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Dynamic relationship between Chinese RMB exchange rate index and market anxiety: A new perspective based on MF-DCCA

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ABSTRACT

This paper employs multifractal detrended cross-correlation analysis (MF-DCCA) to study the cross-correlations between the Chinese RMB exchange rate index and market anxiety using data from June 21, 2010 to December 28, 2018. Cross-correlation statistics and coefficients verify the existence of cross-correlations, and the MF-DCCA method quantitatively confirms the presence of multifractality between the Chinese RMB index and market anxiety for both the long- and short-term. The results of the rolling window analysis reveal that cross-correlation scaling exponents of the Chinese RMB index and market anxiety are sensitive to external shocks.

1. Introduction

The Chinese RMB exchange mechanism was reformed on July 21, 2005 when the RMB exchange rate underwent significant changes with a managed floating exchange rate system and adjusted with reference to a basket of currencies. In order to enhance the elasticity and the efficiency of the RMB exchange regime, the People's Bank of China (PBOC), the Central Bank, kept its FX market operations again ever since May 2007. On August 11, 2015, it was announced by the PBOC that it would renew the RMB exchange formation mechanism by frequently adjusting the mid-price quotation of the USD/CNY exchange rate to enlarge the range of the "managed" rate fluctuations and increase the elasticity of the FX regime further.

In recent few years when facing the economic slowdowns, the Chinese monetary authority also conducted a series of FX market operations and interventions to cope with the pro-cyclical behavior in the exchange movements to avoid market panic. For instance, the PBOC introduced inverse periodic factor management in the middle price quotation in February 2017 and August 2018. The purposes of those are to strengthen the macro-prudential management of international capital flows and avoid the extreme situations of the market volatility. The above-mentioned Central Bank's FX market operations and policy interventions would be eventually influenced and reflected by the market sentiments of the RMB exchange market. There exists a kind of the linkage between policy operations, market interventions, and the FX market sentiments measured by various market panic index, such as the VIX, CBOT Volatility Index.

Traditional methods for analyzing exchange rate fluctuations such as Dynamic Stochastic General Equilibrium(DSGE), VAR, and GARCH neglect the impacts of market sentiment on exchange rate determination. In this paper we explore how market sentiment would influence on the RMB exchange movements and FX volatility by using VIX, CBOT Volatility Index.

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The VIX here is calculated from the implied volatility of the S&P 500 index, which is widely used to reflect the degree of panic among investors in the post-market; this index is sometimes known as the "panic index". The second volatility index used in this paper is the spread between the US effective federal funds rate and Shanghai Interbank Offered Rate (SHIBOR).

While many studies have explored the VIX, few have focused on the relationship between market anxiety and the foreign exchange market. Lu et al. [1] employed MF-DCCA to study the dynamic relationship between Japanese Yen exchange rates and market anxiety. Fractal theory was introduced by Mandelbrot [2], who described a fractal as a natural phenomenon or mathematical set that shows a repeating pattern at every scale. Peng et al. [3] proposed the detrended fluctuation analysis (DFA) approach and Kantelhardt et al. [4] conducted an study proposing MF-DFA as a multifractal form of DFA. MF-DCCA approach was developed by Zhou [5] based on MF-DFA and DCCA methods. Li et al. [6] employed MF-DCCA to test multifractal cross-correlations between the crude oil market and five exchange rate markets. MF-DFA and MF-DXA is employed to study the relationship of daily volume changes and daily price changes of global stock market [7]. Wang et al. [8] apply multiscale multifractal detrended cross-correlation analysis (MM-DCCA) and Lempel–Ziv complexity (LZC) to research the return intervals of Chinese stock market. Li et al. [9] found strong positive persistence between the RMB index and stock market liquidity. RMB exchange rates and international commodity prices are anti-persistent cross-correlated, as shown by Lu et al. [10]. Sun et al. [11] contributed to the literature by examining effects of US monetary policy on the US dollar index and on WTI crude oil using the MF-DCCA approach. In addition, Lu et al. [1] confirmed the presence of a multifractal cross-correlation between Japanese Yen exchange rates and market anxiety. Cao et al. [12] use MF-DCCA and Nonlinear Granger causality test to study the risk conduction between Chinese stock market and foreign stock markets. Zhang et al. [13] examine the dynamic relationship of volume and return in the bitcoin market. By using MF-DFA and MF-DCCA, Ruan et al. [14] find that there exists strong multifractal relationship between seasonal affective disorder and stock market.

The present study seeks to expand the existence research by testing the dynamic relationship between the Chinese RMB exchange rate index and market anxiety. This paper attempts to analyze three important issues. First, we explore whether cross-correlations exist between the RMB exchange rate market and two forms of market anxiety. Second, we examine whether such cross-correlations exhibit multifractal behavior. Third, we aim to determine whether recent external shocks have had significant impacts on cross-correlations between the two markets.

The rest of this paper is organized as follows. Section 2 discusses the MF-DCCA methodology. Section 3 provides a description of the data used and preliminary test statistics. Section 4 presents our empirical analysis, and Section 5 summarizes our conclusions.

2. Methodology

The MF-DCCA approach based on multifractal theory can remove the influence of local trends at the time series scale and can be used to analyze the cross-correlations between two simultaneous and nonstationary time sequences. The basic principles of MF-DCCA are as follows [4].

1. Suppose that there are two time series $x(i)$ and $y(i)$ ($i = 1, 2, \ldots, N$) where N is the length of the time series.

$$X(i) = \sum_{k=1}^{i}(x(k) - \bar{x}) \qquad Y(i) = \sum_{k=1}^{i}(y(k) - \bar{y}) \tag{1}$$

where $\bar{x}$ and $\bar{y}$ are the means of the two time series, respectively.

2. Time series $x(i)$ and $y(i)$ are divided into $Ns = int[N/s]$ non-overlapping sub-intervals, each of which has the same length s [5]. Since length N may not be an integer multiple of sub-interval length s, the same processing is applied in the reverse order of the time series. Thus, $2Ns$ segments are obtained together.

3. Calculate the detrended covariance, which is determined as follows. For $\lambda = 1, 2, \ldots, Ns$

$$F^2(s,\lambda) = \frac{1}{s}\sum_{i=1}^{s}\{X\left[(\lambda-1)s+i\right] - x_\lambda(i)\} \times \{Y\left[(\lambda-1)s+i\right] - y_\lambda(i)\} \tag{2}$$

For $\lambda = Ns + 1, \ldots, 2Ns$

$$F^2(s,\lambda) = \frac{1}{s}\sum_{i=1}^{s}\{X\left[N-(\lambda-N_s)s+i\right] - x_\lambda(i)\} \times \{Y\left[N-(\lambda-N_s)s+i\right] - y_\lambda(i)\} \tag{3}$$

4. Take the mean of the local trends of all segments to obtain the q-order fluctuation function

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{\lambda=1}^{2N_s}\left[F^2(s,\lambda)^{q/2}\right]\right\}^{1/q} \qquad q \neq 0 \tag{4}$$

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{\lambda=1}^{2N_s}\left[\ln F^2(s,\lambda)\right]\right\} \qquad q = 0 \tag{5}$$

5. Calculate the fluctuation function $F_q(s)$ corresponding to different scales s.

If there is a long-term cross-correlation between the two time series, fluctuation function $F_q(s)$ and time segments s have the following power-law expression

$$F_q(s) \sim s^{H_{xy}(q)} \tag{6}$$

Another expression of this formula is

$$\log F_q(s) = H_{xy}(q)\log(s) + \log C \tag{7}$$

scaling exponent $H_{xy}(q)$ is the generalized Hurst exponent, which is the slope of the $logF_q(s)$ and $log(s)$ functional diagram.

If $H_{xy}(q)$ differs with diverse values of q, the cross-correlation between the two time series has multifractal features. When $q = 2$, the value of $H_{xy}(2)$ is the Hurst index, and MF-DCCA reduces to DCCA. When $X(i)$ and $Y(i)$ represent the same time series, MF-DCCA reduces to MF-DFA.

If $H_{xy}(q) = 0.5$, the two time series have no long-range correlation, and the time series can be described as random walk. If $0<H<0.5$, the two time series are anti-persistence series, which indicates that if one time series increases, the other time series may decline. If $0.5<H<1$, there are persistent cross-correlations between the two time series with reference to q, which indicates that the two time series change in the same direction. In addition, when $q>0$, $H_{xy}(q)$ describes significant fluctuations and when $q<0$, $H_{xy}(q)$ characterizes minor fluctuations.

6. According to Shadkhoo and Jafari [15], the relationship between the generalized Hurst exponent $H_{xy}(q\ )$ obtained from MF-DCCA and the multifractal scale index $\tau(q)$ is as follows.

$$\tau(q) = qH_{xy}(q) - 1 \tag{8}$$

If $\tau(q)$ and q are linear, the cross-correlation of the two series is monofractal. Otherwise, there is a multifractal feature between them.

7. Then, from the Legendre transform, the multifractal spectrum $f(\alpha)$ is obtained

$$\alpha = H_{xy}(q) + qH'_{xy}(q) \tag{9}$$

$$\mathrm{f}(\alpha) = (\alpha - H_{xy}(q)) + 1 \tag{10}$$

where α is a singularity index describing the degree of singularity of the time series. $f(\alpha)$ is a multifractal spectrum that reflects the fractal dimension of α.

Multifractal intensity can be measured from the width ΔH of the multifractal spectrum [16,17].

$$\Delta H = H_{max}(q) - H_{min}(q) \tag{11}$$

The larger ΔH is, the stronger multifractality is and vice versa.

3. Data and preliminary test statistics

In this paper, we use daily closing prices of the RMB nominal effective exchange rate index and of two market anxiety indices. The data were from the period of June 21, 2010 to December 28, 2018. The RMB nominal effective exchange rate index and market anxiety indices are obtained from the wind database.

The daily returns of Chinese RMB exchange rates are measured as the difference in the logarithm of daily closing price $P_{t.}$

$$r_t = log(P_t) - log(P_{t-1}) \tag{12}$$

Since *VIX* is quoted as a percentage, following Sarwar [18] we use daily changes in *VIX* in this paper.

$$\Delta VIX = VIX_t - VIX_{t-1} \tag{13}$$

The second measure of market anxiety is called the spread, which is obtained by calculating the difference between the US effective federal fund rate and the Shanghai Interbank Offered Rate.

$$\Delta spread = spread_t - spread_{t-1} \tag{14}$$

Table 1 describes descriptive statistics on daily returns of the RMB index(CNYX), VIX, and spread.

Descriptive statistics for the VIX, spread and daily returns of the RMB index are shown in Table 1. In the sample, the means of daily returns of the RMB index are fairly close to zero and means of the VIX and spread are greater than zero especially for the VIX (volatility of volatility), which reaches 16.6618. The standard deviation of all three series is greater than zero. For each series, the skewness is not equal to zero and kurtosis exceeds a value of three, which suggests that all of the series have a non-normal distribution with fat-tails and leptokurtosis. The Jarque–Bera statistics for the three variables reject the null hypothesis of the Gaussian distribution at the 1% significance level.

Table 1
Descriptive statistics for the RMB index returns, daily VIX and daily spread.

	CYNX	spread	VIX
Minimum	−7.8863e−03	−0.9300	9.1400
Maximum	5.3593e−03	13.3440	48.0000
Mean	2.7200e−05	2.1531	16.6618
Std.dev	1.0039e−03	1.1247	5.5929
Skewness	0.9294	1.6189	1.7129
Kurtosis	2.3760	11.0199	6.7390
Jarque–Bera	641.2000***	6.4259e + 03***	2.1371e + 03***

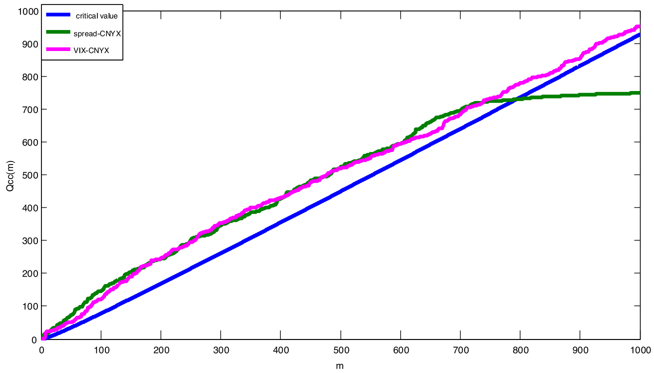

Fig. 1. The cross-correlation statistic *Qcc(m)* for daily VIX changes, daily spread changes and daily returns of the Chinese RMB index. The blue line denotes the critical value of the cross-correlation statistic.

4. Empirical results

4.1. Cross-correlation test

To examine whether cross-correlations exist between the fluctuations in the time series, we refer to a new cross-correlation test index *Qcc(m)* proposed by Podobnik et al. [19], and Ruan et al.'s [20] also use the method to research the relationship between Baltic Dry Index and crude oil prices.

For time series $\{x_t,\ t = 1, 2, \ldots, N\}$ and $\{y_t,\ t = 1, 2, \ldots, N\}$, the cross-correlation statistic *Qcc(m)* is defined as follows

$$Q_{cc}(m) = N^2 \sum_{i=1}^{m} \frac{c_i^2}{N-i} \tag{15}$$

The cross-correlation function C_i is shown in formula (16).

$$c_i = \frac{\sum_{k=i+1}^{N} x_k y_{k-i}}{\sqrt{\sum_{k=1}^{N} x_k^2 \sum_{k=1}^{N} y_k^2}} \tag{16}$$

The cross-correlation statistic *Qcc(m)* approaches $\chi^2(m)$ with m degrees of freedom. When the cross-correlation test fits the $\chi^2(m)$ distribution, there is no cross-correlation between the two time series, and otherwise there is a cross-correlation between the two time series at the given significance level.

Fig. 1 presents cross-correlation statistics for daily VIX changes, daily spread changes and daily returns of the RMB index. The critical value of cross-correlation statistic *Qcc(m)* at the 5% significance level is denoted by the blue line with degrees of freedom m ranging from 0 to 1000.

The purple line denotes the cross-correlation statistic for daily VIX changes and daily returns of the RMB index. The green line denotes cross-correlation statistics for daily spread changes and daily returns of the RMB index. Both lines shift above the blue line as m increases, suggesting the presence of statistically significant cross-correlations between all of the time series studied.

4.2. DCCA coefficient

To further examine the cross-correlations, we use the method recently developed by Podobnik et al. [19] to test cross-correlations between the two time series. The DCCA coefficient is quite different from the traditional Pearson correlation

Table 2
The value of ρ_{DCCA} for a given window size s.

Size(s)	4	8	16	32	64	128
CNYX-VIX	0.0861	−0.0348	−0.0170	−0.0014	0.0487	0.1809
CNYX-spread	0.0250	−0.0399	0.0269	0.0640	0.1022	−0.0862

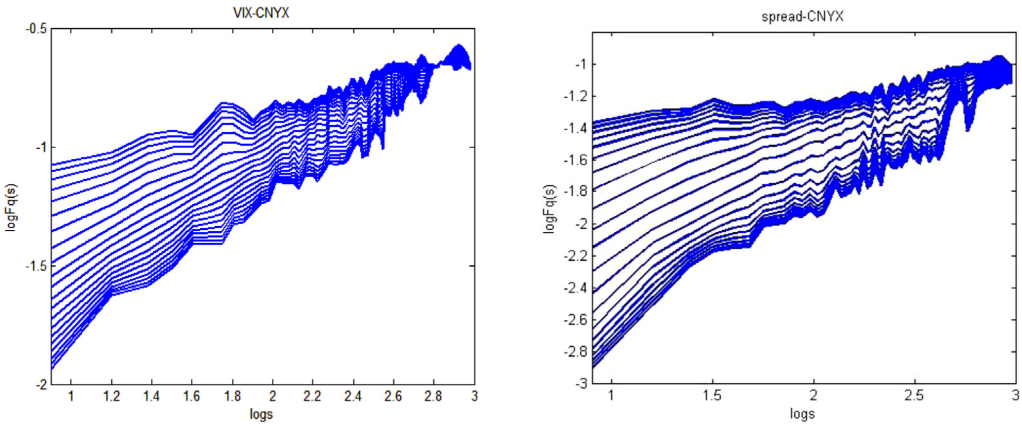

Fig. 2. Log–log plots of fluctuation function $F_q(s)$ versus time scale s for the CNYX and VIX, the CNYX and spread.

coefficient, as the Pearson correlation coefficient remains at a fixed value while the DCCA coefficient differs when q takes different values [21,22]. Coefficient ρ_{DCCA} is the ratio of the detrended covariance's function F^2_{DCCA} to the product of two detrended variance functions F_{DFA}. Fang and Lu [23] used this coefficient to investigate cross-correlations between carbon emissions allowance and stock series and their dynamics for European and Chinese markets, respectively.

The function is defined as follows

$$\rho_{DCCA} = \frac{F^2_{DCCA}(s)}{F_{DFA1}(s)F_{DFA2}(s)} \tag{17}$$

ρ_{DCCA} ranges from −1 to 1. When $\rho_{DCCA} = 0$, there is no cross-correlation between the two time series. When $\rho_{DCCA} = 1$, the two time series are completely anti-persistent and positively correlated. When $\rho_{DCCA} = -1$, the two time series are completely negatively correlated. Based on the different window size values s ($n = 8, 16, 32, 64, 128$), Table 2 presents calculation results for ρ_{DCCA}. The results presented in Table 2 show that all of the figures fall within the interval at $[-1, 1]$, further verifying the cross-correlation test results.

4.3. Scaling behavior analysis

While the above section only tests the existence of the cross-correlations, in this section we study the observed cross-correlations quantitatively via MF-DFA and MF-DCCA. Fig. 2 shows Log–log plots of the fluctuation function $F_q(s)$ versus time scale s for the two time series of the CNYX and VIX, the CNYX and spread.

For each time series there is a time scale s^* called a "crossover". When $s > s^*$ or $s < s^*$, cross-correlation exponents $H_{xy}(q)$ are clearly different. The "crossover" divides cross-correlations into long-term ($s > s^*$) and short-term ($s < s^*$) features. The short-term characteristics of time series are easily influenced by external features of the market while long-term characteristics are determined by internal features of the series.

As is shown in Fig. 2, the crossover of the CNYX and VIX falls approximately at $\log(s^*) = 2.1584$ (144 days), and the crossover of the CNYX and the spread is positioned at $\log(s^*) = 2.2041$ (160 days). To understand dynamic features of the cross-correlation exponents at different times when the values of q are different, we calculate Hurst exponents for $s < s^*$ and $s > s^*$ when q is equal to $-10, -9, -8 \ldots$ and 8, 9, 10. The results are shown in Table 3.

4.4. Multifractal detrended cross-correlation analysis

In Table 3, when $q = 2$ and $s < s^*$, cross-correlation exponents between the CNYX and VIX are valued at 0.4420, cross-correlation exponents between the CNYX and spread are valued at 0.4389, suggesting that there are weakly anti-persistent cross-correlations between time series CNYX and VIX and the CNYX and spread over a short period. For $s > s^*$, cross-correlation exponents between the CNYX and VIX are valued at 0.3505, cross-correlation exponents between the CNYX and spread are valued at 0.3957, implying that there are strongly anti-persistent cross-correlations between time series CNYX and VIX, the CNYX and spread. The above data indicates that over the short term an increase in the CNYX is

Table 3
Cross-correlation exponents for the RMB index returns, daily VIX changes and daily spread changes.

q	CNYX-VIX		CNYX-spread	
	$S^* = 144$		$S^* = 160$	
	$S < S^*$	$S > S^*$	$S < S^*$	$S > S^*$
−10	0.6066	0.6932	0.7623	0.9999
−9	0.5988	0.6786	0.7529	0.9923
−8	0.5900	0.6616	0.7417	0.9826
−7	0.5803	0.6418	0.7279	0.9701
−6	0.5696	0.6186	0.7109	0.9528
−5	0.5582	0.5918	0.6901	0.9279
−4	0.5460	0.5614	0.6654	0.8904
−3	0.5329	0.5274	0.6377	0.8325
−2	0.5187	0.4907	0.6111	0.7466
−1	0.5032	0.4529	0.5891	0.6361
0	0.4833	0.4159	0.5414	0.5330
1	0.4662	0.3811	0.5107	0.4462
2	**0.4420**	**0.3505**	**0.4389**	**0.3957**
3	0.4116	0.3247	0.3629	0.3654
4	0.3749	0.3035	0.2959	0.3465
5	0.3366	0.2867	0.2420	0.3338
6	0.3017	0.2734	0.2001	0.3248
7	0.2726	0.2629	0.1674	0.3180
8	0.2494	0.2547	0.1417	0.3126
9	0.2309	0.2481	0.1211	0.3082
10	0.2161	0.2429	0.1044	0.3045
ΔH	0.3905	0.4503	0.6579	0.6954

likely to occur along with a decrease in the VIX and spread while this tendency is strengthened over the long term. The two time series exhibit cross-mean-reversion behavior. We can further show that over the short term the market is more efficient than it is over the long term because when $s < s^*$, the cross-correlation exponents are quite close to 0.5.

For $s < s^*$, when $q < 0$, cross-correlation exponents for the CNYX-spread and CNYX-VIX exceed a value of 0.5 for the time period and are less than 0.5 when $q > 0$. For $s > s^*$, when $q > 0$, cross-correlation exponents for the CNYX-spread are less than 0.5 but are greater than 0.5 when $q < 0$; finally, when $q > -2$, cross-correlation exponents for the CNYX-VIX are less than 0.5 but are larger than 0.5 when $q < -2$. All of these results indicate that the cross-correlated behavior of minor fluctuations is persistent while large fluctuations present the opposite pattern for all two pairs of time series over the long-term and short-term.

As is shown in Table 3, with an increase in q values cross-correlations decrease, showing that there are multiple fractal features between different time series. ΔH in Table 3 denotes the degree of multifractality, which is calculated from Eq. (11). The results given in Table 3 indicate that the degree of multifractality is larger over the long term than over the short term for all two time series, meaning that over the long run the market experiences more fluctuations than over the short run.

Finally, when $x(i)$ and $y(i)$ are exactly the same time series, the MF-DCCA reduces to MF-DFA [4], and cross-correlation exponents $H_{xy}(q)$ becomes generalized Hurst exponent $H_{xx}(q)$ or $H_{yy}(q)$. When Zhou [5] constructed two time series by applied the binomial measure method with the P model, the following relationship was found

$$H_{xy}(q) = [H_{xx}(q) + H_{yy}(q)]/2 \tag{18}$$

We calculate the scale exponents of each time series via MF-DFA and their average according to Eq. (13) for the long- and short-term. The results are shown in Figs. 3 and 4.

Over the short run, when $q < 1$, for CNYX exchange rate returns and daily VIX changes, the average scaling exponents are larger than the cross-correlation exponents. When $q > 1$, the average scaling exponents are smaller than the cross-correlation exponents; for the CNYX and spread, the same rules as those of the CNYX and daily VIX changes apply. When $q < 0$ nearly occurs, the average scaling exponents are larger than the cross-correlation exponents and when $q > 0$, the average scaling exponents are smaller than the cross-correlation exponents.

Regarding each individual series, for daily CNYX and VIX changes, the scaling exponents of daily VIX changes are the largest when $q < -6$ and the smallest when $q > -2$, and the scaling exponents of CNYX are the largest when $q > -6$; for the CNYX and spread, scaling exponents of the spread are the largest when $q<0$ and the smallest when $q>0$. Scaling exponents of the CNYX are the smallest when $q<0$ and the largest when $q>0$.

Over the long run, for daily VIX changes and the CNYX, when $q < -8$ and $q>8$, the cross-correlation exponent and average scaling exponent are consistent with one another. The average scaling exponent is larger than the cross-correlation exponent when q falls within the $(-8, 8)$ interval; for the CNYX and spread, the cross-correlation exponent is smaller than average scaling exponent when $q<0$ and the cross-correlation exponent is larger than average scaling

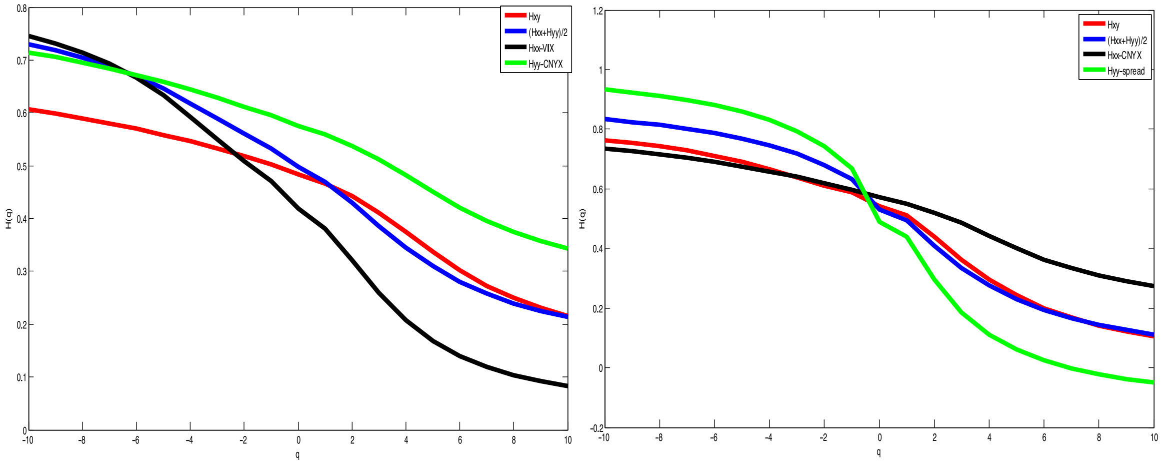

Fig. 3. The short-term nonlinear relationship between $H_{xy}(q)$ and q for the CNYX and VIX, the CNYX and spread.

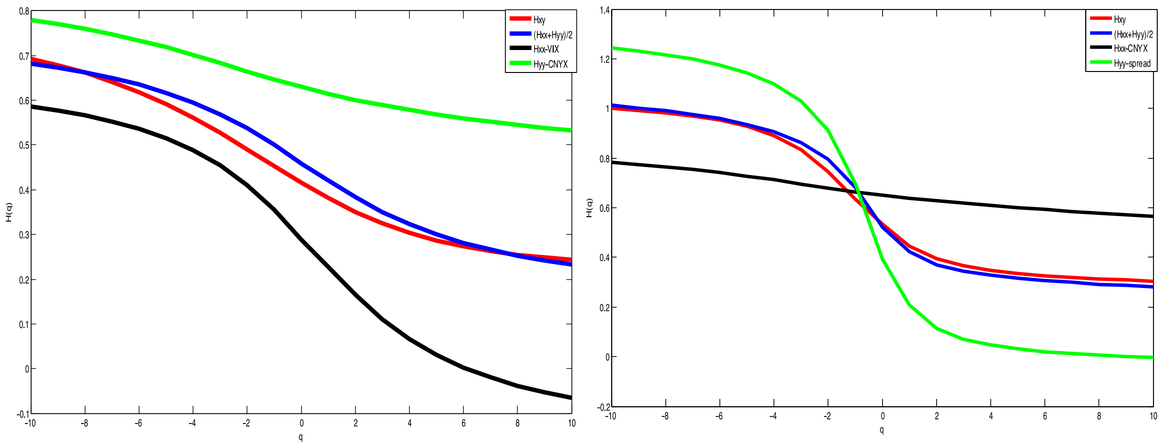

Fig. 4. The long-term nonlinear relationship between $H_{xy}(q)$ and q for the CNYX and VIX, the CNYX and spread.

exponent when $q>0$. Thus, the relationships between cross-correlation and average scaling exponents vary in different markets.

Regarding each individual series, for the CNYX and VIX, the scaling exponent of the CNYX is always the largest and the scaling exponent of the VIX is always the smallest; for the CNYX and spread, the scaling exponent of the spread is always the largest and the scaling exponent of the CNYX is always the smallest when $q<0$, and the scaling exponent of the spread is the smallest and that of the CNYX is the largest when $q>0$.

From the above graph and analysis we can see that large fluctuations are anti-persistent while minor fluctuations are often accompanied by persistent features. For each individual market, large fluctuations follow the rules of mean-reverting while small fluctuations exhibit features of predictability and long-range memory; large fluctuations in the CNYX change inversely with the VIX and spread while small fluctuations in the CNYX present similar fluctuations of the same direction as the VIX and spread.

Fig. 5 and Fig. 6 respectively describe the dynamic relationship between Renyi exponent $\tau(q)$ and different values of q over the short and long term. From the figures, we can see that relationships between $\tau(q)$ and q for the two time series are nonlinear over the short and long term. This finding is consistent with the research conclusions drawn above.

We use Eqs. (9)–(10) to calculate the values of α and $f(\alpha)$ and describe their relationships in Fig. 7. Monofractality exists when the multifractal spectrum appears as a point; otherwise, multifractality appears. From Fig. 7, we can see that the two pairs of time series and each individual series present multifractal features because no multifractal spectra present as a point.

Furthermore, the strength of multifractality is determined from the width of the spectrum, which is described by $\Delta\alpha = max\alpha_{xy} - min\alpha_{xy}$. The narrower the spectrum is, the weaker the strength of the multifractality of cross-correlations, and vice versa.

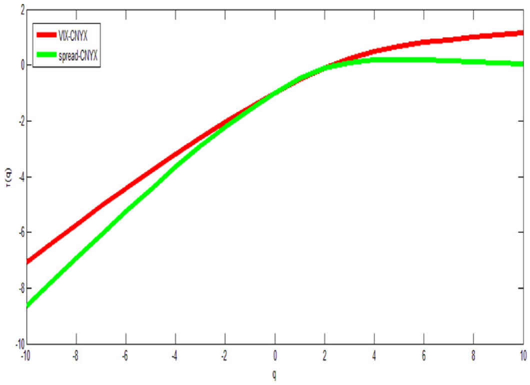

Fig. 5. The short-term relationship between $\tau(q)$ and q for the CNYX and VIX, the CNYX and spread.

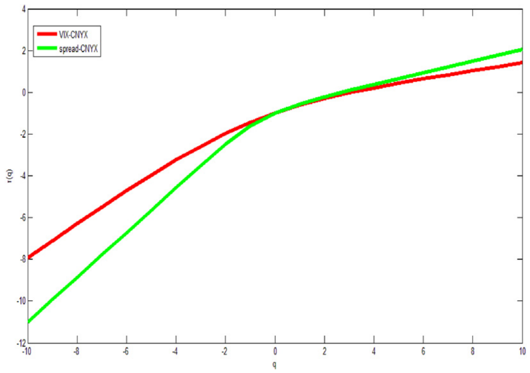

Fig. 6. The long-term relationship between $\tau(q)$ and q for the CNYX and VIX, the CNYX and spread.

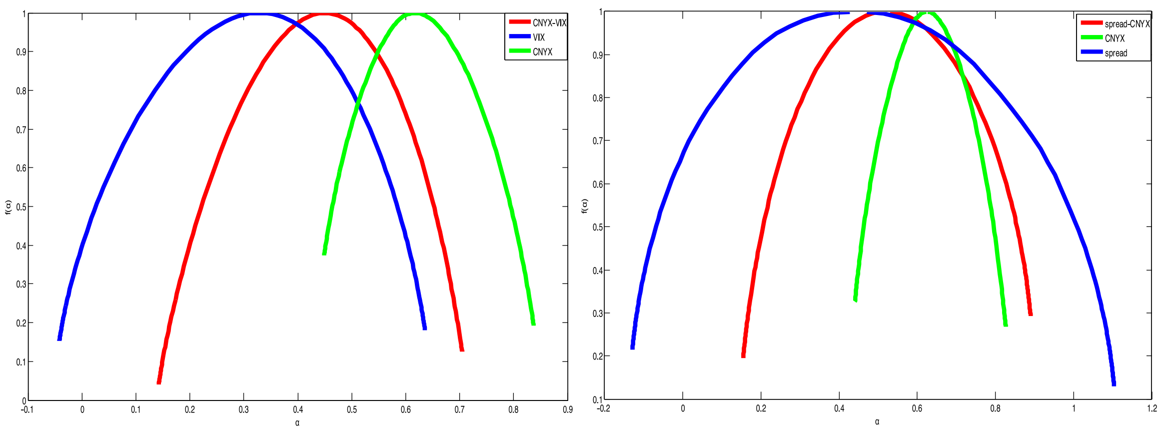

Fig. 7. The multifractal spectra $f(\alpha)$ for the CNYX and VIX, the CNYX and spread.

From Fig. 7, we can see that the multifractal spectrum of the market anxiety index(VIX and the spread) is the broadest while the strength of the multifractality of the bivariate series ranks between the CNYX and the market anxiety index, implying that the volatility of the spread and VIX is more turbulent than the CNYX.

In sum, all of the above results prove that two pairs of the time series present strong multifractal characteristics.

4.5. Rolling window analysis

From the analyses presented in the previous sections we can see that the RMB index and market anxiety are nonlinear. To further analyze cross-correlations between the CNYX and market anxiety, we use the rolling window analysis method

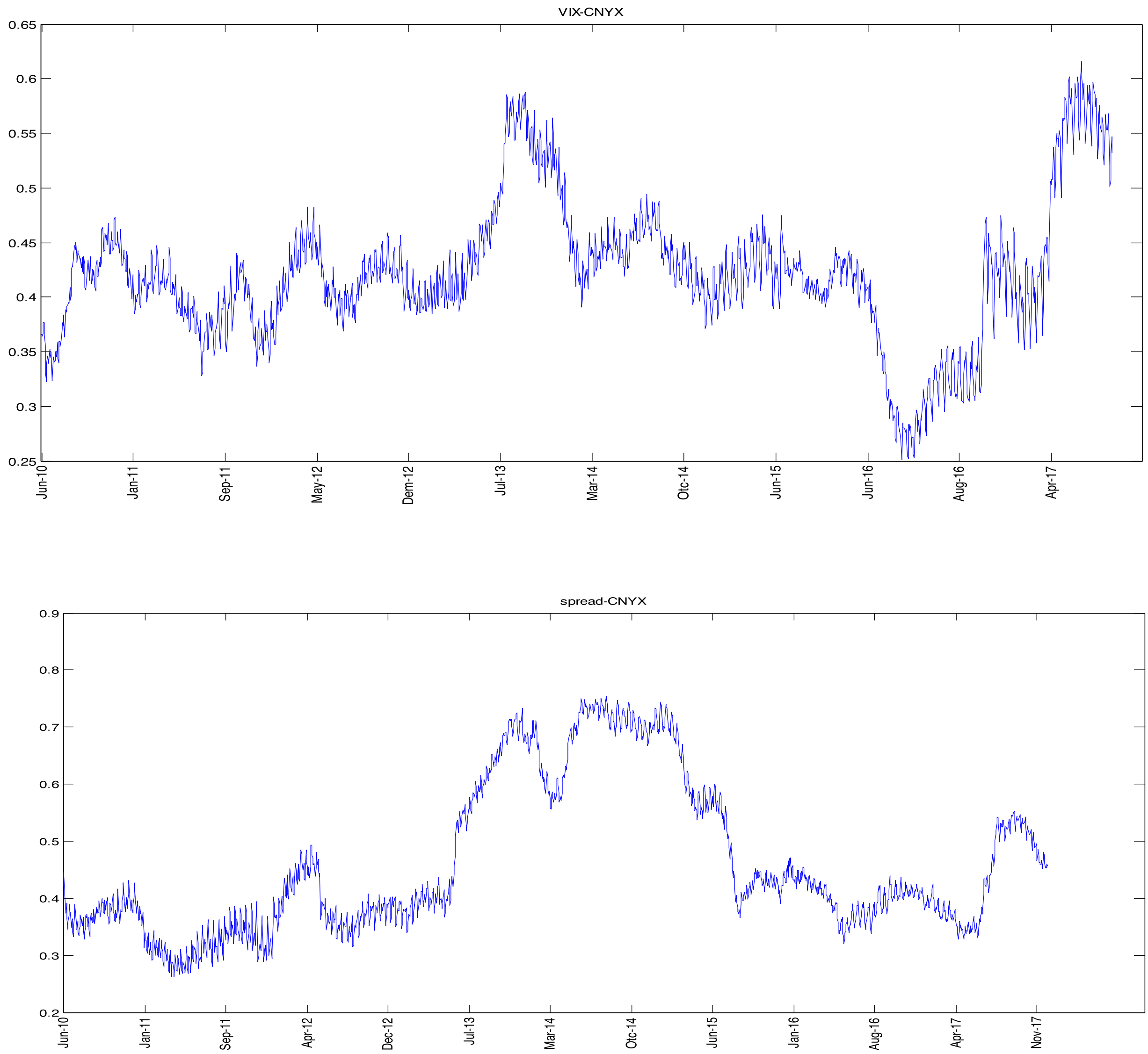

Fig. 8. Dynamics of the cross-correlation exponents for $q = 2$ with window moving.

to thoroughly study the dynamic relationship between them. The rolling window length differs for various research purposes [24–27]. Cajueiro and Tabak [28] use a rolling window analysis to study the impacts of external shocks with financial time series.

In this paper, we set the rolling window length as 250 days; take the first 250 days of the time series, set the value of q to 2, and calculate cross-correlation exponents $H_{xy}(q)$. The sample is then rolled forward one day, and the above steps are repeated to the end of the sample period. Finally, the daily cross-correlation exponents $H_{xy}(q)$ are obtained. Fig. 8 shows cross-correlation scaling exponents $H_{xy}(q)$ obtained through the above steps for June 21, 2010 to December 28, 2018.

We can see from Fig. 8 that the cross-correlation exponents are valued at less than 0.5 accounting for the vast majority of all two series. This finding illustrates that the cross-correlations between Chinese RMB exchange rates and the market anxiety index present anti-persistent features most of the time.

For the two time series, the cross-correlation exponents become more volatile during the period of November 2010–June 2012, June 2013–July 2014, August 2015–September 2016, and August 2017–December 2018. These fluctuations are attributable to external events such as QE2, the continued appreciation of the RMB, RMB exchange reforms, the Chinese stock market meltdown, the introduction of inverse periodic factors and the Sino-US trade war. These events have disrupted cross-correlated behavior.

5. Conclusions

In this paper we use MF-DCCA to investigate cross-correlations between the Chinese RMB index and market anxiety index by constructing two time series. We found that Chinese RMB exchange rates and market anxiety form part of a complex system and that many factors affect their relationships.

We first use cross-correlation statistic $Qcc(m)$ to verify cross-correlations of the series, as the corresponding results are larger than the critical value. Then, the results for ρ_{DCCA} further determine the existence of nonlinear relations. The MF-DCCA quantitative analysis method proves the existence of multifractality in cross-correlations between the Chinese RMB index and market anxiety.

The empirical results show that the cross-correlations of each pair of Chinese RMB indices and market anxiety are strongly multifractal. Large fluctuations are anti-persistent, however, while minor fluctuations are often accompanied by persistent features. Large fluctuations in the CNYX change inversely with the VIX and spread while small fluctuations in the CNYX undergo similar fluctuations of the same direction as the VIX and spread. For each individual market, large fluctuations follow mean-reverting rules, while small fluctuations are predictable and exhibit long-range memory.

Furthermore, the multifractality strength of cross-correlations between the Chinese RMB index and market anxiety is smaller in the short term than in the long term. For each individual time series, the multifractality strength of the market anxiety (VIX and the spread) is stronger than CNYX. For which we may conclude that the volatility of market anxiety is more turbulent than that of the CNYX, implying that the market participants could be more sensitive for any FX news and the market tends to be overreacted to the volatile exchange rate movements.

Finally, our rolling window analysis suggests that cross-correlation scaling exponents of the RMB exchange rate market and the two forms of market anxiety are sensitive to external shocks, meaning that economic uncertainties and risk have great influence on the cross-correlation.

In general, for the Chinese RMB exchange rate market, the VIX and the spread can serve as good measurements for the market anxiety, and market panic indexes have strong influence on volatility of the RMB exchange rate market.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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