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Full Length Research Paper

Are Chinese soybean future markets efficient? A fractal analysis

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China is the world's fourth-largest soybean producer and is also the biggest soybean importer. Although China has the largest non-genetically modified soybean futures markets, "whether Chinese soybean future markets are efficient or not" is always the matter at issue in academia. Through reviewing related literatures, we find that most of them adopt traditional econometric model. However, their conclusions are contradictory. Part of the literatures is improper for understanding efficiency, data selection and method application. According to fractal market theory, the article measures the Hurst index and Hausdorff fractal dimension of return series of Chinese soybean futures dominant contract by using R/S, R/S (q), V/S and V/S (q). The results show that the return series of Chinese soybean futures dominant contract has long-term memory; thus, Chinese soybean futures markets are not weak-form efficient.

Key words: Weak-form efficiency, fractal market, soybean futures markets, fractal dimension.

INTRODUCTION

China is the world's fourth-largest soybean producer and is also the biggest soybean importer (Zhao et al., 2010). And according to trade volume of futures and options, the three biggest commodity exchange of mainland China all ranked top twenty in the global 52 exchanges at the end of 2008. By the end of July, 2009, mainland China futures market has owned 21 varieties and trading volume of commodity futures has accounted for 1/3 of the total trading volume of global commodity futures. China's futures market has become the second largest commodity futures market and the first biggest agricultural futures market. With the increase of soybean imports and the establishment of the world's largest non-genetically modified soybean futures markets, China Dalian Commodity Exchange (DCE) has become the world second largest soybean futures exchange only next to Chicago Board of Trade (CBOT). China's soybean futures markets thereby become a hot issue in current literature (Chen et al., 2005; Chan et al., 2004). Now the realistic question urgently to be answered is, whether China's soybean futures markets are weak-form efficient.

Efficient market theory considers that price on weak-form efficient market has fully reflected all the historic price information, including trading price and volume (Fama, 1991). Any trend analysis for market price is in vain, in other words, price series on weak-form efficient market doesn't have long-term memory. Therefore, we can calculate fractal dimension to test whether market has long-term memory according to fractal market theory, thereby verifying whether market is weak-form efficient. Thus, the paper is organized as following: in the first part of paper is introduction section; section Ⅱ presents an overview of models on R/S, R/S(q), V/S and V/S(q); section Ⅲ gives data material used in the paper; section Ⅳ is the results and section Ⅴ is conclusions and discussions.

LITERATURE REVIEW

The efficient market theory considers that financial market is a linear isolated system, and price movement obeys Brownian motion. However, with development of computing technology, more and more empirical research has attested to falsity of this hypothesis. Especially after the proposing of fractal market theory, more evidence indicates that it's closer to reality to take financial market as a non-linear and open dissipative system with positive-feedback system. If market has fractal characteristic, then

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price changes has long-term memory in this market, namely has regularity. If market has fractal characteristic, then market is cyclic in a certain period, which can explain why the effects of events will not disappear immediately. In addition, if market has fractal characteristic, then we may anticipate that there will be return series with similar statistics characteristic appearing in much smaller time increment.

Based on partition function and multifractal spectrum analysis, Chen and He (2010) investigated the nonlinear dynamical mechanisms in China's agricultural futures markets. They found nontrivial multifractal spectra in 4 representative futures markets in China, that is, Hard Winter wheat, Strong Gluten wheat Soybean meal and Soybean #1.

He and Chen (2010a) investigated the multifractality and its underlying formation mechanisms in international crude oil markets, that is, Brent and WTI, by using multifractal detrended fluctuation analysis (MF-DFA) and multifractal singular spectrum analysis (MF-SSA). They also applied multifractal detrended fluctuation analysis (MF-DFA) to study wheat, soybean, corn, and soybean meal futures markets in China and USA. Their results suggested that the futures markets above exhibit multifractal properties except US soybean market (He and Chen, 2010b). Moreover, for investigating nonlinear dependency of price-volume relationships in the futures markets above, they performed a new statistical test to detect cross-correlations and applied an efficient algorithm called multifractal detrended cross-correlation analysis (MF-DCCA) (He and Chen, 2011).

To portray fractal characteristic of market is mainly to calculate fractal dimension of price series or return series and other related index. Common fractal dimensions include correlation dimension, information dimension and Hausdorff dimension. Methods for calculating fractal dimension mainly include estimating dimension by using measure relations for dimension, correlation function, distribution function or spectrum (Sun, 2004). To calculate Hausdorff fractal dimension directly need to determine the non-scale territory, but the method for seeking non-scale territory is either strong subjectivity or difficult to calculate. Using R/S method to measure fractal dimension can avoid aforementioned problems.

R/S method was first proposed by British hydrology expert Hurst (1951) and applied to the Nile hydrological research. It will affect the limit distribution of R/S statistics when series has short-term relevance. Therefore, Lo (1991) proposed the adjusted R/S method. In fact, classic R/S analysis judges whether there is long-term memory through correlation measures of fractional Brownian motion series and relationship between Hurst indexes, not considering the hypothesis; therefore we can not say that adjusted R/S analysis must be superior to R/S analysis (Wang and Ma, 2009). Giraitis et al. (2003) put forward V/S analysis by replacing extreme difference in adjusted R/S analysis with variance. Cajueiro and Tabak (2005) compared effects of R/S and V/S when measuring Hurst index, whose results showed that V/S method had overcome the defect of R/S method.

R/S is also called as rescaled range method. This method does not need to suppose series' distribution features. That is to say, results obtained from R/S will not be affected whether the series is normal distribution or not.

Expression of R/S is as follows:

$$(R/S)_n = \frac{1}{S_n}[\max_{1\le t\le n}\sum_{k=1}(x_k-\bar{x}_n)-\min_{1\le t\le n}\sum_{k=1}(x_k-\bar{x}_n)] \qquad (1)$$

We get following relational expression on the basis of model (1): $(R/S)_n \propto (n/2)^H$ or $(R/S)_n \propto n^H$. Here, S_n is the standard deviation of the series and superscript H means Hurst index. The same symbol below has the same meaning. If series has autocorrelation, R/S can be revised by standard deviation whose order of phase lag is *q*. Expression of adjusted R/S is as follows:

$$(R/S(q))_n = \frac{1}{S_n(q)}[\max_{1\le t\le n}\sum_{k=1}(x_k-\bar{x}_n)-\min_{1\le t\le n}\sum_{k=1}(x_k-\bar{x}_n)] \qquad (2)$$

Here $S_n(q)=\hat{\gamma}_0+2\sum_{j=1}^{q}(1+\frac{j}{1+q})\hat{\gamma}_j$, and q<n.

$(R/S(q))_n \propto (n/2)^H$ or $(R/S(q))_n \propto n^H$ still holds true.

Replace extreme difference in adjusted R/S analysis with variance, thus expression of V/S based on adjusted R/S is as follows:

$$(V/S)_n = \frac{1}{n^2 S_n^2}[\sum_{t=1}^{n}(\sum_{k=1}^{t}(x_k-\bar{x}_n))^2-\frac{1}{n}(\sum_{t=1}^{n}\sum_{k=1}^{t}(x_k-\bar{x}_n))^2] \qquad (3)$$

Comparing with model (1), model (3) uses sum of squares of deviations of the original series to replace the original standard deviation, besides replace extreme difference with variance of partial sums series.

MATERIALS AND METHODS

Chinese soybean futures include non-genetically modified soybean futures (soybean #1), genetically modified soybean futures (soybean #2), soybean meal futures and soybean oil futures. Soybean futures are the most active futures with the largest trading volume in China except soybean #2. Data used in the paper are returns of dominant contracts, which are used to reflect returns of representative contract in soybean futures markets. All the data are from the DEC database. And the dominant contracts are produced on the computer by the criterion:

$$DC_t : Max\{TV_{t,i} \div \sum_i TV_{t,i}\} \qquad (4)$$

Here DC_t is dominant contract of certain futures on the trading day

Table 1. Frequency of proportion of trading volume and position of dominant contract.

Variables	Proportion of trading volume		Proportion of position	
	Proportion range	Frequency	Proportion range	Frequency
Soybean #1 dominant contract	80%=<X<=100%	715	80%=<X<=100%	164
	60%=<X<80%	503	60%=<X<80%	608
	40%=<X<60%	320	40%=<X<60%	624
	X<40%	80	X<40%	222
Soybean #2 dominant contract	80%=<X<=100%	433	80%=<X<=100%	224
	60%=<X<80%	229	60%=<X<80%	124
	40%=<X<60%	187	40%=<X<60%	231
	X<40%	41	X<40%	311
Soybean meal dominant contract	80%=<X<=100%	916	80%=<X<=100%	531
	60%=<X<80%	358	60%=<X<80%	422
	40%=<X<60%	265	40%=<X<60%	455
	X<40%	79	X<40%	210
Soybean oil dominant contract	80%=<X<=100%	619	80%=<X<=100%	428
	60%=<X<80%	148	60%=<X<80%	298
	40%=<X<60%	123	40%=<X<60%	113
	X<40%	0	X<40%	51

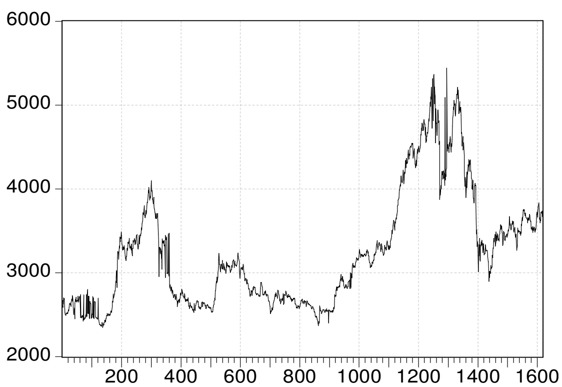

Figure 1. Price series of the soybean #1.

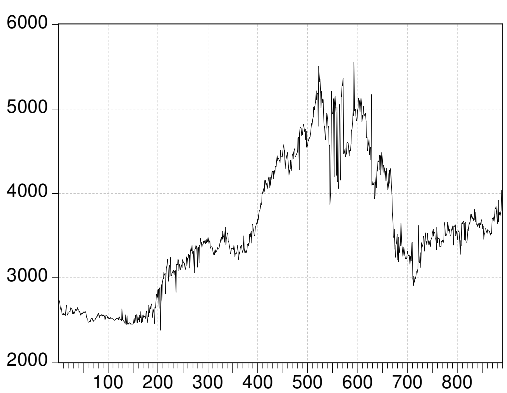

Figure 2. Price series of the soybean #2.

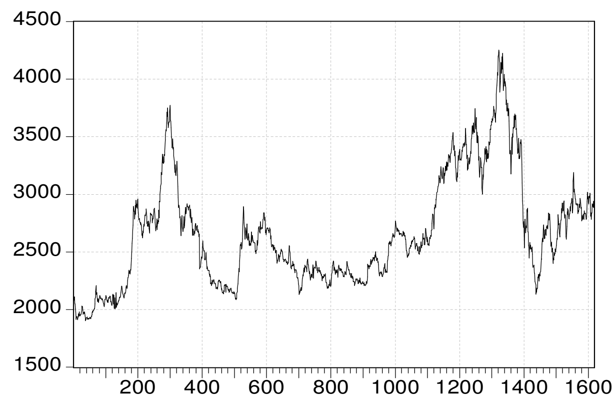

Figure 3. Price series of the soybean meal.

t. $TV_{t,i}$ is trading volume of certain futures contract whose number is marked as i (such as 200903).$\sum_i TV_{t,i}$ is total of trading volume of certain futures on the trading day t.

The dominant contracts produced by (4) are more representative than other contracts mentioned in existing literatures which usually referred to nearby contracts. Because the criterion (4) ensures that the contract produced is the most active contract on every trading day.

Table 1 gives frequency of proportion of trading volume and position of dominant contract. Statistics revealed that trading volume proportion over 95% of each of the three varieties' sample is not smaller than 40% and position volume over 65% of that is not smaller than 40% either, which also indicates that dominant contracts are representative. Figures 1 to 4 are price series of dominant contracts, which represent closing price series of soybean

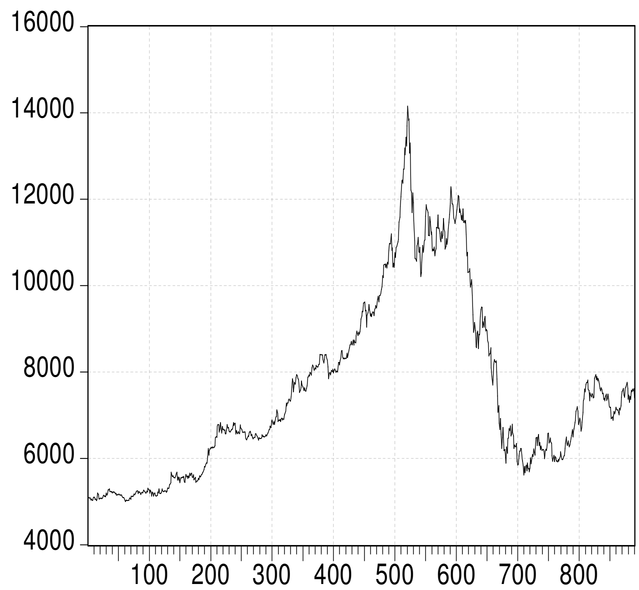

Figure 4. Price series of the soybean oil.

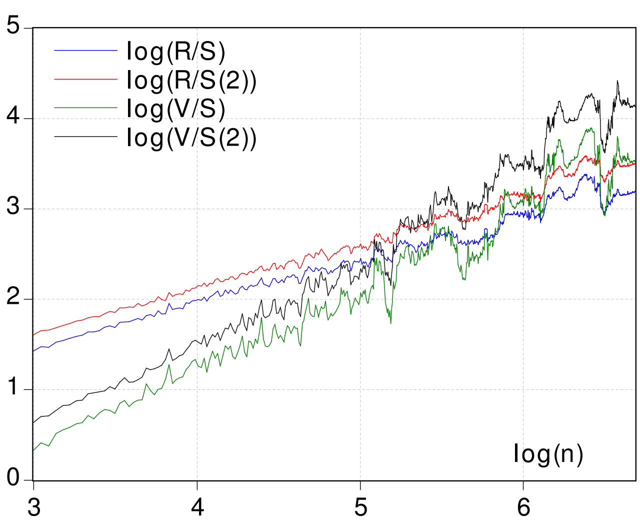

Figure 5. Diagram of double logarithm of soybean #1.

#1, soybean #2, soybean meal and soybean oil dominant contract respectively.

The return of dominant contract is calculated according to r_t=*LnP*$_t$-*LnP*$_{t-1}$, P_t here refers to closing price. Primary data derives from Dalian Commodity Exchange. Time span of soybean #1 and soybean meal are from 2nd January, 2003 to 3rd August, 2009, whose number of valid samples is 1617. Time span of Soybean #2 and soybean oil (listing and trading from 9th January, 2006) are from 9th January, 2006 to 31st August, 2009, whose number of effective samples is 889.

In order to make conclusions more persuasive, the paper uses R/S, adjusted R/S, V/S and adjusted V/S methods to verify weak-form efficiency of soybean futures markets. If series has autocorrelation, model (3) can be revised by variance whose order of phase lag is *q*. Expression of adjusted V/S is as follows:

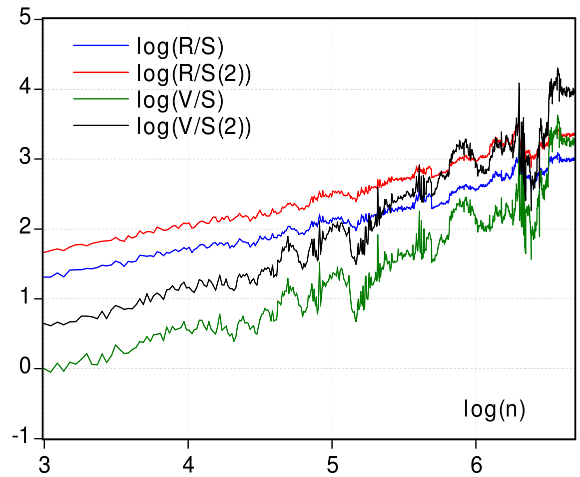

Figure 6. Diagram of double logarithm of soybean #2.

$$(V/S(q))_n = \frac{1}{n^2 S_n^2(q)}\left[\sum_{t=1}^{n}\left(\sum_{k=1}^{t}(x_k-\bar{x}_n)\right)^2 - \frac{1}{n}\left(\sum_{t=1}^{n}\sum_{k=1}^{t}(x_k-\bar{x}_n)\right)^2\right] \quad (5)$$

Relationship between V/S and n or between adjusted V/S and n can be expressed as $(V/S)_n \propto n^{2H}$ or $(V/S(q))_n \propto n^{2H}$. Value of lag item *q* in the model can be determined by autocorrelation and partial autocorrelation. Here *q*=2.

If a time series is random walking, thus H=0.5. When 0<H<0.5, corresponding time series in each self-similarity time scale take on inverse correlation. In other words, the series is constituted by frequent reversals. When 0.5<H<1, corresponding time series in each self-similarity time scale take on positive correlation. If H=1, it indicates that series is completely positive correlation, which is the characteristic of deterministic system (Tu, 2008). When Hurst index of time series is between 0.5 and 1, it means the series has long-term memory. If Hurst index is not smaller than 1, thus indicates the series is non-stationary series with unlimited variance.

Relationship between Hausdorff fractal dimension D and Hurst index H is expressed by model (6). Using Hurst index to calculate Hausdorff fractal dimension can avoid determining the non-scale territory, thus improving accuracy of results:

$$D=2-H \quad (6)$$

RESULTS

First, took logarithm of R/S, adjusted R/S, V/S and adjusted V/S. Then used least square method to do regression analysis on log(R/S) and log(n), log(R/S(2)) and log(n), log(V/S) and log(n), log(V/S(2)) and log(n), respectively. And the slope calculated is Hurst index. We recorded them as $H_{R/S}$, $H_{R/S(2)}$, $H_{V/S}$ and $H_{V/S(2)}$ respectively. Hausdorff fractal dimension calculated from model (6) were recorded as $D_{R/S}$, $D_{R/S(2)}$, $D_{V/S}$ and $D_{V/S(2)}$ respectively.

Figures 5 to 8 respectively show relationship between log(R/S), log(R/S(2)), log(V/S), log(V/S(2)) and log(n) of returns of dominant contract of soybean #1, soybean meal and soybean oil. Hurst index and Hausdorff fractal

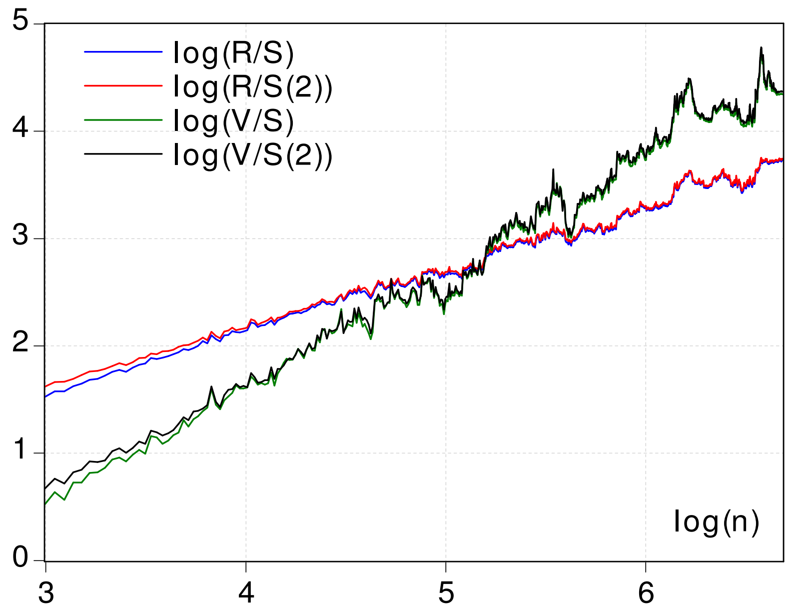

Figure 7. Diagram of double logarithm of soybean meal.

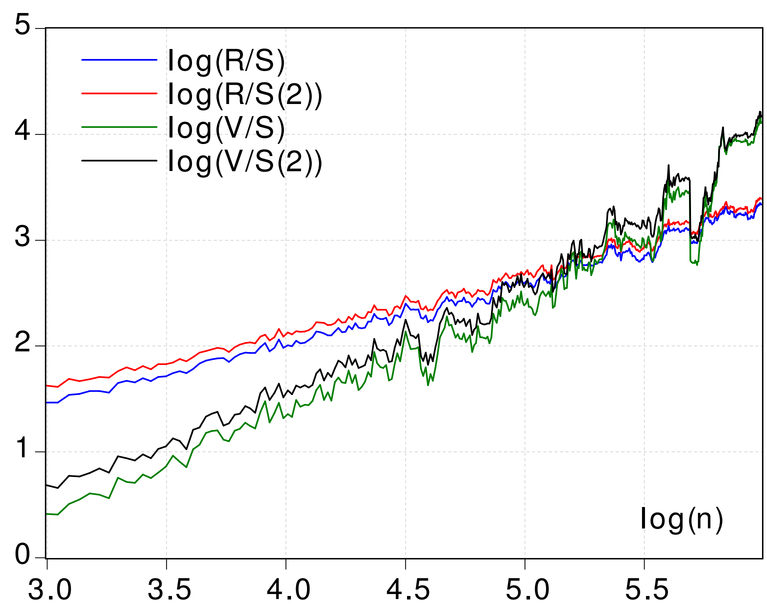

Figure 8. Diagram of double logarithm of soybean oil.

dimension obtained by regression analysis are listed in Table 2.

DISCUSSION AND CONCLUSIONS

We get the following conclusions from results of Hurst index and fractal dimensions: First, fractal dimension of return series is bigger than 1, thus soybean futures markets have obvious non-linear characteristic. Second, Hurst index of return series of soybean meal and soybean oil dominant contract is between 0.5 and 1, which indicates return of the two futures contract no longer take on normal distribution and each observed value of time series is not mutually independent. It also indicates that series has long-term memory. Third, $H_{R/S}$ and $H_{V/S}$ of soybean #1 and #2 return series fall into interval (0, 0.5) and $H_{R/S(2)}$ and $H_{V/S(2)}$ of that fall into interval (0.5, 1). From diagram of autocorrelation and partial autocorrelation of soybean #1 and #2 return

Table 2. Hurst index and Hausdorff fractal dimension of returns of soybean futures dominant contract.

Variables	$H_{R/S}$	$H_{R/S(2)}$	$H_{V/S}$	$H_{V/S(2)}$	$D_{R/S}$	$D_{R/S(2)}$	$D_{V/S}$	$D_{V/S(2)}$
Soybean #1	0.493	0.547	0.471	0.533	1.507	1.454	1.529	1.468
Soybean #2	0.474	0.599	0.469	0.629	1.526	1.401	1.531	1.371
Soybean meal	0.588	0.581	0.543	0.542	1.412	1.419	1.457	1.459
Soybean oil	0.635	0.614	0.611	0.590	1.365	1.387	1.389	1.410

series, we can see that the series has short-term memory. Results will be influenced if series has short-term memory, thus we should use adjusted R/S or V/S to calculate Hurst index. Results calculated by adjusted R/S or V/S all fall into interval (0.5, 1), which indicates return series of soybean #1 and #2 futures dominant contracts also have long-term memory.

Every return series satisfy $0.5 < H < 1$, $1 < D < 1.5$, thus the long term trends are neither random nor irreversible. Hurst index of return series of soybean #2 contract during 8th May, 2000 to 28th April, 2006 calculated by Li and Zou (2007) is 0.579. He et al. (2008) used R/S analysis method to study fractal and multi-fractal characteristics of soybean meal futures price. They found medium-term and long-term return ratios of soybean meal futures price present positive tendency and have long-term memory for historic information, which further verify the conclusion that soybean futures return has long-term memory and its trend is persistent. But they did not calculate the appropriate lag correlation, our results show that the appropriate lag length is 2. Our Hurst and fractal dimension values are a little different from existing research, because their data materials are nearby or other contracts, but ours are produced by a more appropriate criterion.

In summary, Chinese soybean futures markets are not weak-form efficiency and the market has obvious fractal characteristic. Existing hedge theory, asset pricing theory and risk management theory are all proposed on the basis of efficient market hypothesis. How to consummate the existing system based on the fractal market hypothesis will be the future goal of this working field. In addition, other hybrid methods will be applied in our work in future.

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REFERENCES

Cajueiro DO, Tabak BM (2005). The Rescaled Variance Statistic and Determination of the Hurst Exponent. Math. Comput. Simul., 70(3): 172-179.

Chan KC, Fung HG, Leung WK (2004). Daily Volatility Behavior in Chinese Futures Markets. J. Int. Financ. Market. Institut. Money, 14(5): 491-505.

Chen GM, Firth M, Xin Y (2005). The Response of Volume and Returns to the Information Shocks in China's Commodity Futures Markets. J. Futures Markets, 25(9): 893-916.

Chen SP, H LY (2010). Multifractal Spectrum Analysis of Nonlinear Dynamical Mechanisms in China's Agricultural Futures Markets. Physica A, 389(7): 1434-1444.

Fama EF (1991). Efficient Capital Markets: II. J. Financ., 49(5): 1575-1617.

Giraitis L, Kokoszka P, Leipus R, Teyssiere G (2003). Rescaled Variance and Related Tests for Long Memory in Volatility and Levels. J. Econ., 112(2): 265-294.

He LY, Chen SP (2011). Nonlinear Bivariate Dependency between Price and Volume Relationships in Agricultural Commodity Futures Markets: A Perspective from Multifractal Detrended Cross-Correlation Analysis. Physica A, 390 (2): 297-308.

He LY, Chen SP (2010a). Are Crude Oil Markets Multifractal? Evidence from MF-DFA and MF-SSA Perspectives. Physica A, 389(16): 3218-3229.

He LY, Chen SP (2010b). Are Developed and Emerging Agricultural Futures Markets Multifractal? A Comparative Perspective. Physica A, 389(18): 3828-3836.

He LY, Zhou SD, Xu CH (2008). Fractal and Multi-fractal Features in China's Agricultural Commodity Futures Prices. Chinese Agric. Sci. Bull., 24(3): 481-485.

Hurst HE (1951). Long-term Storage Capacity of Reservoirs. Trans. Am. Soc. Civ. Eng., 1951: 770-799.

Li J, Zou K (2007). Empirical Research on Fractal Structure of Chinese Soybean Futures. Zhejiang Financ., 8: 38-39.

Lo A (1991). Long Term Memory in Stock Market Prices. Econometric, 59(5): 1279-1313.

Sun BL (2004). Fractal Dimension and Its Measuring Method. J. Northeast For. Univ., 32(3): 113-119.

Tu XS (2008). Securities Market Risk Management. Beijing: Science Press.

Wang HH, Ke BF (2005). Efficiency Tests of Agricultural Commodity Futures Markets in China. J. Agric. Res. Econ., 49(2): 125-141.

Xin Y, Chen GM, Firth M (2006). The Efficiency of the Chinese Commodity Futures Markets: Development and Empirical Evidence. China World Econ., 14(2): 79-92.

Zhao Y, Yang MM, Zhang Y, Qi CJ (2010). Impact on the Chinese Soybean Markets from International Prices Volatility: Empirical Study based on VEC Model. Afr. J. Agric. Res., 5(15): 1943-1950.