

## Research Article

# Dollar's Influence on Crude Oil and Gold Based on MF-DPCCA Method

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This paper analyzed the influence of dollar on crude oil and gold based on the multifractal detrended partial cross-correlation analysis method. It showed that affected by the dollar, the crude oil and gold markets have a partial cross-correlation relationship which is stronger than their own cross-correlation. The partial cross-correlation is long-term and has multifractal characteristics. Through shuffled and Fourier-phase randomization, it is found that this multifractal feature is caused by the combined effect of the long-term cross-correlation between the returns and the fluctuation fat-tailed distribution, where the influence of the fat-tailed distribution is slightly greater than that of the long-term cross-correlation between the returns.

## 1. Introduction

Since the establishment of the Bretton Woods system, the dollar's status as a world currency has been established. In recent years, as the world's major financial markets have fallen into crisis, the U.S. economy and the credit of U.S. dollar have also begun to decay, and its influence on the global economy have been relatively declining [1]. The status of U.S. dollar in the international financial system has been challenged. Some countries such as China and Russia are increasingly looking to dedollarize and use their domestic currencies in international transactions [2]. Although Russia and China seem to be leading the depreciation of the dollar, analysts pointed out that Europe is also moving towards the diversification (<https://www.kitco.com/news/2019-03-18/Gold-Benefitting-As-Central-Banks-De-Dollarize-BoAML.html>). In particular, affected by COVID-19 and many other reasons, there is a serious decline in the U.S. economy [3–5]. As one of the important indexes in the international financial markets, the U.S. dollar index has been showing a downward trend [6] and broke 90 by December 17, 2020, since April 2018 [7]. Some experts in Morgan predict that the outlook for the dollar index will continue to weaken [8]. The

spread of COVID-19 also has made the global economy extremely difficult [9]. Part of the reason for the decline in oil future prices is the structural imbalance between supply and demand, especially, after the COVID-19 outbreak in large emerging countries such as China, energy demand has fallen sharply [10, 11]. And, the spread of the virus in the USA has had a negative impact on the commodity futures market [12]. But as the stimulus measures of central banks and governments are beneficial to gold, it has promoted the rise of gold as investors fled to safe havens. Refinitiv's metal research team believes that gold prices will continue to be supported by unprecedented stimulus measures, low to negative interest rates, global economic downturn, and ongoing geopolitical tensions [13].

In this context, the relationship between the three financial markets of the crude oil, gold, and U.S. dollar is worth exploring.

With the continuous development of economic globalization, capital flows and information dissemination between financial markets are also deepening. The international financial market or the various submarkets within a country's financial market have shown obvious mutual influence. There are more and more research studies

on the interrelationship of different financial markets. The U.S. dollar, crude oil, and gold directly constitute the main part of the financial market, as well as the main place for policy authorities to implement financial control policies. After Wang [14] observed the effectiveness of the crude oil market by the local Hurst index through the rolling window of multifractal detrended fluctuation analysis, scholars successively compared the crude oil market with stocks [15, 16], gold [17, 18], foreign exchange [18, 19], agricultural product futures [11, 20], and other financial markets [21–24]. At the same time, Mali and Mukhopadhyay [25] used the multifractal detrended fluctuation analysis to study the correlation of the gold consumer price index and the gold market prices of the three major gold consuming countries in China, India, and Turkey and found that they all have multifractal characteristics.

In recent years, multifractal analysis has become one of the main interests of researchers in interdisciplinary fields to reveal the correlations and fractal characteristics of markets in various fields. Econophysicists have shown that multifractal analysis provides an alternative way in studying market risks. Quite a few efforts have been made to apply multifractal analysis to quantifying market inefficiency, measuring financial volatility, and so on. And, extreme events have a strong influence on the apparent multifractality of time series, especially for market crashes. In most cases, the market became more inefficient with a wider singularity width after a crash. The degree of market efficiency changes with different market states. Multifractal strengths can be used as measures to quantify market inefficiency and market risks. A perfectly efficient market should be characterized by the absence of any pattern, so that relative price changes are pure white noise. In contrast, the presence of multifractality reveals remarkable features. See [26] for these and the multifractal analysis method.

In order to reveal the relationship between the two time series, Podobnik proposed a method based on detrended cross-correlation analysis (DCCA), which studied the cross-correlation between the two time series and its characteristics [27]. Then, Zhou developed multifractal detrended cross-correlation analysis (MF-DCCA), which uses a  $q$ -order fluctuation function instead of the local trend in DCCA [26, 28]. This method has been widely used in the correlation and fractal characteristics of the market in various fields [29–33]. As the complexity of the market increases, the interrelationships between time series are often complicated and do not exist in the form of a single influence. Scholars have gradually discovered that the relationship between the two markets may also be affected by other variables. Common external forces will affect people's understanding of the relationship between the two markets. At the same time, the multifractal phenomenon not only appears between two markets but also the interrelationship between three or more. In response to this problem, Qian and Yuan et al. proposed multifractal detrended partial cross-correlation analysis (MF-DPCCA) [34, 35]. When analyzing the relationship between two time series, first remove the common external influence factors of the time series and then analyze the partial cross-correlation relationship

between the two time series. This method has prominent advantages in analyzing partial cross-correlation relationships among multiple time series. Therefore, Liu et al. first applied it to the research related to age changes. By calculating the DPCCA coefficient to explore the age-related changes of event-related potentials, they found that the DPCCA coefficient between young people and old people is different with different neural communication methods [36]. Sai used this method to analyze the impact of the composite index of some Asian markets based on the Nasdaq market. The results show that, after removing the external factor (the Nasdaq Composite Index), the Asian stock markets still have long-range partial cross-correlation behavior and multifractal characteristics. By calculating the Hurst index, it is found that it has a significant impact on the analyzed Asian stock markets [37].

In all, scholars have used various measurement methods to empirically study the cross-correlation relationship between different financial markets in different countries. Most of these studies focus on the cross-correlation relationship between the two markets. Especially, according to [17, 23], it is found that there is a long-term negative correlation between gold and the US dollar with multifractal characteristics, and the negative correlation is nonlinear and dynamic. There is also a strong cross-correlation relationship between crude oil and the US dollar with multifractal characteristics, and the strength of the multifractal increases with the increase of the sample period. The same is true between gold and crude oil markets, but its cross-correlation has a strong multifractal characteristic in the short term and has weak multifractal characteristic in the long term. This paper puts the U.S. dollar index, gold, and crude oil into the same framework to study and further uses MF-DPCCA to quantify the common impact of the U.S. dollar on crude oil and gold. To a certain extent, it reduces the interference of financial market price endogeneity on analysis conclusions and makes the conclusions more true and reliable. We hope that it could not only help to deeply understand the relationship between financial markets but also help other countries prevent financial risks and financial market reforms. Note that the causality-in-variance test introduced by [38] yielded useful information on the temporal dynamics and cross-correlation between two time series, which is very different from MF-DPCCA.

## 2. Methodology

In order to analyze the partial cross-correlation relationship and fractal characteristics between crude oil, gold, and U.S. dollar, we adopt MF-DPCCA, see [34, 35, 37]. Here, we take the modulus of the detrended partial cross-covariance function in order to compare the results with MF-DCCA method, and we consider the external force U.S. dollar on crude oil and gold markets.

Assume three time series  $x_t$ ,  $y_t$ , and  $z_t$ ,  $t = 1, \dots, N$ , where  $N$  is the length of time series. And, assume  $x_t$  and  $y_t$  are simultaneously affected by  $z_t$ . The MF-DPCCA is presented as the following steps:

- (1) First divide each time series into nonoverlapping and equal length subsequences, where each subsequence contains  $s$  data. Let  $N_s := \lfloor N/s \rfloor$ . Since  $N$  may not be an integral multiple of  $s$ , there will be residual data at the end of the original sequence. In order not to discard these data, the same process is repeated for the inverse sequence of the original sequence, so that  $2N_s$  subsequences can be obtained. In the  $\nu$ -th subinterval  $[\ell_\nu + 1, \ell_\nu + s]$ , where  $\ell_\nu = (\nu - 1)s$ . The linear regression gives

$$\begin{aligned} \mathbf{x}_\nu &= z_\nu \beta_{x,\nu} + \boldsymbol{\gamma}_{x,\nu}, \\ \mathbf{y}_\nu &= z_\nu \beta_{y,\nu} + \boldsymbol{\gamma}_{y,\nu}. \end{aligned} \quad (1)$$

Here,  $\mathbf{x}_\nu = (x_{\ell_\nu+1}, \dots, x_{\ell_\nu+s})'$ ,  $\mathbf{y}_\nu = (y_{\ell_\nu+1}, \dots, y_{\ell_\nu+s})'$ ,  $\mathbf{z}_\nu = (x_{\ell_\nu+1}, \dots, x_{\ell_\nu+s})'$ , and  $\boldsymbol{\gamma}_{x,\nu}, \boldsymbol{\gamma}_{y,\nu}$  are the vectors of the error terms. Note that  $\beta_{x,\nu}$  and  $\beta_{y,\nu}$  can be obtained by the least squares method. Thus, estimated value  $\hat{\beta}_{x,\nu}$  and  $\hat{\beta}_{y,\nu}$  can be obtained which leads to have the residual sequences:

$$\begin{aligned} \boldsymbol{\gamma}_{x,\nu} &= \mathbf{x}_\nu - \mathbf{z}_\nu \hat{\beta}_{x,\nu}, \\ \boldsymbol{\gamma}_{y,\nu} &= \mathbf{y}_\nu - \mathbf{z}_\nu \hat{\beta}_{y,\nu}. \end{aligned} \quad (2)$$

- (2) For the two new sequences  $\boldsymbol{\gamma}_{x,\nu}$  and  $\boldsymbol{\gamma}_{y,\nu}$ , construct two new time series:

$$\begin{aligned} R_{x,\nu}(k) &= \sum_{i=1}^k \boldsymbol{\gamma}_x(\ell_\nu+i), \\ R_{y,\nu}(k) &= \sum_{i=1}^k \boldsymbol{\gamma}_y(\ell_\nu+i). \end{aligned} \quad (3)$$

- (3) Use the least square method to calculate the local trend function  $\hat{R}_{x,\nu}(k)$  and  $\hat{R}_{y,\nu}(k)$  for each point in the subinterval  $\nu$  and calculate the detrended partial cross-correlation

$$F_{xy;z}^2(\nu, s) = \frac{1}{s} \sum_{k=1}^s |R_{x,\nu}(k) - \hat{R}_{x,\nu}(k)| \times |R_{y,\nu}(k) - \hat{R}_{y,\nu}(k)|. \quad (4)$$

- (4) Define the  $q$ -order the detrended partial cross-correlation:

$$F_{xy;z}(q, s) = \begin{cases} \left\{ \frac{1}{2N_s} \sum_{\nu=1}^{2N_s} [F_{xy;z}^2(\nu, s)]^{q/2} \right\}^{1/q}, & \text{if } q \neq 0, \\ \exp \left\{ \frac{1}{4N_s} \sum_{\nu=1}^{2N_s} \ln [F_{xy;z}^2(\nu, s)] \right\}, & \text{if } q = 0. \end{cases} \quad (5)$$

- (5) The scaling relation is expected when

$$F_{xy;z}(q, s) \sim s^{h_{xy;z}(q)}. \quad (6)$$

If the log-log plot for  $F_{xy;z}(q, s)$  vs.  $s$  has a linear relationship, that is,  $\log F_{xy;z}(q, s) = h_{xy;z}(q) \log s +$

$\log C$ , then it can be explained that there is a long-term cross-correlation relationship between  $x(t)$  and  $y(t)$ . Here,  $h_{xy;z}(q)$  is called generalized Hurst index. When  $q$  takes a positive value,  $h_{xy;z}(q)$  describes the behavior of the period with large fluctuations, while  $q$  takes a negative value, it describes the behavior of the segment with small fluctuations. If  $h_{xy;z}(q)$  depends on  $q$ , the cross-correlation of the two time series has multifractal characteristics; otherwise, it has single fractal characteristics. The Hurst index  $h_{xy;z}(2)$  (that is, when  $q = 2$ ) is used to express the partial cross-correlation relationship between time series.  $h_{xy;z}(2) = 0.5$  means that the two series do not have a partial cross-correlation relationship;  $h_{xy;z}(2) > 0.5$  indicates that there is a long-term persistent partial cross-correlation relationship between the two series;  $h_{xy;z}(2) < 0.5$  indicates that there is an antipersistence partial cross-correlation relationship. The closer the  $h_{xy;z}(2)$  to 0, the stronger the antipersistence.

To characterize the multifractal feature, the multifractal mass exponent  $\tau_{xy;z}(q)$  is

$$\tau_{xy;z}(q) = q h_{xy;z}(q) - 1. \quad (7)$$

If  $\tau_{xy;z}(q)$  is a nonlinear function of  $q$ , then the partial cross-correlation of the time series has multifractal characteristics. According to the Legendre transform, the singular strength function  $\alpha$  and its multifractal spectrum  $f_{xy;z}(\alpha)$  can be obtained by

$$\begin{aligned} \alpha_{xy;z}(q) &= \tau'_{xy;z}(q) = h_{xy;z}(q) + q h'_{xy;z}, \\ f_{xy;z}(\alpha) &= q \alpha_{xy;z}(q) - \tau_{xy;z}(q). \end{aligned} \quad (8)$$

If the partial cross-correlation between two time series has multifractal characteristics, the graph of  $f_{xy;z}(\alpha) \sim \alpha$  appears as a single peak, and the multifractal strength can be measured by the width of the multifractal spectrum. The wider the multifractal spectrum is, the stronger the multifractal strength of the partial cross-correlation relationship of the time series is, and vice versa.

### 3. Empirical Results

**3.1. Sample Selection and Descriptive Statistics.** We selected the daily data of the U.S. dollar index, the closing price of US SPDR gold, and WTI crude oil futures from January 4, 2010, to October 9, 2020, a total of 2806 groups, which are downloaded from WIND database. For the missing values of unequal time in the three markets, we established autoregressive-moving-average (ARMA) models separately to complement them for each market. And, we took the logarithmic return, that is,  $r_t = \ln(p_t/p_{t-1})$ , where  $p_t$  is the closing price at time  $t$ .

It can be seen from Figure 1 that the logarithmic return of crude oil market has the largest fluctuation and the U.S. dollar index has the smallest fluctuation. Combining with the descriptive statistics of the three markets logarithmic

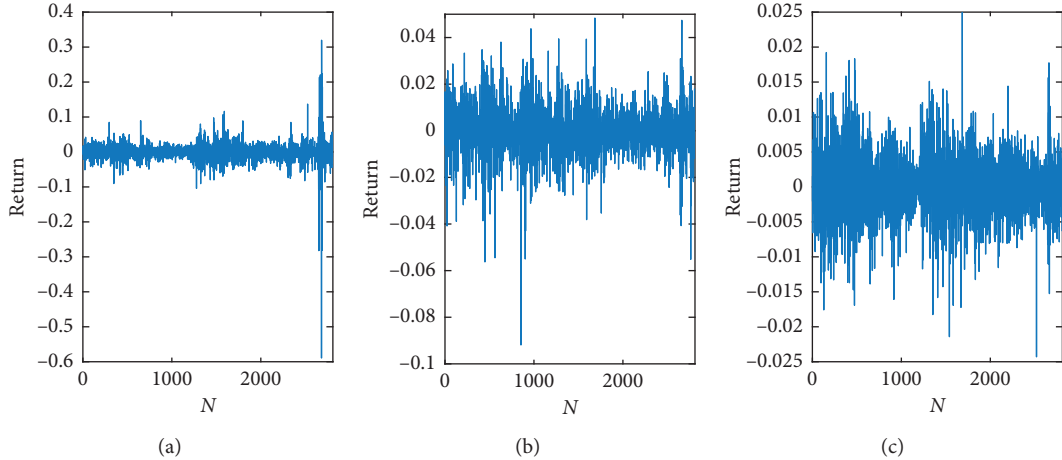


FIGURE 1: The daily logarithmic return of crude oil, gold, and dollar. (a) Oil market. (b) Gold market. (c) Dollar index.

return series shown in Table 1, it can be seen that the skewness of the three log return series is not 0, and the kurtosis is greater than 3. The Jarque–Bera statistical test results show that, at 5% significance level, the logarithmic return series of these three markets do not obey the null hypothesis of normal distribution. The augmented Dickey–Fuller (ADF) test results show that the above three series are all stationary series.

**3.2. Cross-Correlation Test.** In order to prove the existence of the cross-correlation relationship between the logarithmic return rate series of the financial market, the method proposed by Podobnik [8] is used to test the cross-correlation relationship between crude oil and the U.S. dollar index and gold and the U.S. dollar index. For two time series  $x_t$  and  $y_t$ ,  $t = 1, 2, \dots, N$ , construct statistic

$$Q_{cc}(m) := N^2 \sum_{i=1}^m \frac{c_i^2}{N-i}, \quad (9)$$

where  $c_i = (\sum_{k=i+1}^N x_k y_{k-i}) / \sqrt{(\sum_{k=1}^N x_k^2)(\sum_{k=1}^N y_k^2)}$  which is the cross-correlation function. The statistic  $Q_{cc}(m)$  is approximately distributed  $\chi^2(m)$  with the degree of freedom  $m$ . If  $Q_{cc}(m)$  is different from the critical value, it indicates that there is a cross-correlation between the two time series significantly at a certain significance level. Figure 2 shows the test results of the cross-correlation relationship between crude oil and U.S. dollar index, gold and U.S. dollar index, crude oil and gold price, and the critical value of chi-square distribution with a significance level of 5%. It is found that, for different degrees of freedom, the test statistic approximately obeys the distribution, but there is a certain degree of deviation from the critical value. It shows that there is a cross-correlation between them. As everyone knows, the  $Q_{cc}(m)$  test can only qualitatively test whether there is cross-correlation between two time series. The characteristics of the cross-correlation between the two series of these markets and the partial cross-correlation between crude oil and gold will be analyzed in Section 3.3.

TABLE 1: Descriptive statistics of each market's return series.

Item	Crude oil	Gold	Dollar index
Maximum	0.319634	0.048370	0.024952
Minimum	-0.589346	-0.091905	-0.024300
Mean	-0.000248	0.000178	0.000056
Standard deviation	0.028354	0.009884	0.004489
Skewness	-2.958346	-0.567234	0.017911
Kurtosis	90.997520	8.953020	4.994415
Jarque–Bera statistics**	909120.6000	4292.2880	465.0426
ADF statistics**	-21.9856	-53.8956	-53.2274
Prob.	0.0000	0.0000	0.0000

\*\*5% significance level.

**3.3. MF-DPCCA Analysis.** In this section, we further use MF-DPCCA to consider the markets of crude oil and gold affected by the U.S. dollar. The length of the subinterval is chosen according to the recommendation in Peng [39]:  $s_{\min} = 5$  and  $s_{\max} = N/5$ , which eliminates the influence of the sample and the scaling behavior of the fluctuation function that does not obey the power law. Hence, conservatively, let  $s$  be in  $\{50, 60, \dots, 500\}$ . And, in order to analyze the small and large fluctuations in the time series, the value range of  $q$  is set between  $-10$  and  $10$ , with an interval of  $1$ . The fluctuation function of crude oil ( $x_t$ ) and gold ( $y_t$ ) affected by the U.S. dollar index ( $z_t$ ),  $F_{xy:z}(q, s)$ , is shown in Figure 3. It can be seen that there is a power-law correlation between the fluctuation functions  $F_{xy:z}(q, s)$  and  $s$ .

As shown in Figure 4, when  $q$  changes from  $-10$  to  $10$ , the Hurst index  $h_{x:z}(q)$  (see the footnote for this notation). Here,  $h_{x:y}(q)$  is the Hurst index between time series  $x_t$  and  $y_t$ , which is calculated according to MF-DCCA. The authors take modulus of the detrended covariance function in MF-DCCA (see [30, 32, 40] etc.). For such treatment,  $h_{y:z}(q)$ ,  $h_{x:y}(q)$ , and  $h_{xy:z}(q)$  of the crude oil, gold, and U.S. dollar index are not constant, which means that there is a multifractal cross-correlation between the above financial markets. Among them, the crude oil market and the gold market not only have a partial cross-correlation relationship affected by the U.S. dollar index but their partial cross-correlation relationship also has multifractal characteristics.

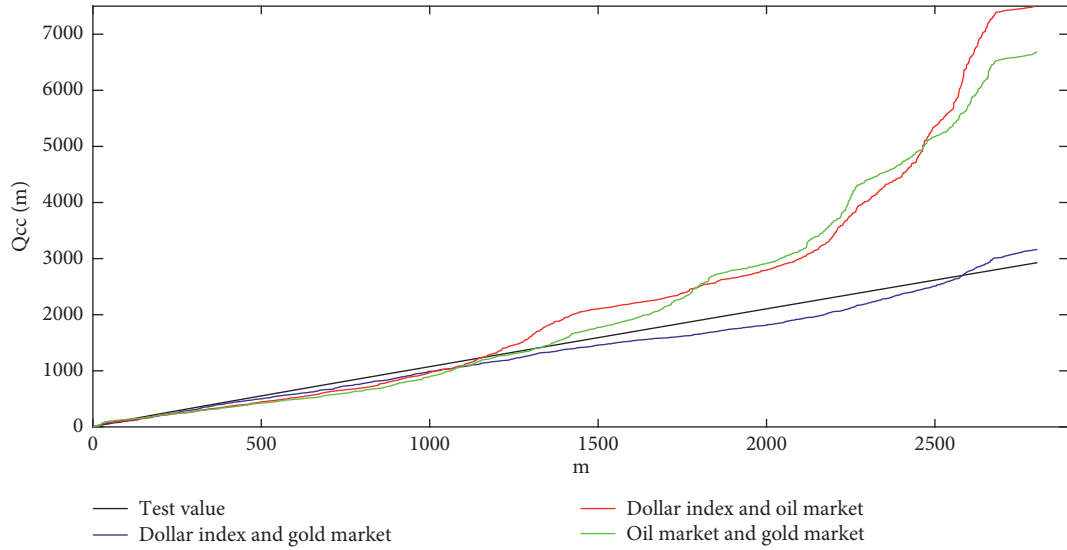


FIGURE 2: The cross-correlation statistic.

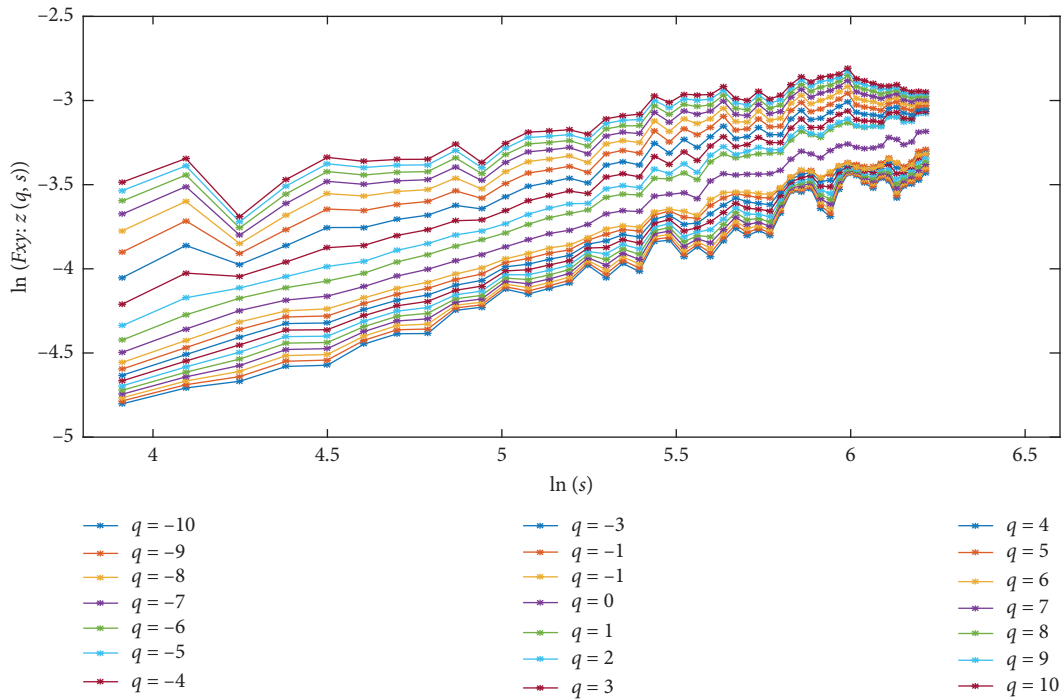


FIGURE 3: Log-log plots of  $F_{xy:z}(q, s)$  vs.  $s$ .

For intervals  $q < -1$  and  $q > 1$  Hurst index  $h_{x:y:z}(q)$  shows a monotonous decreasing trend indicating it is high multifractal characteristics. However, Figure 4 also shows that the curve of  $h_{x:y:z}(q)$  increases from 0.54 to 0.6 in the interval of  $-1 < q < 1$  indicating it is moderately multifractal [21].

In Table 2, we obtained the Hurst index through multifractal detrended cross-correlation analysis and multifractal detrended partial cross-correlation analysis. Obviously, Hurst index  $h_{x:y}(q)$  between crude oil and gold series shows a decreasing trend with increasing  $q$ , and  $h_{x:z}(q) \neq h_{y:z}(q) \neq h_{xy:z}(q)$ . It means that crude oil and gold price returns have a cross-correlation relationship with

multifractal characteristics, and the U.S. dollar index also has a significant impact on the partial cross-correlation relationship between the two markets. Table 2 also shows the multifractal degree  $\Delta h = h_{\max}(q) - h_{\min}(q)$ . Among them, the multifractal degree  $\Delta h = 0.31$  of the cross-correlation between crude oil and gold is affected by the U.S. dollar index. From a numerical point of view, the generalized Hurst index  $h_{x:y:z}(q)$  is slightly smaller than  $h_{x:z}(q)$ ,  $h_{y:z}(q)$ , and  $h_{x:y}(q)$ . It can be seen that the dollar index, as a common external force, has a weaker impact on the partial cross-correlation relationship between the crude oil and gold markets than those cross-correlations between the crude oil,

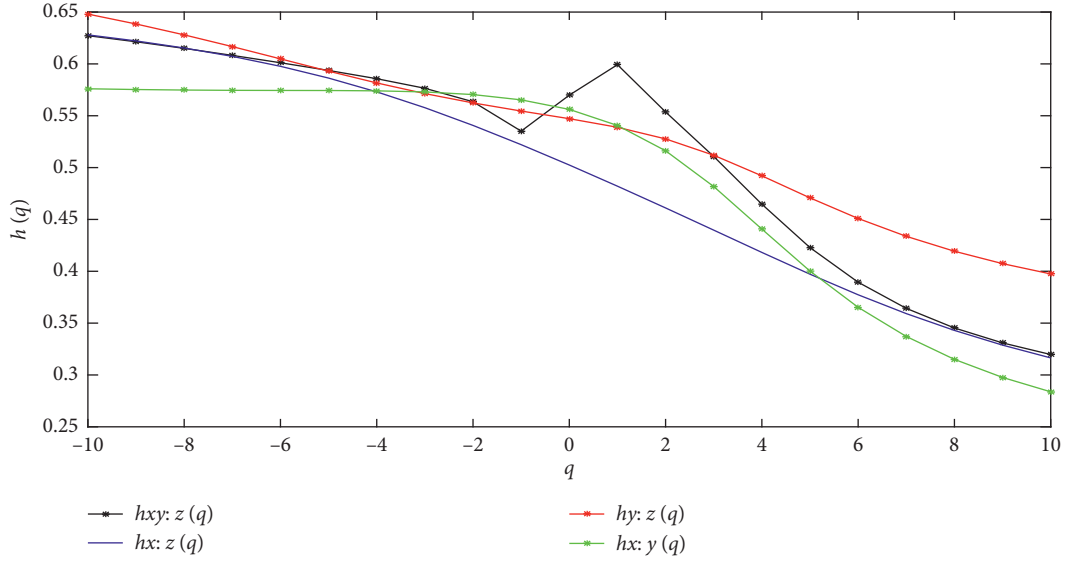


FIGURE 4: Generalized Hurst index.

TABLE 2: Generalized Hurst index among various markets.

$q$	$h_{xy:z}(q)$	$h_{x:z}(q)$	$h_{y:z}(q)$	$h_{x:y}(q)$
-10	0.6272263	0.6280002	0.6480410	0.5760098
-9	0.6213409	0.6221774	0.6385016	0.5752960
-8	0.6149852	0.6153460	0.6280080	0.5747894
-7	0.6082220	0.6072685	0.6166944	0.5745056
-6	0.6011212	0.5976815	0.6048594	0.5744031
-5	0.5936910	0.5863316	0.5929820	0.5743408
-4	0.5857305	0.5730370	0.5816459	0.5740265
-3	0.5764880	0.5577637	0.5713630	0.5729683
-2	0.5635075	0.5406769	0.5623790	0.5704245
-1	0.5351630	0.5221167	0.5545418	0.5653273
0	0.5698492	0.5024799	0.5471707	0.5561330
1	0.5992305	0.4820786	0.5388807	0.5406397
2	0.5536593	0.4610930	0.5276715	0.5162277
3	0.5107301	0.4396853	0.5119128	0.4817407
4	0.4646855	0.4181886	0.4920531	0.4406914
5	0.4228323	0.3971793	0.4707981	0.4001724
6	0.3894462	0.3773279	0.4509153	0.3652485
7	0.3642258	0.3591675	0.4337104	0.3371389
8	0.3453119	0.3429717	0.4193129	0.3150261
9	0.3309200	0.3287742	0.4073696	0.2976178
10	0.3197183	0.3164512	0.3974339	0.2837566
$\Delta h$	0.3075080	0.3115490	0.2506071	0.2922532

gold markets, and the dollar index. When  $q = 2$ , the aforementioned Hurst index is not equal to 0.5, indicating that there is a long-term cross-correlation between crude oil and the U.S. dollar index, gold and U.S. dollar index, and crude oil and gold prices. And,  $h_{xy:z}(2) = 0.55$ , which represents the long-term correlation of the partial cross-correlation relationship between crude oil and gold markets. This also proves that the relationship between crude oil, gold, and the U.S. dollar index is not a linear relationship in the traditional sense. We should consider in a nonlinear way of thinking that the financial market is affected by its own fluctuation and the synergistic impact of fluctuation with other markets.

Figure 5 shows that there is an obvious nonlinear relationship between  $\tau_{x:z}(q)$ ,  $\tau_{y:z}(q)$ ,  $\tau_{x:y}(q)$ , and  $\tau_{xy:z}(q)$ , which once again proves that there is a partial cross-correlation between the crude oil and gold market returns series and the multiple fractal features. Figure 6 shows the multifractal spectrum of the cross-correlation between the crude oil, gold, and the U.S. dollar index returns series. The multifractal spectrum describes the complex dynamic mechanism between time series, and its width  $\Delta\alpha = \alpha_{\max} - \alpha_{\min}$  is often used to estimate the strength of the multifractal and reflect the complexity of the market. Figure 6 shows that there are indeed single peak bells with right hook, and the width of the multifractal spectrum is significantly not 0. From a numerical point of view, the widths of  $f_{x:z}(\alpha)$ ,  $f_{y:z}(\alpha)$ ,  $f_{x:y}(\alpha)$ , and  $f_{xy:z}(\alpha)$  are the largest because the yield sequence of the crude oil and gold markets is affected by the U.S. dollar index. The multifractal spectrum widths of  $f_{x:z}(\alpha)$ ,  $f_{y:z}(\alpha)$ , and  $f_{x:y}(\alpha)$  are all around 0.45, indicating that the crude oil and dollar index, gold and dollar index, and crude oil and gold price itself have significant cross-correlation with multifractal characteristics, but the multifractal characteristics of the partial cross-correlation relationship between crude oil and gold market yield series are the most significant. This means that the external influence of the U.S. dollar index on the crude oil and gold markets is stronger than the influence of the U.S. dollar index on the fluctuations of its individual markets, and it is also stronger than the cross-influence of the crude oil and gold markets themselves.

**3.4. Causes of Multifractal Characteristics.** There are generally two reasons for multifractal characteristics: one is due to the long-term correlation between the logarithmic returns of financial market prices; the other is due to the fluctuating fat-tailed distribution between the series of logarithmic returns [41, 42]. The shuffled transformation and Fourier-

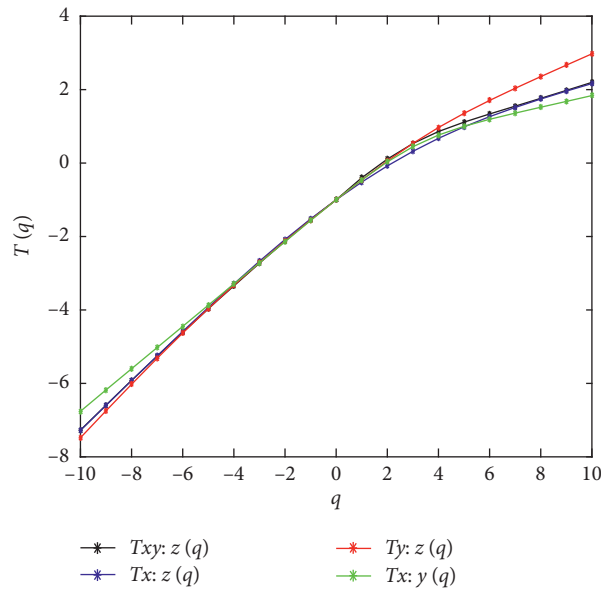


FIGURE 5:  $\tau(q)$  vs.  $q$ .

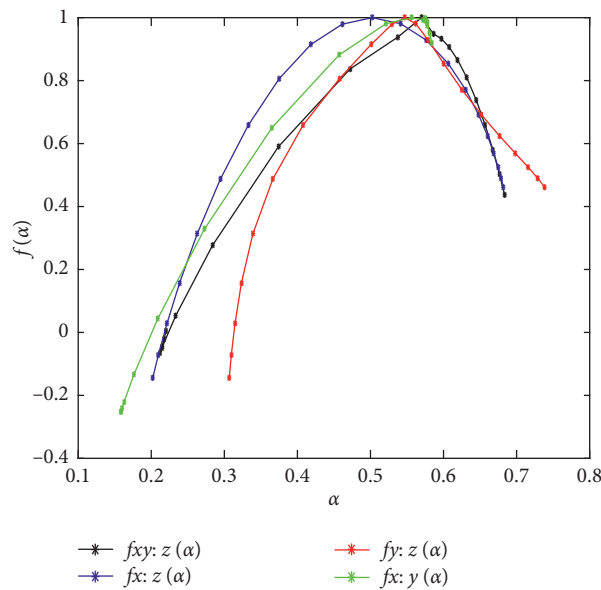


FIGURE 6: The strength of the multifractality.

phase randomization of the data can be used to find the contribution strength of the above influencing factors to the multifractal characteristics.

The shuffled transformation includes the following steps:

- (1) Randomly generate a natural number pair  $(p, q)$ , where  $p$  and  $q$  are less than or equal to the length of the time series  $N$
- (2) Exchange the  $p$  and  $q$  data in the time series
- (3) Repeat the above steps  $20N$  times to ensure that the sequence is completely out of order

The phase randomization process includes the following steps:

- (1) Carry out discrete Fourier transform on the original sequence
- (2) Randomly rotate the sequence obtained by a phase angle
- (3) Carry out an inverse Fourier transform again

It can be seen from Figure 7 that the Hurst index  $h_{xy:z}(q)$  calculated by the shuffled transformation and Fourier-phase randomization processing of the crude oil, gold, and U.S. dollar index logarithmic return series is different from the  $h_{xy:z}(q)$  of the original series, but in different degrees, the above still shows a decreasing change with the change of the order  $q$  and is not a constant. The  $\tau_{xy:z}(q)$  graphs of the processed logarithmic return series

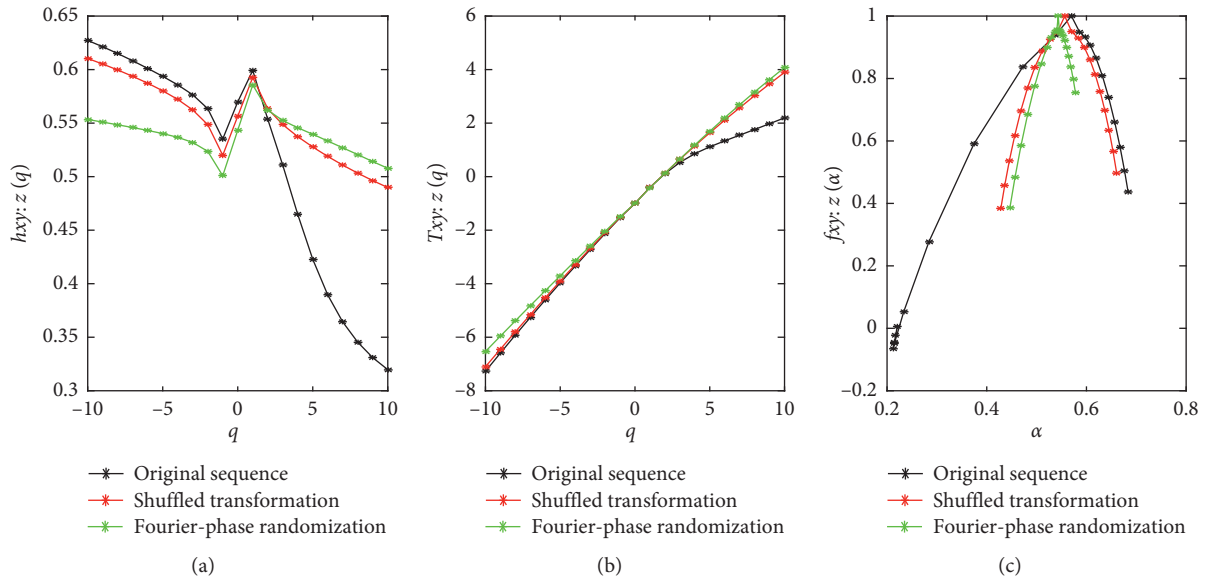


FIGURE 7: Results of shuffled transformation and Fourier-phase randomization.

also have obvious nonlinearity, and the width of the multifractal spectrum is also different. This shows that the long-term correlation of the return series of crude oil, gold, and the U.S. dollar index and the fat-tailed distribution of fluctuation all lead to multifractal characteristics. It can also be seen from Figure 7 that the multifractal degree  $\Delta h$  of the return series after the shuffled transformation is greater than that calculated by Fourier-phase randomization, and the multifractal spectrum width of the data after the shuffled transformation is also greater than that calculated by Fourier-phase randomization. It can be judged that when the external force of the U.S. dollar index affects the multifractal characteristics of the crude oil and gold markets, the long-term correlation has a slightly greater influence on the fractal characteristics than the fluctuation fat-tailed distribution.

#### 4. Conclusion

In the past few decades, various researchers have conducted extensive research on financial markets based on cross-correlation and multifractal characteristics. This paper uses MF-DPCCA to investigate the partial cross-correlation relationship between American financial markets. Empirical research found that there are significant cross-correlation relationships between crude oil and U.S. dollar index, gold and U.S. dollar index, and crude oil and gold prices, which have multifractal characteristics. Furthermore, the obtained results show that the U.S. dollar index, as an external factor, have fractal characteristics for the partial cross-correlation between the crude oil market and the gold market. The multifractal characteristics of the sequence after the shuffled transformation and Fourier-phase randomization indicates that the multifractal characteristics of the crude oil and gold market logarithmic return series are the result of the combined

effect of long-term correlation and fluctuation fat-tailed distribution. The impact of long-term correlation is slightly higher than that of fat-tailed distributions.

#### Data Availability

The three time series data used to support the findings of this study have been deposited in the WIND database (<https://www.wind.com.cn/en/data.html>).

#### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

#### Authors' Contributions

All authors contributed equally to this work.

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