinking that, in most cases, financial assets and the stock index show a weak positive correlation, and the correlation degree in the medium and long term is more significant than that in the short term. Besides, the causality in the quantile method has enhanced our understanding of the role of these selected financial assets. We hope to explore whether global financial assets play a predictive role in the stock market; that is, in addition to the role played in the stock portfolio, which is to provide a certain reference for

policymaking and market regulation. The results show that Granger causality is significant in most cases, and the global financial assets have different degrees of predictive capacity to a stock index, especially in the middle quantile.

2. Literature Review

This paper involves three aspects of literature. The first part is about the dependence of four kinds of global financial assets on the stock markets. For example, Maghyereh and Abdoh [32] revealed the right-tail dependence between Bitcoin returns and the S&P 500 in the long term based on a quantile cross-spectral approach. Through one empirical research study, Raza et al. [33] found that gold had a positive impact on the stock markets of large emerging economies of Brazil, Russia, India, China and South Africa (BRICS), and a negative impact on the stock markets of Mexico, Malaysia, Thailand and other countries, while oil prices harmed the stock markets of all emerging economies. By using the nonlinear wavelet copula method, Bekiros et al. [34] found that gold plays a leading role in the stock market during the depression. There is a time-varying, positive and asymmetric dependence between gold and the stock market, which may be greater in the depression than in the boom. Based on the newly developed methods of quantile coherency, the nonparametric conditional value-at-risk causality and the NCoVaR Granger causality tests, Tiwari et al. [35] suggested the presence of a long-run quantile coherency between most of the BRICS stock markets and oil prices. The oil market can pose systemic risks to BRICS equity markets. In addition, many scholars use the Granger causality test and two-factor volatility spillover model to deeply analyze the feedback influences between the two and dig out a deeper and more accurate dependence relationship [36,37]. Although these conclusions are different, it is undeniable that there is an empirical relationship between global financial assets and stock markets. This paves the way for us to revisit the role of Bitcoin, traditional gold, crude oil and the U.S. dollar for stock markets from a new quantile perspective to provide fresh evidence for policymakers and investors.

The second part is about the role of four kinds of financial assets in the stock market and their role in the stock portfolio. Only a few people think that Bitcoin can be used as a hedging tool in the stock markets [13,15]. Most research results suggest that Bitcoin should be served as a diversified investment tool for portfolio or stock market investment [38–40], and there are even downside risks in extreme cases [41]. That may be because it has special risks that are hard to hedge. With the dynamic conditional correlational (DCC) model, Chkili [21] found that adding gold as a safe haven in a portfolio during a financial crisis is a good choice because it reduced the risk of the portfolio without lowering its expected return. After that, from the perspective of hedging, Chkili [42] also concluded that gold is a weak hedging tool through Markov switching approach in the next year, which can enhance the hedging capacity against market volatility. This was also seen in Kumar [22] with asymmetric dynamic conditional correlational model and bivariate generalized autoregressive conditional heteroskedasticity model (VAR-ADCC-BVGARCH), Alkhazali et al. [24] with stochastic dominance (SD) approach and Hoang et al. [43] with the same stochastic dominance (SD) approach. Due to the complexity and variability of crude oil assets, there is no unified conclusion on the role of crude oil. Tiwari et al. [44] found that it is beneficial to diversify portfolios of the BRICS stocks by including oil during an oil crisis through the quantile coherency method. They used time-constant, time-varying and time-varying Markov-copula models to reveal that crude oil plays a different role in the stock markets of different countries. The crude oil market is a good channel for Japanese and French investors to diversify their investments. However, there are different dependence structures in the BRICS and G7 countries. When investigating the usefulness of gold and crude oil in hedging the portfolio of the stock market, Maghyereh and Abdoh [45] interpreted that oil and gold are both weak hedging instruments for the stock market and could be weak safe havens by establishing a dynamic conditional correlational generalized autoregressive conditional heteroskedasticity model (DCC-GARCH). However, due to high transaction costs and other costs, the benefits may be offset by costs. Naresh et al. [20]

established the autoregressive distributed lag (ARDL) model and concluded that in the global stock market downturn, investors will increase their investment in the U.S. dollar to avoid the loss of speculative investment in risky assets. Wen and Cheng [9] added gold as a comparison in their research on the role of the U.S. dollar. By calculating the low-high tail dependence between markets via copulas and the downside risk gains of portfolios, they found that both gold and the U.S. dollar can serve as a safe haven for emerging stocks, with the U.S. dollar being better than gold in some cases. In general, the research results of these papers provide us with a great reference value which is of constructive significance for us to carry out further analysis.

The third part of the literature review is about the new QC method and CIQ method. The QC method was developed by Baruník and Kley [29]. It was proposed in 2019 and has been widely used in different fields and markets. For example, Maghyereh and Abdoh [46] used the quantile cross-spectral dependence method to analyze the interdependence between investor sentiment and commodities in different income quantiles and time frequencies. On the other hand, in recent years, the application of the quantile-in-causality method has been a hot research topic. The framework of Nishiyama et al. [47] and Jeong et al. [48] proposed a quantile-based causality analysis method. Chuang et al. [49] used the quantile-in-causality method to research the causality relationship between stock return and trading volume. Balcilar et al. [50] used this method to analyze news-based economic policy uncertainty (EPU) and equity market uncertainty (EMU) to predict stock returns and volatility. So far, there is no literature applying these two novel approaches to re-examine the portfolio role and trend forecasting role of cryptocurrencies, gold, oil and the US dollar in the stock markets.

To sum up, the previous literature on the role of global financial assets in the stock market, on the one hand, has mainly used the conventional copula methods, which may lack consideration from multiple perspectives and situations. The novel quantile method employed here can make up for this defect. On the other hand, most of the literature studies the role of global financial assets in the stock market from the perspective of the asset portfolio, ignoring their role in predicting the trend of the stock market potential for investors and market monitors. This prompted us to conduct in-depth research and analyses.

The remainder of this paper is as follows. Section 3 introduces the main methodology utilized in this paper. Section 4 shows the dataset and some preliminary results based on the raw data. Section 5 illustrates the empirical results from a quantile perspective. Section 6 concludes the paper.

3. Methodology

3.1. Quantile-Coherency Approach

Baruník and Kley [29] proposed a quantile-coherency approach, providing a method to measure the dependence deduced by quantile of the joint distribution between two sets of time series in the frequency domain from different time horizons. The characteristic of this method is that it can enable the presentation of dependencies in different parts of quantiles and the conclusion can come out at different frequencies.

We define the return of a global financial asset and a stock index to be two sets of time series $X = \{x_t\}$ and $Y = \{y_t\}$, $t \in \mathbb{Z}$. The dynamic dependence between two series can be defined by such a following relation:

$$\mathcal{R}^{X,Y}(\omega, \tau_1, \tau_2) = \frac{F^{X,Y}(\omega, \tau_1, \tau_2)}{\left(F^{X,X}(\omega, \tau_1, \tau_2)F^{Y,Y}(\omega, \tau_1, \tau_2)\right)^{1/2}} \quad (1)$$

where $-\pi < \omega < \pi$, $\tau \in [0, 1]$, $F^{X,Y}$, $F^{X,X}$ and $F^{Y,Y}$ represent quantile cross-spectral, and quantile spectral densities of processes $\{x_t\}$ and $\{y_t\}$, obtained respectively from the Fourier transform of a kernel matrix of quantile cross-covariance:

$$\Gamma_k(\tau_1, \tau_2) = (Y_k^{\tau_1, \tau_2}(\tau_1, \tau_2))_{XY} \quad (2)$$

where

$$Y_k^{\tau_1, \tau_2}(\tau_1, \tau_2) = cov(I\{x_{t+k} \leq q_X(\tau_1)\}, I\{y_t \leq q_Y(\tau_2)\}) \quad (3)$$

For $k \in \mathbb{Z}$, and $I(\cdot)$ is the general indicator function, while $q_X(\cdot)$ and $q_Y(\cdot)$ are quantile functions of X and Y , respectively. When the case of continuous variables is taken into account, this method above corresponds to the difference of the copula of (x_{t+k}, y_t) and the independence copulas. Varying k can not only provide information about cross-section dependence, but also present information about serial dependence. Accordingly, the following metric for the frequency domain is obtained:

$$F(\omega, \tau_1, \tau_2) = (2\pi)^{-1} \sum_{k=-\infty}^{\infty} Y_k^{\tau_1, \tau_2}(\tau_1, \tau_2) e^{-ik\omega} \quad (4)$$

One can compare with the imaginary parts of $F(\omega, \tau_1, \tau_2)$ listed above to eliminate the sources of extraneous coherence. We focus on the real part because it denotes the spectrum of the processes $(I\{x_t \leq q_X(\tau_1)\})_{t \in \mathbb{Z}}$ and $(I\{y_t \leq q_Y(\tau_2)\})_{t \in \mathbb{Z}}$.

We estimate two sets of coherency matrices (left tail and right tail), while each set consists of three quantile and all their combinations: (0.01, 0.05 and 0.5) and (0.1, 0.5 and 0.9). In particular, following Jiang et al. [51], three frequencies are considered in this paper i.e., short term (one week), medium term (one month) and long term (one year).

3.2. Causality-in-Quantiles Approach

We apply the nonlinear causality method to examine the causality-in-quantiles [49] between global financial assets (y_t) and stock market indexes (x_t). According to Jeong et al. [48], (x_t) does not cause (y_t) in the θ quantile concerning the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$, if $Q_\theta\{y_t y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\} = Q_\theta(y_t y_{t-1}, \dots, y_{t-p})$.

However, x_t potentially causes y_t in the θ th quantile with regards to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if $Q_\theta\{y_t y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\} \neq Q_\theta(y_t y_{t-1}, \dots, y_{t-p})$.

Where $Q_\theta(y_{t*})$ is the θ th quantile of y_t and the conditional quantiles of y_t and $Q_\theta(y_{t*})$ are determined by t , $0 < \theta < 1$.

After that we define the vectors $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, and $Z_t = (Y_t, X_t)$. The functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ are defined as the conditional distribution functions of y_t dominated, respectively, by vector Z_{t-1} and Y_{t-1} . For nearly all Z_{t-1} , the conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is presumed to be continuous in y_t . We can find that $F_{y_t|Z_{t-1}}(Q_\theta(Z_{t-1})|Z_{t-1}) = \theta$ happens with a probability equal to one as we define $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$. Therefore, the causality-in-quantiles hypothesis can be listed as:

$$H_0 : P\{F_{y_t|Z_{t-1}}(Q_\theta(Y_{t-1})|Z_{t-1}) = \theta\} = 1 \quad H_0 : P\{F_{y_t|Z_{t-1}}(Q_\theta(Y_{t-1})|Z_{t-1}) = \theta\} < 1$$

The estimator of the unknown regression residue can be expressed as:

$$\hat{\varepsilon}_t = 1\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta \quad (5)$$

In this equation, the quantile estimator $\hat{Q}_\theta(Y_{t-1})$ yields one estimate of the θ th conditional quantile of y_t . Such a $\hat{Q}_\theta(Y_{t-1})$ is estimated by the nonparametric kernel method as:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta Y_{t-1}) \quad (6)$$

where $\hat{F}_{y_t|Y_{t-1}}^{-1}(y_t Y_{t-1})$ represents the Nadarya-Watson kernel estimator demonstrated as:

$$\hat{F}_{y_t|Y_{t-1}}^{-1}(y_t Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) 1\{y_s \leq y_t\}}{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \quad (7)$$

where $L(*)$ denotes a known kernel function and h denotes the bandwidth used in the kernel approach.

On the other hand, we examine the causality-in-variance because the rejection of causality in the moment m may not mean that non-causality happened in the moment k for $m < k$. The function is listed as follows:

$$y_t = g(X_{t-1}, Y_{t-1}) + \varepsilon_t \quad (8)$$

Accordingly, the high order causality-in-quantiles can be examined as:

$$H_0 : P\left\{F_{y_t^k|Z_{t-1}}(Q_\theta(Y_{t-1})|Z_{t-1}) = \theta\right\} = 1, k = 1, 2 \dots K$$

$$H_0 : P\left\{F_{y_t^k|Z_{t-1}}(Q_\theta(Y_{t-1})|Z_{t-1}) = \theta\right\} < 1, k = 1, 2 \dots K$$

We test that y_t Granger caused x_t in quantile θ up to the K th moment, constructing the feasible kernel-based test statistic for each k . When carrying out joint density-weighted nonparametric tests for all $k = 1, 2, \dots, K$, we used the sequential testing approach shown in Nishiyama et al. [47]. Furthermore, we chose the best lag order by AIC and the Schwarz Information Criterion (SIC), and the bandwidth for causality-in-quantiles is by the least-squares cross-validation method. After that, we select the Gaussian-type kernels for $L(*)$ and $K(*)$.

4. Data

The dataset contains four global assets: Bitcoin, U.S. dollar, crude oil and gold. Besides, following some recent contributions such as in Zhao et al. [36] and Jiang et al. [51], this paper considers the stock market indexes of four countries: the United States (S&P 500 Index), China (Shanghai (securities) composite index, SHCI), the United Kingdom (FTSE 100) and Japan (Nikkei 225). The daily sample period of the analysis available is from January 2013 to June 2020, and there were 1757 observations. In this paper, we used the daily return series (The calculation method is $r_t = \log(p_t/p_{t-1})$ and p_t is the daily closing price of each asset) of each asset and Table 1 presents the descriptive statistics of these series. Bitcoin has the highest average yield and standard deviation in the ranks of global financial assets, while gold and the U.S. dollar have relatively stable performance. In contrast, crude oil shows a negative yield and a higher standard deviation, indicating that the crude oil market is very volatile. The average return and standard deviation (of the stock market indexes) of these four countries are relatively low, with little fluctuation. Except for Bitcoin and the U.S. dollar, return series of other financial assets and stock market indexes all show varying degrees of negative skewness. Bitcoin and the U.S. dollar are positively skewed, and Bitcoin has the largest skewness coefficient. Additionally, the kurtosis of each series is higher than that of a normal distribution, which indicates that all the series are leptokurtic. Finally, the ADF test shows that all series are stationary.

Figure 1 shows the linear correlation between various global financial assets and stock market indexes of different countries. In addition to the weak negative correlation between Japan's stock index and gold, almost all stock market indexes have varying degrees of weak positive correlation with the asset returns of Bitcoin, U.S. dollar, crude oil and gold. From the horizontal comparison, it is clear that the correlation between crude oil and the stock market indexes of various countries is slightly higher than that of the other three global financial investment instruments, but in general all four global financial assets are not strong hedging tools for the stock market indexes of various countries.

Table 1. Descriptive statistics of the data.

Variables	Mean	Max	Min	S. D.	Skew	Kurt	J.B	ADF
Bitcoin	0.3709	147.4180	−84.8829	7.2686	3.8040	114.8219	919644 ***	−21.0670 ***
USD	0.0108	2.4952	−2.1420	0.4363	0.0601	5.1998	355 ***	−42.7640 ***
Oil	−0.0566	41.2023	−64.3699	3.3629	−2.8817	104.2638	753137 ***	−43.6660 ***
Gold	0.0040	5.1334	−9.5962	0.9542	−0.7036	12.5744	6856 ***	−41.7860 ***
USA	0.0426	8.9683	−12.7652	1.1022	−1.1237	26.9138	42235 ***	−13.2640 ***
CHINA	0.0154	6.3691	−8.8732	1.4334	−0.9995	9.7368	3615 ***	−40.1480 ***
UK	0.0007	8.6668	−11.5124	1.0455	−0.9781	18.2644	17338 ***	−42.1210 ***
JAPAN	0.0418	7.7314	−8.2529	1.3861	−0.1704	7.5277	1509 ***	−43.3080 ***

Note: *, ** and *** represent passing the significance test of 10%, 5% and 1%, respectively, the same below.

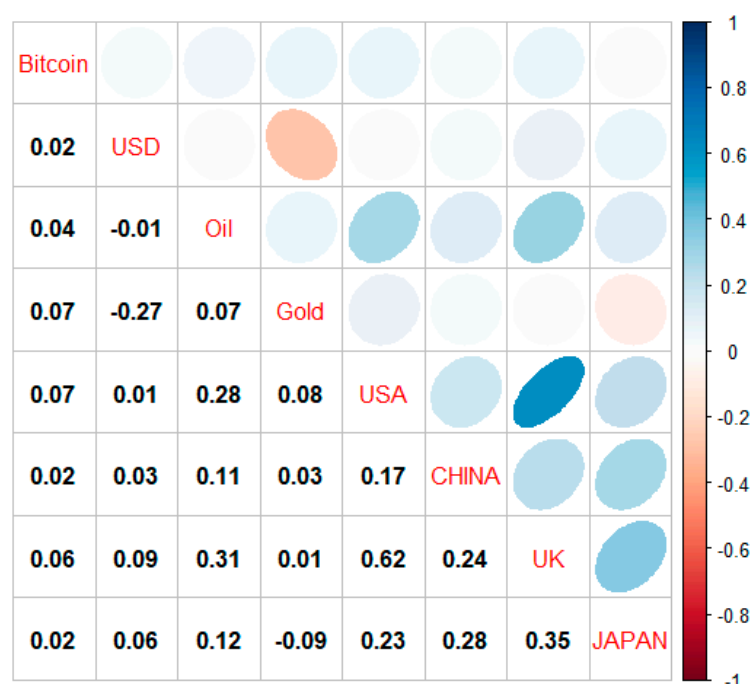


Figure 1. Pearson's correlation.

5. Results

5.1. Analysis of Quantile Coherence Result

Figure 2a–c shows the empirical results of the quantile cross-spectral (coherency) approach in different quantiles (0.01, 0.05 and 0.5) between the return on global financial assets and the return on stock indices. The QC matrix in Figure 2a–c, respectively, presents their short-term (one week), medium-term (one month), and long-term interdependence (one year). (The results are qualitatively similar if we change the short-, medium- and long-term time horizons by one day, one week and one month, respectively, and the results can be obtained upon request).



Figure 2. Cont.

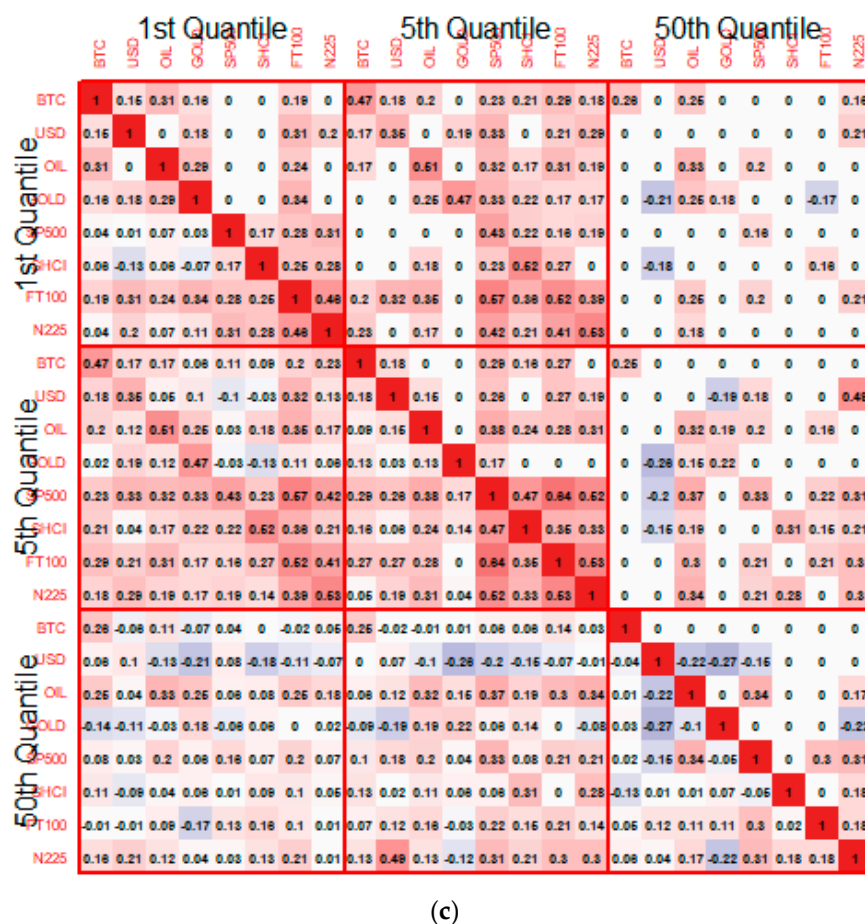


Figure 2. Quantile coherency (QC) matrices (quantile at 1%, 5% 50%). Note: Above the diagonal, non-significant values at 5% significance level are set to zero. Red and blue grids denote positive and negative values, respectively: (a) Short-term QC matrix; (b) Medium-term QC matrix; (c) Long-term QC matrix.

In Figure 2a, it is clear that in the lower yield quantiles (0.01 and 0.05), except for the negative correlation in (0.01, 0.01) between China's Shanghai index and gold, Bitcoin, U.S. dollar, crude oil, and gold are weakly positively correlated with stock market indexes of various countries in the case of extremely low yields (0.01, 0.01), (0.05, 0.01), (0.01, 0.05), (0.05, 0.05). Specifically, in the short term (one week), the U.S. stock index maintains a stable and significant positive correlation with Bitcoin when returns are low. However, it is worth noting that in the short term, the correlation between the U.S. dollar and the stock market indexes on all quantiles is not significant. The correlation between the Chinese stock market and global financial assets is mostly reflected in oil and gold. This shows that in the short term if the market is in recession, the global financial assets can act as the diversification tool for the stock markets to some extent. However, once the economy recovers or the market turns become optimistic in the short term, investors need to adjust their short-term investment strategies appropriately. Particularly investors who own a portfolio made up of gold need to adjust their positions promptly in the short term.

Figure 2b shows the medium-term (one month) QC matrix. In the mid-term QC matrix, we observed a different picture from the short-term matrix. In the case of low returns, the positive correlation between the U.S. dollar and stock index returns of various countries is enhanced in the medium term, and its correlation with stock index returns becomes significant in the QC matrix, especially in the quantile (0.01, 0.01) and (0.01, 0.05).

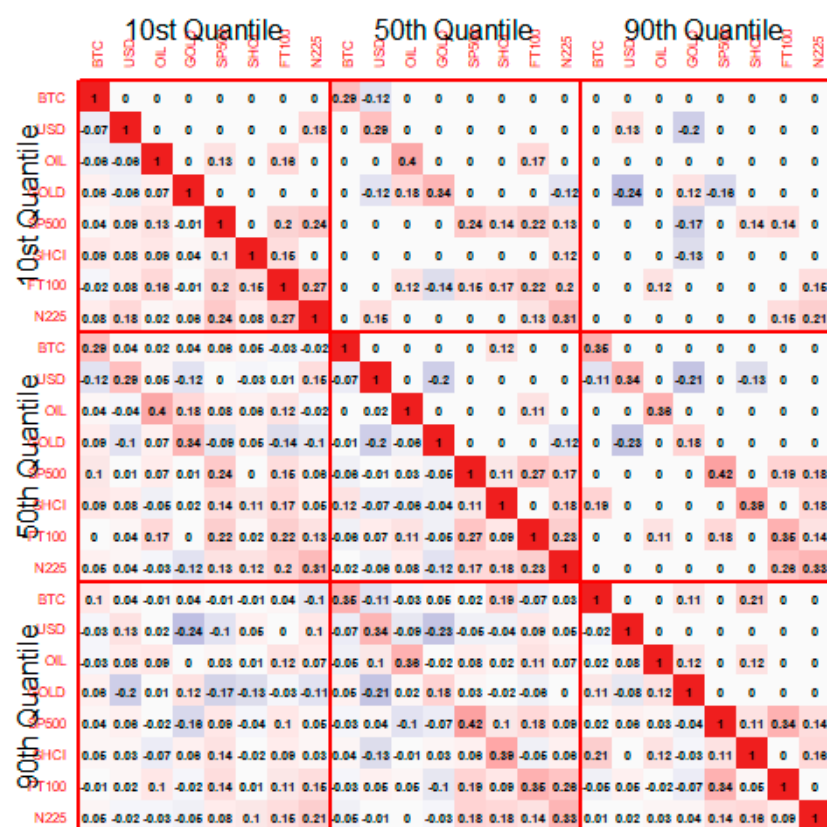
Meanwhile, the relationships between each stock index and Bitcoin weakened over the medium term compared with those in the short term, as well as the correlation with crude oil in the downturn of various countries' markets, which only shows significant

performance in the middle quantile 0.5. Similarly, the same situation goes for gold, and things also have changed for different countries. Specifically, the global financial assets with significant correlation with the U.S. stock shift from the short-term Bitcoin to U.S. dollar currency in the medium term. In general, the QCs of the U.S. dollar show a significant positive correlation at a lower yield, while the correlation between other financial assets and the stock index weakens in the medium term. The role of financial assets is diversified for different countries, for example, one can see the significant positive correlation between UK stock and global financial assets in low returns.

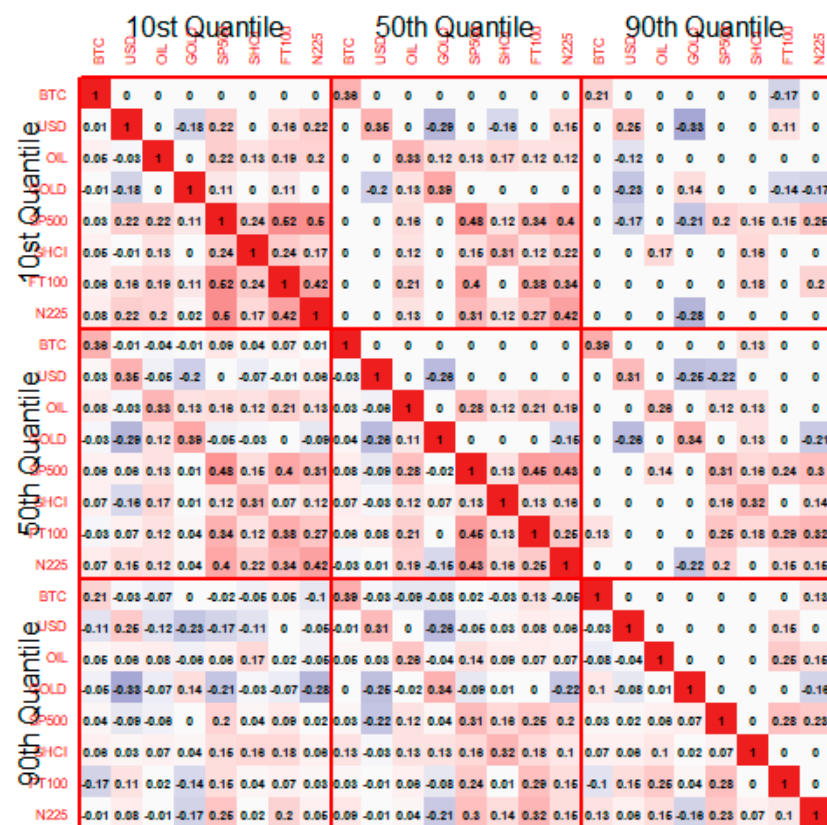
The long-term (one year) QC matrix (Figure 2c) is similar to the medium-term QC matrix to some extent, except that there are more red grids above the diagonal of the long-term QC matrix compared with the short-term and medium-term ones. In the long run, the U.S. dollar still has a relatively significant positive correlation with the stock index at the low yield level of various countries. The global assets still have a relatively significant positive correlation with the UK stock market at the low quantile (0.01 and 0.05). Furthermore, gold is a powerful hedge against the Japanese stock market at the median quantile in the long term.

The above analysis in the low and middle quantile range (0.01, 0.05, 0.5) shows that global financial assets can act as hedging tools for various countries' stock markets only in a few cases and specific quantile returns, however, global financial assets such as Bitcoin, U.S. dollar, gold and crude oil are mostly diversification tools for the stock market, which is in line with Raza et al. [33]. In the low- and middle-quantile range, the correlation between various global finance and stock markets in the short term is different from that in the medium and long term. The reason may be that the speculation and arbitrage for short-term investors make the yield rate fluctuate frequently on various financial assets. The medium-term and long-term correlation tends to be more general, showing some similarities between the mid-term QC matrix and the long-term QC matrix. However, in the long run, other factors in variable sets have a slight influence on the index relatively, so global financial assets show a more significant weak positive correlation with stock indexes of various countries in different market situations. Furthermore, in the medium and long term, the correlation between the dollar and all the stock indexes is significantly stronger than that of other assets.

To get a more accurate conclusion, we set the quantile level at (0.1, 0.5 and 0.9) to analyze the situation in extreme market conditions. Figure 3a–c, respectively, represents the short, medium, and long QC matrices with quantiles of (0.1, 0.5, and 0.9). In the short-term QC matrix, the white grid above the diagonal is in the majority, which means that the correlation between various global assets and the stock markets of various countries gradually becomes insignificant at different quantiles as the return rate rises. However, it should be noted that at the extremely high yield of 0.9, gold and the U.S. index showed a significant negative correlation (0.01, 0.9); there is a significant negative correlation between the U.S. dollar and the Chinese stock market (0.5, 0.9). Therefore, the role of global financial assets changes when the stock markets of various countries are highly profitable, such as in Jiang et al. [52], where it shows the extreme quantiles can have some different patterns. This implies that the policymakers and investors need to mind the variation within the market conditions.



(a)



(b)

Figure 3. Cont.

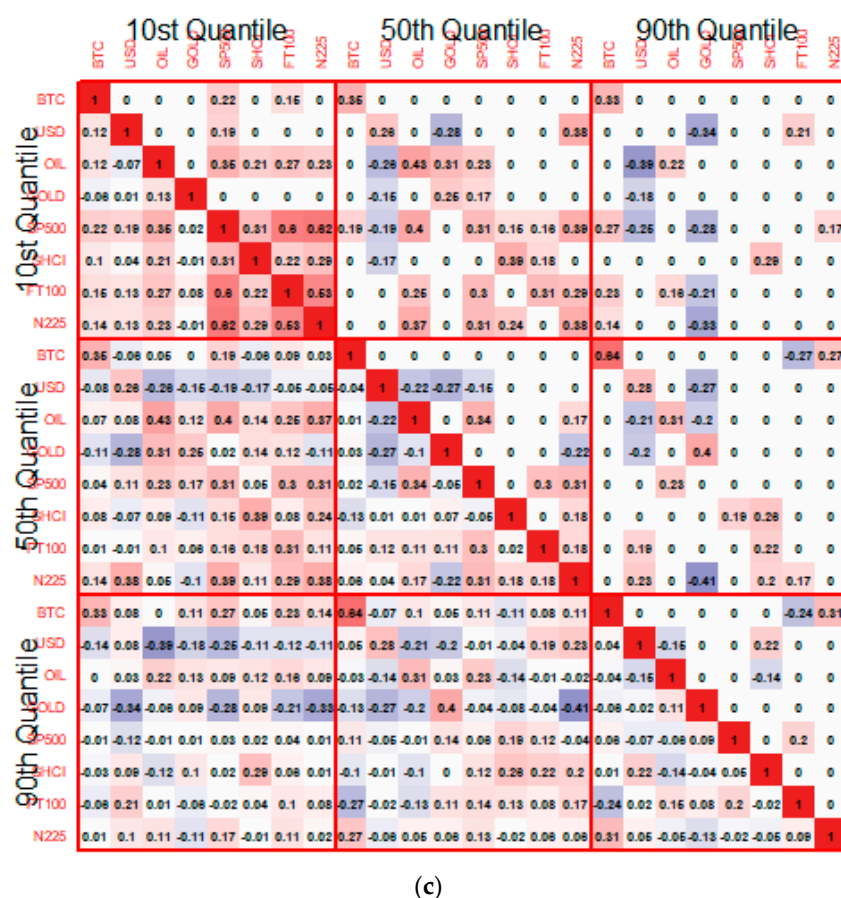


Figure 3. Quantile coherency (QC) matrices (quantile at 1%, 5% 50%). Note: Above the diagonal, non—significant values at 5% significance level are set to zero. Red and blue grids denote positive and negative values, respectively: (a) Short—term QC matrix; (b) Medium—term QC matrix; (c) Long—term QC matrix.

Perhaps some phenomena are not obvious in the short term due to speculative capital. After adding the medium and long-term QC matrix, we can see that in addition to the significant positive correlation and zero correlation initially seen, there are also significant negative correlations in some grids. For example, in the high quantile of the mid-term QC matrix, the Japanese stock index and gold presented a significant negative correlation (0.5, 0.9) (0.1, 0.9). In the long-term QC matrix, gold and N225 (0.5, 0.9) (0.1, 0.9) and Bitcoin and FT100 (0.5, 0.9) (0.9, 0.9) all showed significant negative correlation.

Thus, it can be seen that in the context of the stock market downturns and economic recessions, various global assets should mostly be diversified instruments of the stock market, showing significant positive correlation to different degrees with stock indexes of various countries, and it is difficult to effectively serve as hedging instruments of the stock markets. This significant positive correlation increases over time horizons, and thus increases risk contagion during the market recessions. In addition, the positive feedback effect is likely to push the market deeply into the whirlpool. However, in the case of market prosperity and economic expansion, except for the significant positive correlation and some insignificant ones, global assets are negatively correlated to the stock market yield to varying degrees, indicating that global assets are partly transformed into hedging tools for stock markets. Similarly, this effect increases with the extension of the time horizons.

5.2. Analysis of Causality-in-Quantiles Result

Furthermore, we analyzed the correlation between various global financial instruments and national stock indexes by using the causality-in-quantiles approach shown in

Figures 4–7 for a clear representation of the results. The main takeaway from the chart is that: (i) in most cases the causality-in-mean curve is different from the causality-in-variance. To be more specific, the null hypothesis of Granger causality-in-variance from global assets to stock indexes of all countries is rejected, namely, the causal relationship in the second moment is significant, which is similar with Mo et al. [25], and it shows the predictability of stock indexes, even if Granger causality-in-mean is not significant in some cases. (ii) In most cases, the causality-in-quantiles graph is arched, indicating that various global assets have a strong predictive ability for stock indexes near the median quantile.

More specifically, we found that Bitcoin is not significant at the 5% significance level with the first and second order of the US stock index at all quantiles. For the Japanese stock market, the causal flow (in both the mean and the variance) with Bitcoin is evident across all the quantiles. The Granger causality between Bitcoin and the UK stock market is similar to those in China. This means that the mean-in-causality is not significant at the lower and higher quantiles, while the first- and second-order causalities are both significant at the middle quantile, indicating that Bitcoin has a certain predictive capability when the stock index is at a normal rate of return. For the dollar, the Granger causality in the mean and variance of the national indices is evident at all quantiles. The evidence of the causality-in-variance from the dollar to stock market indexes may lead to an increase in uncertainty among investors. Gold and crude oil behave similarly, and for developed countries such as the United States, the United Kingdom and Japan, the Granger causality in the first and second order is significant at all quantile levels, but for developing countries such as China, we can see the asymmetry of the causality. Therefore, our empirical results show that the performance of various global financial assets in the QIC approach has a certain commonness, and they have a certain ability to predict the stock index of each country. But to some extent, there will be slight differences due to the different characteristics and the different nature of the stock indexes in different countries, which requires investors and policymakers to make reasonable judgments for different situations.

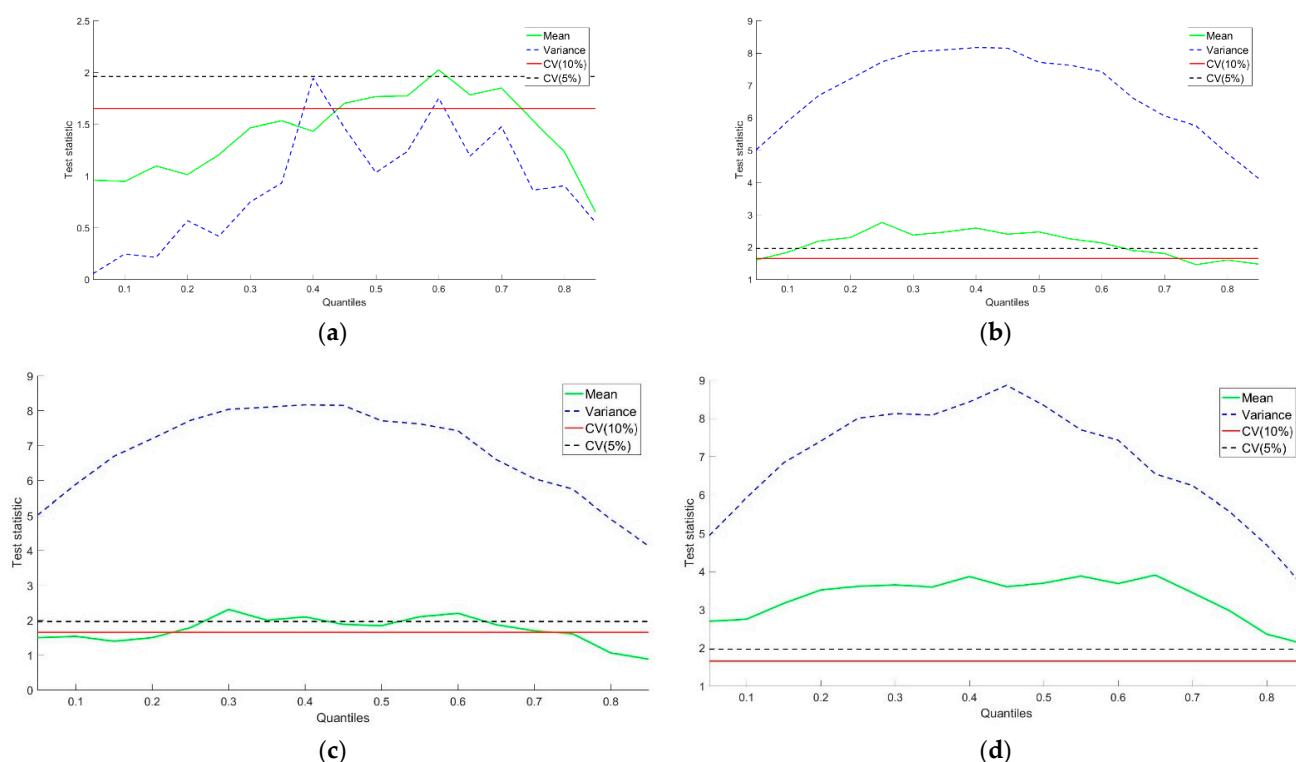


Figure 4. Non-parametric causality-in-mean, in-variance and the 5% and 10% critical values (CV) from Bitcoin returns to the stock market returns at various quantiles, respectively: (a) Bitcoin-US; (b) Bitcoin-CHINA; (c) Bitcoin-UK; (d) Bitcoin-JAPAN.

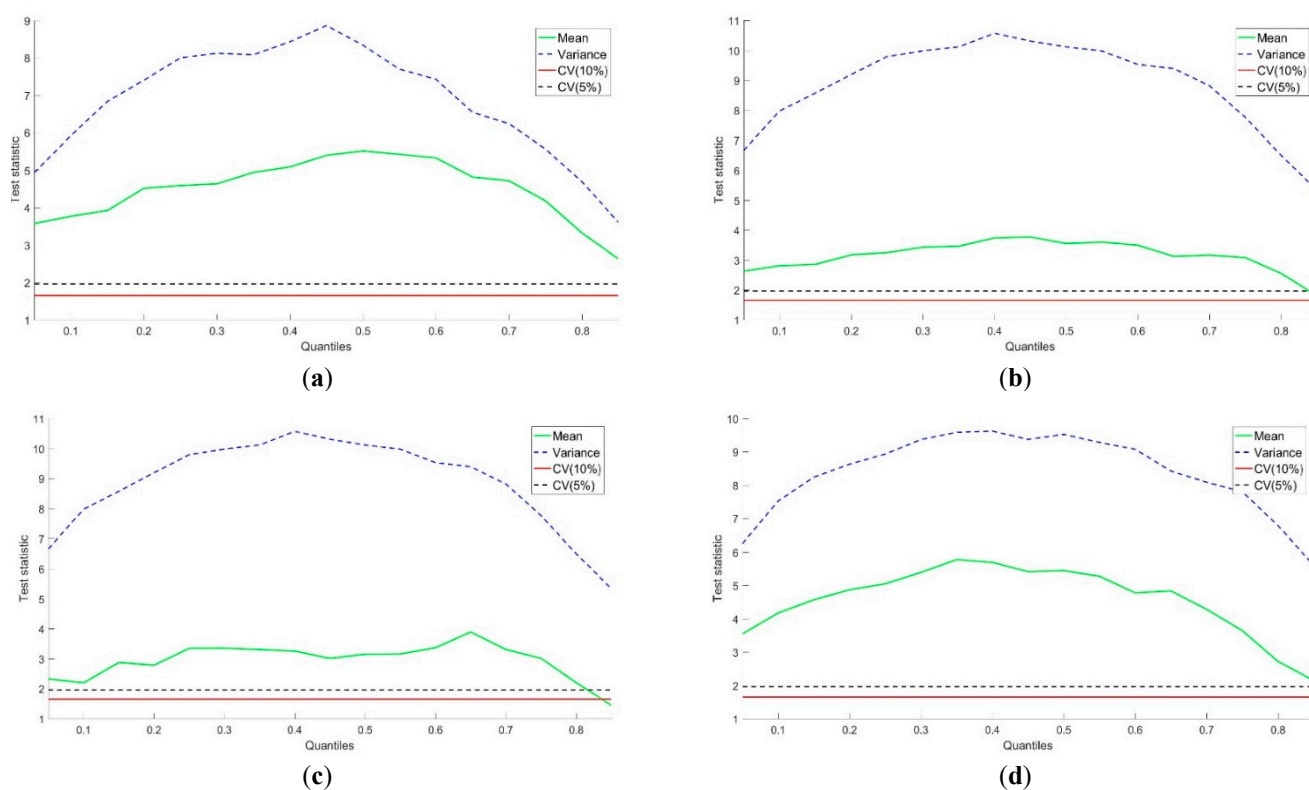


Figure 5. Non-parametric causality-in-mean, in-variance and the 5% and 10% critical values (CV) from USD returns to the stock market returns at various quantiles, respectively: (a) USD-US; (b) USD-CHINA; (c) USD-UK; (d) USD-JAPAN.

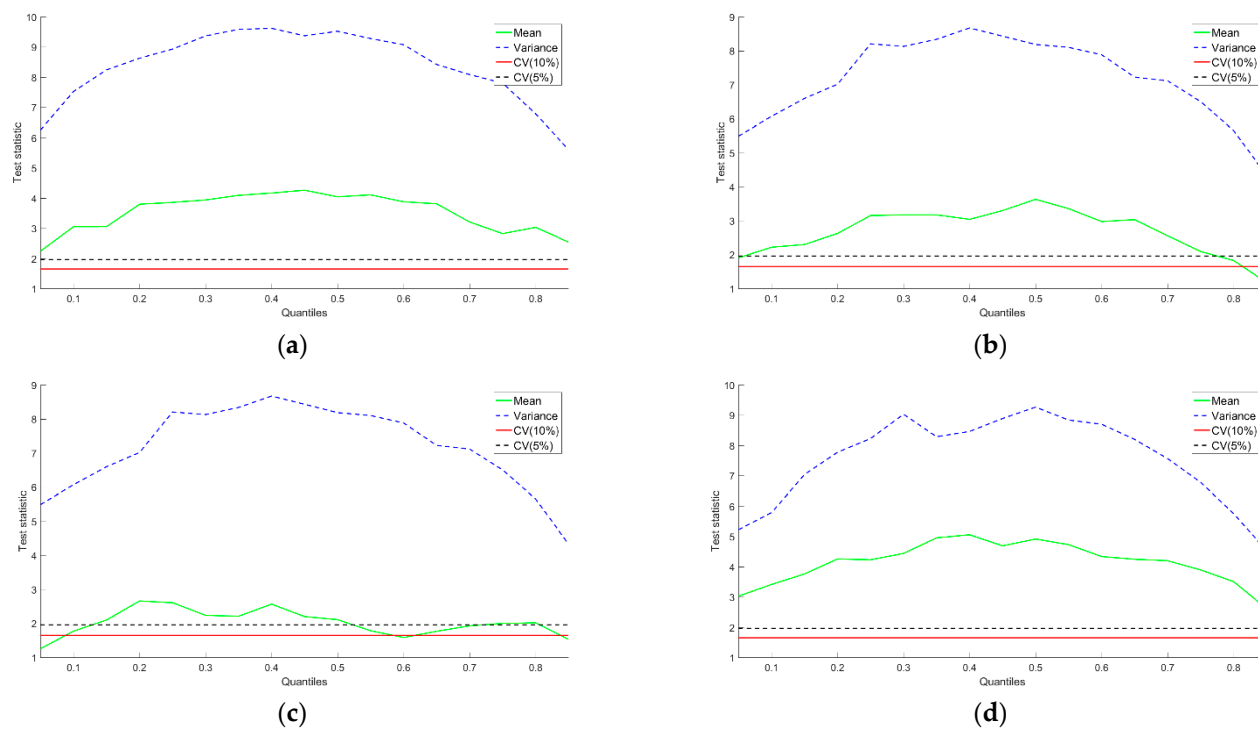


Figure 6. Non-parametric causality-in-mean, in-variance and the 5% and 10% critical values (CV) from oil returns to the stock market returns at various quantiles, respectively: (a) OIL-US; (b) OIL-CHINA; (c) OIL-UK; (d) OIL-JAPAN.

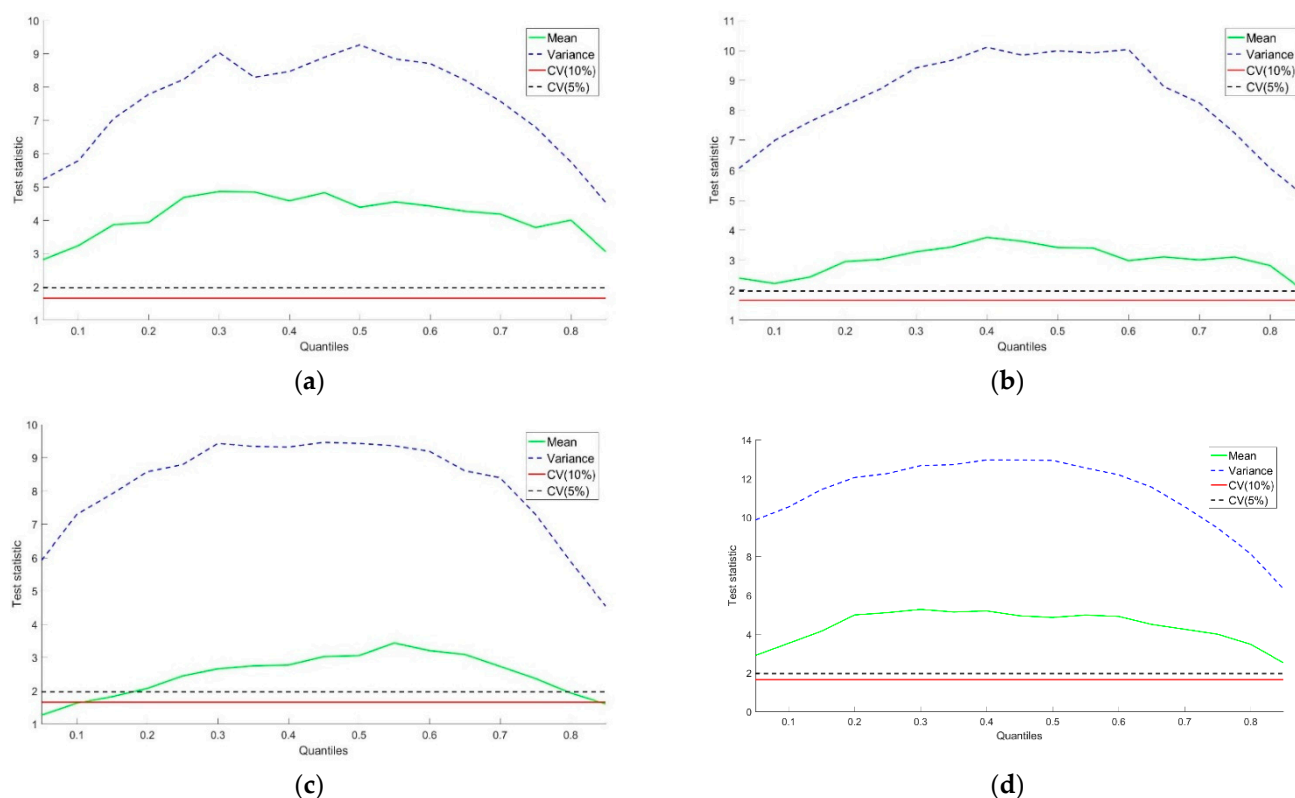


Figure 7. Non-parametric causality-in-mean, in-variance and the 5% and 10% critical values (CV) from gold returns to the stock market returns at various quantiles, respectively: (a) Gold-US; (b) Gold-CHINA; (c) Gold-UK; (d) Gold-JAPAN.

6. Conclusions

Daily data from 7 January 2013 to June 2020 was used to analyze the role of four global financial assets (Bitcoin, U.S. dollar, gold and crude oil) in the return rate of stock market indexes in four countries. This paper adopts the QC method for the correlation between global financial assets and stock market indexes under different frequencies and different quantiles. Furthermore, the CIQ method is used to detect the predictive capacity of global financial assets on the performance of stock indexes.

The empirical results show that financial assets have different effects on stock indexes in different time frequencies and quantiles, which means that the role of global financial assets in stock markets will change at any time, in line with Jiang et al. [51]. The empirical analysis results are as follows: Firstly, excluding some insignificant cases, most global financial assets maintain a significant positive correlation with stock indexes during the economic recession (i.e., the lower quantile), which indicates that there may be a cross-contagion of downside risks between stock markets and global financial assets in the case of a market downturn. Secondly, the QCs in the median are not significant, but there is a significant negative correlation in the higher quantiles. It denotes that when market returns are rising, global financial assets are a buffer to restrain market bubbles and can serve as a powerful hedging instrument, such as in Mo et al. [53]. Thirdly, except for a few financial assets, the long-term and medium-term correlation (positive or negative) is significantly stronger than the short term in most cases, especially in the long term. This can be noticed at different quantiles. Therefore, different investment lengths should correspond to different investment strategies. Fourthly, in the short term, the correlation is more apparent in Bitcoin, crude oil and gold, while the correlation is reflected in the U.S. dollar in the medium and long term. This result clarifies that investors should make structural adjustments according to the period when selecting global financial assets, and these results are more comprehensive compared with Jiang et al. [51], where they only considered the hedging role of bitcoin in stock markets. Fifthly, the predictive capacity of Bitcoin for

stock indexes of various countries is different, while the U.S. dollar is predictable for stock indexes of four countries. The predictive capacity of gold and crude oil for developed countries is significant, but for developing countries it is only reflected in the median.

On one hand, the research results in this paper highlight some implications for international investors to make reasonable investment decisions in response to different market conditions. Investors can use short positions in global financial assets to hedge long positions in the equity market when the stock market is under pressure and reverse positions to hedge in the bull market. Besides, specific investment instruments can be selected according to the investment length: bitcoin gold and crude oil can be selected in the short term, and U.S. dollars can be selected in the medium and long term. On the other hand, the findings also provide some suggestions for policymakers. They should pay attention to the contagion risk of different asset markets when the market is depressed.

The main limitation of this paper is that we only explored the role of four global financial assets (Bitcoin, U.S. dollar, gold and crude oil) for four stock markets from a new quantile perspective, while we ignored some other assets such as commodities due to limited space. In addition, the quantile method cannot present the results from the time domain; in this case, we may not be able to detect some important effects of the financial crisis because of COVID-19. The framework used in this paper can be extended in many aspects. For example, an avenue for future research is that we can introduce more assets or financial markets into our empirical analysis to provide both global and regional evidence.

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