Study on the cross-correlation between two country for soybean futures price and exchange rate

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Abstract. The paper investigates the connection between two countries’ foreign exchange and futures market for soybean, DCE NO.1 soybean and CBOT soybean as the research object by using multifractal detrended cross-correlation analysis (MF-DCCA). Results indicate a significant multifractal cross-correlation among USDCNY and two country’s soybean futures. By contrasting the multifractality of the original series to processed series, we discover that the fat-tailed distribution serves as the primary cause for USDCNY-DCE sets while the long-range correlation explains the other. Our result shows that the soybean futures in China has a higher multifractality degree, but the fluctuation of exchange rate has a better pass-through effect on the price of US soybean futures’ market.

1. Introduction
Soybean represents an important grain and oil crop in the world which provides much protein for humans. The supply and demand for future soybean are reflected by the price of soybean futures. Influenced by a great number of factors including natural conditions, hedging, policy and exchange rate, soybean futures fluctuates frequently.

Studying the soybean markets in China and the US has attracted extensive attention. On the one hand, China’s soybean consumption is highly dependent on imports. Although soybean is the fourth largest grain variety in China and Chinese soybean output reached 19.65 million tons, soybean imports 88.51 reach million tons. On the other hand, the US is the biggest soybean exporter in the world, attributing more than a third of the world’s production. It’s also notable that China is the largest importer of American soybean, even after the China-US trade war. For bilateral exchange rate serves as a significant index of foreign trade, investors are much concerned about the relationship between exchange rate and futures prices. This will help them make investment decisions and control risks.

Several researches on the correlation between soybean price and exchange rate have been conducted. The lead-lag relationships among soybean prices in the US, Brazilian and China had been investigated by Li, Hayes, and Dermot, whose result shows that long-term speaking, US soybean price leads price changes in China and Brazil [1]. Autoregressive Vector methodology is applied by Silva to study the relationship between exchange rate and soybean complex products [2]. Ye and Ma use principal component analysis to study the variables affecting US soybean pricing in China’s import market and find that USDCNY exchange rate has a significantly strong impact on US soybean pricing [3].

Previous studies are in the context of Efficient Market Hypothesis (EMH) [4], while having limited ability to explain the nonlinear relationship in real inefficient market situations. Mandelbrot put
forward the Fractal Market Hypothesis (FMH) in which system dynamics is applied in studying the characteristics of multifractality [5]. Since then, scholars have started to find the sharp peak and fat tail features in the futures market. Studies proved that the soybean futures has fractal characteristics. For example, He and Chen put forward the point that the agricultural futures markets in China and US exhibit multifractal properties [6].

As the biggest soybean futures market in China, DCE soybean futures is often regarded as the object in previous researches. Wang and Ke tested the efficiency of Chinese soybean futures based on Johansen’s cointegration approach, which showed that the Chinese soybean market is of weak short-term efficiency [7]. Furthermore, Ruan, Cui, and Fan use both multifractal detrended fluctuation analysis (MF-DFA) and multifractal detrended cross-correlation analysis (MF-DCCA) methods to investigate the relationship among bean futures in DCE [8].

The previous literature mainly focused on the nonlinear and complex characteristics of one country’s soybean futures while the fractal influence of exchange rate on the price of China and US soybean futures were rarely studied. DCE No.1 soybean futures consists of domestic non-GMO soybean. Its price mainly reflects the domestic soybean price in China [9]. In addition, the CBOT soybean futures price represents the price of US soybean. Whether the exchange rate has an impact on the price of soybean futures in two countries and the influence degree stays unrevealed. Hence, this paper investigates the connection between foreign exchange and soybean futures market by using MF-DCCA method. DCE No.1 and CBOT soybean futures prices are chosen as the representative future prices in China and the US.

We firstly use MF-DCCA method to testify the cross-correlation between USDCNY exchange rate and two country’s soybean futures prices. Then, we examine the degree and sources of multifractality.

Generally, our study confirms the multifractal characteristics between USDCNY exchange rate and two country’s soybean futures markets, reflecting the complexity of present agricultural futures market. The cross-correlation between USDCNY exchange rate and two country’s futures markets also offers a theoretical foundation for investors to decide trade and an academic basis for two governments setting policy.

This paper is organized as follows: Section 2 describes the MF-DCCA method. Section 3 introduces the source and descriptive statistics of our data. MF-DCCA method is applied in Section 4 to testify the multifractal cross-correlation among three series and study the causes of multifractality. Section 5 concludes.

2. Methodology

Multifractal detrended cross-correlation analysis (MF-DCCA) method is taken to explore the probable relationship among the fluctuation of USDCNY exchange rate series and soybean futures series. We first provide a brief introduction to this method.

Step 1: To reduce the difference between data, sequences $X(t)$ and $Y(t)$ are standardized constructed:

$$X(t) = \sum_{i=1}^{t} (x_i - \bar{x}), t = 1, 2, ..., N$$

$$Y(t) = \sum_{i=1}^{t} (y_i - \bar{y}), t = 1, 2, ..., N$$

(1)

(2)

Among them, $\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i$, $\bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i$.

Step 2: The two series are divided into $Ns$ non-overlapping segments, and the length of each segment is $s$. There is a fact that $Ns = int(N/s)$ so that there is a small segment at the end of the time series will be ignored. Therefore, we reserve the time series and redid the above procedure. We end up with $2Ns$ small segments.

Step 3: Each small series has a different trend, the OLS method is applied to fit local trend function on each interval $v$, where $v = 1, 2, ..., 2Ns$. Next, we use fitted function $X(v,i)$ and $Y(v,i)$ to eliminate the local trends of $X(t)$ and $Y(t)$ respectively. The co-variance of the series is calculated:
\[ v=1,2,\ldots, N_v: \]
\[
F^2(v, s) = \sum_{i=1}^{2N_v} \left[ X[V(v-1)(s+i) - X(i) - Y(v) - Y(i) \right]
\]  
\[ v=N_v, N_v+1, \ldots, 2N_v: \]
\[
F^2(v, s) = \sum_{i=1}^{2N_v} \left[ X[N-(v-1)(s+i) - X(i) - Y(N) - Y(N-i) \right]
\]

Step 4: All the co-variance \( F^2(v, s) \) of each small series are accumulated by the \( q \)th order. We look at the case where \( q \) is equal to 0 and obtain the wave function \( F_q(s) \):

When \( q \) is not equal to 0:
\[
F_q(s) = \sum_{i=1}^{2N_v} \left[ F^2(v, s) \right]^{\frac{1}{q}}
\]

When \( q \) is equal to 0:
\[
F_0(s) = \exp \left\{ \frac{1}{4N_v} \sum_{i=1}^{2N_v} \ln \left[ F^2(v, s) \right] \right\}
\]

Step 5: The value of wave function \( F_q(s) \) varies with the variable \( s \). We take the log of two variables and explore the probable relationship among \( \ln(F_q(s)) \) and \( \ln(s) \). A power-low scaling will be observed between two variables if a long-range cross-correlation exists between \( X(t) \) and \( Y(t) \).

\[
F_q(s) \propto s^{H_{xy}(q)}
\]

Hurst exponent \( H_{xy}(q) \) is the slope of \( s \), which is called generalized cross-correlation exponent academically. The relationship between \( H_{xy}(q) \) and \( q \) will be tested to examine the feature of cross-correlation. Both \( X(t) \) and \( Y(t) \) have a mono-fractal cross-correlation if \( q \) is independent of \( H_{xy}(q) \). By contrast, if \( H_{xy}(q) \) varies with respect to \( q \), a multifractal cross-correlation will be found in two series.

Specifically, the value of \( H_{xy}(q=2) \) is an important index of the correlation characteristics. \( H_{xy}(2) > 0.5 \) indicates that the cross-correlation between the two sequences is positively related and long-lasting. When \( H_{xy}(2) < 0.5 \), the negative correlation is unsustainable. If \( H_{xy}(2) = 0.5 \), the cross-correlation does not exist between the two series.

Furthermore, we can judge the degree of fractal by the range of \( H_{xy}(q) \) value:
\[
\Delta h = \max(H_{xy}) - \min(H_{xy})
\]

We ulteriorly calculate Renyi index \( \tau(q) \), which is associated with the Hurst exponent.
\[
\tau_{xy}(q) = qH_{xy}(q) - 1
\]

\( \alpha_{xy}(q) \) represents the singular exponent, negatively correlating with singularity. We obtain the multifractal spectra \( f_{xy}(\alpha) \) by Legendre transforms.
\[
\alpha_{xy}(q) = H_{xy}(q) + qH_{xy}(q)
\]
\[
f_{xy}(\alpha) = q[\alpha_{xy} - H_{xy}(q)] + 1
\]

Using a generalized multifractal model, Koscielny Bunde finds that the width of multifractal spectra can be defined as \( \Delta \alpha_{xy} \) \[10\]. The value of \( \Delta \alpha_{xy} \) is on behalf of the width of the multifractal spectra and the width indicates the degree of chaos. The formula of \( \Delta \alpha_{xy} \) is as follows:
\[ \Delta \alpha(x) = \max(\alpha(x,q)) - \min(\alpha(x,q)) = h(-\infty) - h(+\infty) \] (12)

3. Data and descriptive statistics
This paper utilizes daily closing prices of DCE NO.1 soybean futures and CBOT soybean futures to represent the soybean prices in two countries. Meanwhile, the close price of USDCNY exchange rate is chosen. All the data covers the period from January 1\textsuperscript{st} 2015 to October 21\textsuperscript{th} 2020. Investing is the source of our data. For the reason that time series vacancies occur on different dates, after removing vacancy data, we end up with 1,375 data sets.

To eliminate the difference of dimensions between the three time series, we use the logarithmic differences of them. \( P_t \) represents the day’s closing price of USDCNY. The change ratio of USDCNY exchange rate is as follows:

\[ e_t = \ln(P_t) - \ln(P_{t-1}) \] (13)

Similarly, DCE NO.1 soybean futures price change ratio is shown follows, where \( Q_t \) is the day’s closing price of DCE NO.1 soybean futures.

\[ d_t = \ln(Q_t) - \ln(Q_{t-1}) \] (14)

\( R_t \) is the day’s closing price of CBOT soybean futures price and the change ratio of CBOT soybean futures price can be acquired by calculation:

\[ c_t = \ln(R_t) - \ln(R_{t-1}) \] (15)

Table I. presents the results of descriptive statistics. The mean values of all series are relatively close to 0, showing the regressive tendency exists among the long-term change of exchange rate and soybean futures price. Then, the skewness and kurtosis of the USDCNY series are 0.8681 and 14.6618, indicating the non-normal characteristics of the series. Two country’s soybean future price change series also have non-gaussian distribution, the skewness and kurtosis of them are not equal to 0, 3 separately.

More intuitively, the Jarque-Bera statistic value confirms that all series rejects the hypothesis of normal distribution at the significance level of 1\%. Hence, the Fractal Market Hypothesis is more suitable for the study of the complicated correlation among three sequences compared to the Efficient Market Hypothesis.

| statistics       | USDCNY    | DCE No.1 Soybean futures | CBOT Soybean futures |
|------------------|-----------|--------------------------|----------------------|
| Mean             | 0.0000    | 0.0000                   | 0.0000               |
| Median           | 0.0000    | 0.0000                   | 0.0004               |
| Maximum          | 0.0135    | 0.1918                   | 0.05172              |
| Minimum          | -0.0184   | -0.1232                  | 0.0488               |
| Std. Dev.        | 0.0020    | 0.0149                   | 0.0088               |
| Skew             | -0.8681   | 1.2771                   | 0.0760               |
| Kurt             | 14.6618   | 35.8903                  | 6.4448               |
| Jarque-Bera      | 7964.19** | 62350.08**               | 681.17**             |
| Probability      | 0.0000    | 0.0000                   | 0.0000               |
| Observations     | 1375      | 1375                     | 1375                 |

4. MF-DCCA analysis
4.1. MF-DCCA test
We set up the minimum of interval length $s$ to be 10 and the maximum to be $N$. Then we observe the power-law relationship by logarithmic two variables. Figure 1 and Figure 2 below present a stable linear relationship between $\ln(s)$ and $\ln(F_q(s))$. Proving that USDCNY and both country’s soybean futures have a long-term correlation.

$H_{xy}$ increases while $q$ changes from -10 to 10. Table II shows the $H_{xy}$ versus $q$ of USDCNY-DCE and USDCNY-DBOT sets respectively.

**Table 2. The Cross-Correlation coefficient.**

| $q$ ( -10−10) | USDCNY-DCE sets | USDCNY-DCE sets |
|---------------|-----------------|-----------------|
| -10           | 0.9963          | 0.8929          |
| -8            | 0.9664          | 0.8657          |
| -6            | 0.9181          | 0.8268          |
| -4            | 0.8390          | 0.7720          |
| -2            | 0.7405          | 0.7058          |
| 0             | 0.6719          | 0.6451          |
| 2             | 0.6313          | 0.5945          |
| 4             | 0.6061          | 0.5516          |
| 6             | 0.5889          | 0.5188          |
| 8             | 0.5756          | 0.4956          |
| 10            | 0.5646          | 0.4791          |

We can observe from the Table II that the $H_{xy}$ of two contrast sequences sets is not independent of $q$. Fig 3 indicates that the $H_{xy}$ of USDCNY exchange rate and DCE NO.1 soybean futures price decreases from 0.9963 to 0.5646 when $q$ increases from -10 to 10. From fig 4, the $H_{xy}$ of USDCNY exchange rate and CBOT soybean futures decrease from 0.8929 to 0.4791. Therefore, both USDCNY-DCE sets and USDCNY-DBOT sets have a multifractal cross-correlation.

In particular, when $q=2$, then both $H_{xy}>0.5$, so there is a positive correlation between USDCNY exchange rate and two country’s soybean futures market.
Figure 3. $H_{xy}$ graph for USDCNY and DCE NO.1 soybean futures price change series.

Figure 4. $H_{xy}$ graph for USDCNY and CBOT soybean futures price change series.

The nonlinear relationship between $\tau(q)$ and $q$ is revealed in Figure 5 and 6. We can see from the figure that $\tau(q)$ is monotonically increasing while $q$ rises. The two groups of time series have visibly multifractal cross-correlation.

Figure 5. Graph of $\tau(q)$ for USDCNY and DCE NO.1 soybean futures price change series.

Figure 6. Graph of $\tau(q)$ for USDCNY and CBOT soybean futures price change series.

4.2. Analysis of multifractal spectra
In part A, we find that $H_{xy}>0.5$ and $\Delta h_1 > \Delta h_2$. $H_{xy}>0.5$ can be explained by the fact that the rise of USDCNY will reduce the import of US soybean and then the price of China’s domestic soybean futures price will increase. Meanwhile, stronger dollars will boost the export price of US soybean and the price of CBOT soybean futures.

$\Delta h_1 > \Delta h_2$ proves that the cross-correlation between USDCNY and DCE NO.1 soybean futures has a stronger fractal degree than the cross-correlation between USDCNY and CBOT soybean future. Therefore, there is a higher financial risk between DCE NO.1 and USDCNY. For inventors, the relationship between exchange fluctuations and the US soybean market is more stable. However, China’s soybean future market is emerging and fluctuating, whose investment value is still worth researching.

We further work out the multifractal spectra of two contrast sequences sets. It can be seen in Table III that $\Delta \alpha$ and $\Delta h$ of DCE NO.1 soybean futures and USDCNY is larger, further attesting that the cross-correlation between China’s domestic soybean future market and USDCNY exchange rate has more significantly fractal strength and greater uncertainty.
Table 3. The multifractal spectra widths.

| Coefficient | USDCNY-DCE sets | USDCNY-DCE sets |
|-------------|-----------------|-----------------|
| $\alpha_{\text{max}}$ | 1.1159 | 1.0059 | |
| $\alpha_{\text{min}}$ | 0.5112 | 0.4095 | |
| $\Delta \alpha$ | 0.6008 | 0.5964 | |
| $\Delta h$ | 0.4317 | 0.4137 | |

Figure 7 and figure 8 below are Multifractal spectra of two sets, and this confirms the above analysis more intuitively.

4.3. Causes of multifractality

Generally speaking, the long-range correlation and fat-tailed distribution are the two causes of multifractality. To examine the impact of long-range correlation, we upset the order of the sequences and retain its original distribution characteristics. Meanwhile, aiming at finding the impact of fat-tailed probability distribution on fractal series, Fourier transform is used to make $H_{xy}$ dependent on $q$ and remove the impact of non-normal distribution of time series. After processing these sequences, we use MF-DCCA method to calculate the fractal degree $\Delta h$ and multifractal spectra width $\Delta \alpha$. The results are shown in Table IV.

For USDCNY-DCE sets, $\Delta \alpha$ decreased from 0.6008 to 0.5441 and $\Delta h$ decreased from 0.4317 to 0.3432 after being shuffled. $\Delta \alpha$ reduced from 0.6008 to 0.4295 and $\Delta h$ reduced from 0.4317 to 0.2724 after phase position’s adjustment. It proves that both long-range correlation and fat-tailed distribution attribute to the multifractal feature of the USDCNY-DCE sets. Further, the decreasing amplitude of surrogate series is large bigger than rearrangement series, which indicates that fat-tailed distribution is the main reason for multifractal characteristics.

As for the cross-correlation between the variation of USDCNY and the fluctuations of CBOT soybean futures price, the result shows that shuffled series $\Delta \alpha$ reduced from 0.5964 to 0.2102 and $\Delta h$ reduced from 0.4137 to 0.1190. On the other hand, the surrogate series $\Delta \alpha$ decreased from 0.5964 to 0.3719 and $\Delta h$ decreased from 0.4137 to 0.2403. Hence, both long-range correlation and fat-tailed distribution are the reasons for multifractality. However, the impact of long-range correlation is much more apparent for the multifractal feature of USD-CBOT sets.
We compare the impact factors of two multifractal series sets and find that the US soybean futures market has better long memory property of USDCNY exchange rate. Moreover, the fat-tailed distribution comes from the nonlinear way of investor’s decision making, so the investors will undertake a higher risk if they make trading decisions in China’s domestic soybean futures market based on the changes in USDCNY exchange rate. This finding further confirms the results provided in part B.

In conclusion, the test results show that the pass-through efficiency of exchange rate fluctuation to China’s market is lower than that of US market.

### Table 4. Multifractality spectra widths of original and processed sequences.

|                | Sequences | $\alpha_{max}$ | $\alpha_{min}$ | $\Delta \alpha$ | $\Delta h$ |
|----------------|-----------|-----------------|-----------------|-----------------|-----------|
| USDCNY         | Original  | 1.1159          | 0.5152          | 0.6008          | 0.4317    |
|                | Shuffled  | 0.8426          | 0.2985          | 0.5441          | 0.3432    |
| DCE No.1       | Surrogate | 0.9515          | 0.5220          | 0.4295          | 0.2724    |
|                | Original  | 1.0059          | 0.4095          | 0.5964          | 0.4137    |
|                | Shuffled  | 0.6970          | 0.4968          | 0.2102          | 0.1190    |
| CBOT           | Surrogate | 0.8898          | 0.5179          | 0.3719          | 0.2403    |

5. Conclusions

We explore the multifractal characteristics of USDCNY exchange rate and soybean futures’ markets between two countries in this paper. Firstly, MF-DCCA method is applied to testify that the cross-correlation between USDCNY and two country’s soybean futures price has multifractal feature. Secondly, we find that the cross-correlation between USDCNY exchange rate and DCE NO.1 soybean futures price is of a higher multifractal degree, which means that the USDCNY exchange rate has a more credible price guidance to US soybean futures market instead of China’s soybean futures.

Thirdly, we explore source of multifractality and discover that both long-range correlation and fat-tailed distribution accounting for the multifractal characteristics of the changes in two country’s soybean futures price and its exchange rate. However, the primary cause of multifractal cross-correlation between USDCNY and DCE NO.1 soybean futures price is the fat-tailed distribution while the cause for the exchange rate and CBOT soybean futures price is the long-range correlation. The price of DCE No.1 soybean futures is more unpredictable based on the changes of exchange rate.

Referring to the above analysis, we can conclude the following implications. For soybean market investors, the change information of USDCNY exchange rate is more valuable for CBOT soybean futures investment. However, Chinese domestic soybean market investors cannot get effective information through the change of exchange rate price.

For Chinese and US government, to boost the development of two soybean futures markets, it is important to maintain the USDCNY exchange rate to stabilize the futures’ domestic soybean price by probable monetary policy adjustment. In addition, the education and supervision of soybean futures investors can not be neglected. Especially, the Chinese government can encourage domestic soybean traders to go abroad to learn and trade with international enterprises so that the pass-through efficiency of exchange rate of China’s soybean market will be improved.

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