Analysis of Nonlinear Characteristics on the Shanghai Stock Market

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Abstract

There are numerous research works on the nonlinear analysis of time series, such as chaotic behavior analysis, heterogeneous variance-covariance structures, etc. However, some studies apply the nonlinear theory to the real financial data without checking the nonlinearity of the time series. In this paper, we detect the nonlinearity by model fitting and confirm the nonlinearity using a statistical test before conducting the analysis of nonlinear characteristics. After confirming the nonlinearity, we then focus on the multifractal analysis of time series and its application to the Shanghai Stock Market. To detect the nonlinear characteristics, the multifractal analysis based on wavelet transform theory is employed in this paper.

Keywords: Nonlinear time series analysis, ARCH model, BDS test, Multifractality

1. Introduction

The empirical research on stock markets has mainly focused on nonlinear modeling analysis recently. It has been observed by a number of researchers that the stock markets bear nonlinearity rather than linearity [10] [13]. Moreover, the financial time series can often be fitted quite well by ARCH (Autoregressive Conditional Heteroscedastic) model which was presented by Engle [6]. This paper, firstly, detects the nonlinearity of time series by model fitting. Both linear and nonlinear models are applied to fit to the stock market data. It can be concluded that nonlinearity may exist if it is more well-fitted by nonlinear model. In order to confirm the nonlinearity, it is needed to employ a statistical test. The BDS (Brock, Dechert and Scheinkman) test is applied in this paper. After checking the linearity or nonlinearity of the series, the multifractal analysis is used to extract the nonlinear properties of the series.

There are many nonlinear properties which have been observed and analyzed by researchers. In this paper, the "Fractality" is our focus and has been considered as one of the important nonlinear properties. Fractal means self-similarity, namely symmetry at different degrees. Fractal phenomena are encountered everywhere, not only in physiological data such as heart records, texture in images of natural terrain, variations of traffic flow, phase transition, electrolysis and chemical oscillation, but also in economic records, such as the distributions of income, the fluctuations of foreign exchange rate and stock indices and so on. These phenomena can hardly be described by common mathematical methods. It is Benoit B Mandelbrot who first founded a nonlinear theory to analyze the phenomena in the 1970s and called them "fractal" [2][11]. In recent years, using the fractal theory to analyze the stock market has already become one of the forefront research fields in finance and computer science. Besides, multifractality can often be observed in the stock market time series. In this paper, the wavelet transform based multifractal theory is used to analyze the characteristics of one of the Chinese stock markets, the Shanghai Stock Market. The Shanghai Stock Market has evolved to be one of the most important financial markets in the world since it was established in the late 1980s. The Chinese market was once abnormal and highly controlled by the Chinese government. After some big reforms set by the government, it has been developing very quickly and tends to be a normal capital market. In this paper, we try to utilize the multifractal theory to detect whether the market has made significant changes during the last 20 years [4][5][7][13].

In this paper, our objective is to present the multifractal property of the Shanghai Stock Market by using the multifractal theory based on wavelet transform. This theory is employed to extract the features of China Stock Market which has been reformed and developed in a relatively short period.

The rest of this paper is organized as follows. In section 2, the methods of nonlinearity detecting by using the model fitting and statistical test are explained. In section 3, the theory and procedure to conduct the nonlinear test, namely BDS test, is presented. In section 4, the multifractal analysis based on wavelet transform which can detect the characteristics of time series is introduced. In section 5, the background of the Shanghai Stock Market is reviewed. In section 6, the empirical analysis is applied to the Shanghai Stock Market. In section 7, the conclusion is given while section 8 states our future research.

2. Model fitting

As mentioned in the introduction, before dealing with the nonlinear time series analysis, it is necessary to check whether the series is nonlinear or not. In this paper, both the model fitting and statistical test are processed. By using model fitting, the general frame of the series can be figured out while the statistical test can confirm the characteristics extracted out definitely. For fitting the linear models, AR model is applied just for simplicity, while conducting the nonlinear model fitting, many nonlinear models can be applied to the financial data. The ARCH model is chosen in this paper since it is the most popular one used by researchers.

2.1 Linear model

A number of linear models can be employed to fit time series data. The most popular linear models are the AR model, the MA model and the ARMA model. Among the three models, ARMA and MA models are widely used in various kinds of linear analysis. However, in general, the MA component adds little to the model, and can be restricted to zero on likelihood ratio grounds [21]. Furthermore the objective of this study is not to build a statistically adequate empirical model, but rather to detect whether the series is linear or not. For simplicity, the AR model is applied in this paper. To choose the autoregressive lag length, the Box-Jenkins interactive procedure or the use of various information criteria is calculated. In this paper only SBIC is used.

The linearity of time series can be checked by the process of conducting regression. If the coefficients are significant, the time series can be considered as linear. If the time series is not independent identically distributed (i.i.d) and the correlation between variables is very small, it will be hard to be fitted to a linear model. In such a case, it can be considered as belonging to a nonlinear model.

2.2 Nonlinear model: ARCH Model

As mentioned, both the linear and nonlinear models are fitted to check whether the time series follows a linear process or not. Firstly, a linear model is applied and whether the coefficient is significant or not is tested. Then, nonlinear model is applied and checked in the same way. ARCH model is chosen to be fitted in this paper. By comparing the two regressions, we can check whether the time series can be expressed in a linear equation or not. If it fits a nonlinear model rather than a linear one, it can be induced that the series is nonlinear. Further, the nonlinearity test - BDS test - is employed to confirm the nonlinearity.

If Y series can be expressed in the following model, it can be defined as ARCH model. In the ARCH model, the error term ε_t follows an uncorrelated and conditional normal distribution with zero mean and variance h_t which is inconstant but varies over time as a result of the linear combination of past error terms.

$$
\begin{aligned}
&Y=\beta_0+\beta_1X_1+\cdots+\beta_jX_j+\cdots+\beta_rX_{t-p}+\varepsilon_t \qquad (1)\\
&\varepsilon_t\,|\,\Psi_{t-1}\sim N(0,h_t)\\
&E(\varepsilon_t\,|\,\Psi_{t-1})=0\\
&Var(\varepsilon_t\,|\,\Psi_{t-1})=h_t=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\cdots+\alpha_q\varepsilon_{t-q}^2
\end{aligned}
$$

In order to test for ARCH effect, the following steps need to be taken:

1. First, run any postulated linear regression of the form given in the equation above.
2. Then square the residuals, and regress them on q own lags to test for ARCH of order q, i.e. run the regression where ε_t is i.i.d. Obtain R^2 from this regression.
3. The test statistic is defined as TR^2 (the number of observations multiplied by the coefficient of multiple correlation) from the last regression, and is distributed as a x^2 (q).

3. Nonlinearity test-BDS test

BDS test was first devised by Brock, Dechert and Scheinkman in 1987 [22]. It has been acknowledged by the researchers as a powerful tool to detect the nonlinearity of time series. This approach is to calculate a formal test statistic which follows a standard normal distribution. The following procedures need to be taken to compute the statistic for BDS test:

1. Compute the 'm-histories' of the series, $x_t^m=(x_t,\ x_{t+1},\ \cdots,\ x_{t+m-1})$ for $t=1,\ \cdots,\ T-m,$ where m is embedding dimension.
2. Calculate the correlation integral $C_m(\varepsilon)$:

$$C_m(\varepsilon)=\frac{1}{(T-m+1)(T-m)}\sum_{\forall t,s} I_\varepsilon(x_t^m, x_s^m) \tag{2}$$

where I_ε is an indicator function that equals one if $\|x_t^m-x_s^m\|<\varepsilon$, and zero otherwise.

3. Calculate the quantity $C_m(\varepsilon)-C_1(\varepsilon)^m$.
4. Calculate the variance :

$$\sigma_m^2(\varepsilon)=4[K^m+2(\sum_{j=1}^{m-1}K^{m-j}C(\varepsilon)^{2j})+(m-1)^2\times C(\varepsilon)^{2m}-m^2KC(\varepsilon)^{2m-2}] \tag{3}$$

where $K(\varepsilon)=\dfrac{6\sum_{t,s,r}h_\varepsilon(x_t^m,\ x_s^m,\ x_r^m)}{[Tm(Tm-1)(Tm-2)]}$ and

$$h_\varepsilon(i,j,k)=[I_\varepsilon(i,j)I_\varepsilon(j,k)+I_\varepsilon(i,k)I_\varepsilon(k,j)+I_\varepsilon(j,i)I_\varepsilon(i,k)]/3$$

5. Compute the BDS test statistic as:

$$BDS_{\varepsilon,m}=T^{1/2}\frac{[C_m(\varepsilon)-C_1(\varepsilon)^m]}{\sigma_m(\varepsilon)} \tag{4}$$

In this paper, the BDS test is processed to confirm the nonlinearity of the time series. After this procedure, one of the nonlinear properties - multifractality - is discussed.

4. Multifractality Analysis

When one mentions the nonlinearity, one may remember the Chaos which is the typical nonlinearity of time series. There are also other nonlinearities like self-similarity which is called fractal feature or multifractal characteristic. If the fractal dimension is constant, it is called mono-fractal; if the fractal dimension is not constant but follows a distribution, it is then named mutifractal. In this paper, the multifractality analysis theory is used to extract the characteristics of time series of the stock market.

In this section, the theory of multifractal analysis by using the wavelet transform is summarized. In order to analyze the multifractility of time series, it is important to find the singularities which are detected by following the wavelet transform local maxima at fine scales. The wavelet transform takes advantage of multifractal self-similarities in order to compute the distribution of their singularities. This singularity spectrum is used to analyze multifractal properties [11][12][14][15][17].

(1) Wavelet transform

Wavelet transform is defined by the following formula:

$$Wf(u,s)=\frac{1}{s}\int_{-\infty}^{\infty}\phi\left(\frac{t-u}{s}\right)f(t)\,dt \tag{5}$$

where s denotes scale and t represents time shift. $f(t)$ is a function which can be transformed into $Wf(u,s)$ by multiplying a wavelet function $\phi\left(\frac{t-u}{s}\right)$. $Wf(u,s)$ is called as the wavelet coefficient. $f(t)$ is expanded as follows: $f(t)=p_v(t)+\varepsilon_v(t), |\varepsilon_v(t)|\leq K|t-v|^{\alpha}$. Here, $p_v(t)$ is a polynomial. By using a wavelet that has $n\geq\alpha$ vanishing moments, it is easy to get $|Wf(u,s)|=|W\varepsilon_v(u,s)|$. Here, α describes the singularity of the function $f(t)$.

(2) Fractal dimension

We assume $S\subset R^n$ and define $N(s)$ as the minimum number of balls of radius s needed to cover S. If S is a set of dimension D, then $N(s)\sim s^{-D}$, so $D=-\lim_{s\to 0}\frac{\log N(s)}{\log s}$. D is called the fractal dimension. $D(\alpha)$ is denoted as the distribution of α. Thus, the following relation is obtained:

$$N(s)\sim s^{-D(\alpha)}$$

(3) Partition function

$$Z(q,s)=\Sigma|Wf(u,s)|^q \tag{6}$$

For each q, the scaling exponent $\tau(q)$ measures the asymptotic decay of $Z(q,s)$ at fine scales s : $\tau(q)=\lim_{s\to 0}\inf\frac{\log Z(q,s)}{\log s}$. It means: $Z(q,s)\sim s^{\tau(q)}$. As the coefficient has been induced as $|Wf(u,s)|\sim s^{\alpha_0+\frac{1}{2}}$, $Z(q,s)$ thus can be expressed as $Z(q,s)\sim\int_E s^{q\left(\alpha+\frac{1}{2}\right)}s^{-D(\alpha)}d\alpha$. When s goes to 0, this integral is dominated by $s^{\min_{\alpha\in A}\left(q\left(\alpha+\frac{1}{2}\right)s^{-D(\alpha)}\right)}$. Thus, $\tau(q)=-\min_{\alpha\in A}\left(q\left(\alpha+\frac{1}{2}\right)-D(\alpha)\right)$. By using the Legendre Transform, $D(\alpha)$ can be calculated with the following equation:

$$D(\alpha) = -\min_{q \in A}\left(q\left(\alpha + \frac{1}{2}\right) - \tau(q)\right)$$

(4) Calculation of the spectrum

To calculate the spectrum of α, the following steps are processed:

Step 1. Compute modulus maxima $|Wf(u,s)|$ such scale s.

Chain the wavelet maxima across scales.

Step 2. Compute partition function $Z(q,s) = \sum |Wf(u,s)|^q$.

Step 3. Compute scaling exponent $\tau(q)$ with a linear regression of the function:

$$\log_2 Z(q,s) \approx \tau(q)\log_2 s + C(q) \tag{7}$$

Step 4. Compute Spectrum $D(\alpha)$:

$$D(\alpha) = -\min_{q \in A}\left(q\left(\alpha + \frac{1}{2}\right) - \tau(q)\right) \tag{8}$$

In section 6, the multifractality theory is applied to the real stock market data and the singularity of the series is then captured.

5. An overview of the China Stock Market development

Since the Chinese government launched a long-term economic development program in the late 1970s, China has carried out economic reforms designed to strengthen its economy by transforming it from a centrally-planned economy into a market-oriented one. The economic reforms initially led to unprecedented economic prosperity. However, it was followed by a large amount of budgetary deficits, shortage of capital supply and inefficient operation of state-owned enterprises (SOEs). To improve this situation, Chinese government began to permit the issuance of bonds and stocks, in an attempt to help SOEs raise funds. China's capital market emerged under such circumstances. In December 1990, the Shanghai Stock Exchanges was established and the Shenzhen Stock Exchanges was set up in the following year [4].

The China's Stock Market has been expanding rapidly in a very short period and the Shanghai market has gradually become the leading market in China and one of the most important markets in the world. The data compiled by the Paris-based World Federation of Exchanges show that, in 2009, its shares were worth USD5 trillion, an increase of 95.7 percent from 2008. The Shanghai Stock Market jumped to the third world largest and Asia's top stock market in terms of trading value in 2009, and became the world's third largest stock exchange by market capitalization at US$3.07 trillion as of May 2010. It has been shown that China's capital markets have experienced the following development procedure, during which Chinese government undertook some important reforms [4][17].

At the beginning of the development, China's stock market was in the status that lacked a unified regulatory and supervisory framework since it emerged as a result of the massive economic transition taking place in China. A number of incidents, such as the well-known "August 10 incident" happened in Shenzhen, exposed the disorder in the market development. Unified regulations and supervision became urgently required for the stock market [4].

In October 1992, the Securities Committee and the China Securities Regulatory Commission were established, which means the capital markets started entering an important new stage of development. To attract foreign capital, the Chinese government undertook a pilot scheme to issue Renminbi-denominated shares to foreign investors, such as B-shares, H-shares, N-shares, L-shares and S-shares. China's stock market developed rapidly in the following years. However, there appeared many problems which needed further improvement of the legal and regulatory frameworks [4][17].

In December 1998, the Chinese government issued the Securities Law and had it enacted the next year. This confirmed the importance of capital markets and formalized their legal status in China for the first time. The law was subsequently amended in 2005. In order to further open the doors to the world, in December 2001, China joined the World Trade Organization (WTO). The financial sector reforms moved forward again while the capital markets grew broader and deeper [4].

Table 1 : Major Events

Date	Event
December 19 1990	Establishment of Shanghai Stock Market
December 1991	Establishment of Shen Zhen Stock Market
December 1991	B-share started
January 1992	Announcement of Dong Shao ping's Talk
November 1992	Establishment of China Securities Council
August 1 1994	Announcement that no IPO within next half year would be listed on the exchanges
May 18 1995	Chinese treasure bond future transaction stopped
December 16 1996	10% price change limit applied
May 8 1997	Increase of transaction tax
July 1 1999	New China Security Law enacted
September 9 1999	Allowing state-owned companies to use their own funds to invest in A share stock
October 23 2001	Temporarily quit transaction of state -owned shares
June 24 2002	Permanently cease transaction of state-owned shares
Feb 4 - Mar 4 2001	Open B shares to domestic investors
July 1 2005	RMB exchange rate regime has been reformed
Nov 2005	Guanquanfenzhi reform enforced
October 30 2009	the Nasdaq-style board for small and medium-sized companies at the Shenzhen Stock Exchange (Beijing Review, Dec. 27, 2010)
April 16 2010	China's first stock index futures started trading (China Daily April 16, 2010)

Sources: Chinese Security Journal, Yearbook of China Securities and Futures Statistical, Beijing Review, China Daily

Since the Shanghai stock market dominates China's whole capital market, in this paper, we utilize the time series of the Shanghai stock market to detect the mulitifractality and figure out the features of the China stock market. Our aim is to find out whether the Chinese stock market is shifting from a centrally-controlled market into a market-oriented one or not.

During the development of China Stock Market, some major events have happened which may be seen as influencing the structure of the market. The main events are chosen and listed in table 1. From the table, it can be seen that some important policies were implemented. For illustration purposes, two of the most important events are picked up. One is that China applied 10% price change limit in China Stock Market. Until 1996, the China Stock Market was strongly central-controlled by the Chinese government, which was not allowed to move beyond the stock price limit stipulated (1%). In order to make the market more consistent with the real capital market, several reforms were conducted, among which the reform launched in 1996 was the biggest one at that period. This reform imposed a 10% daily change limit on any individual stock, which implies that Chinese government never controlled the stock market as strictly as before and the stock market's fluctuation can be more flexible. The other important event is that China reformed the RMB exchange rate in July 2005. Before July 2005, the RMB was pegged to the U.S. dollar. After the reform, it began to fluctuate against a basket of currencies, with a 2% appreciation with respect to the U.S. dollar. In the following paragraphs, a multifractal analysis is used to detect whether there are any significant changes before and after 1996, and before and after 2005. In the same time, the government launched the "Guanquanfenzhi" reform, by announcing the extension of the Non-tradable Stocks program to the entire market. To make the reform palatable to the tradable shareholders, the government stated that the non-tradable shareholders should compensate the tradable shareholders before having their shares to be traded in the markets. This reform was a significant one, which means the China Stock Market was experiencing a big transition from a centrally-controlled market to a market-oriented one. In this paper, the two important years are emphasized and the characteristics of the period before and after 1996, and before and after 2005 are examined.

6. Emperical analysis

6.1 Data Set

In this paper, the daily closing data of Shanghai Stock Exchange Composite Index (SSECI) is used. The time period is selected from 1992.12.9 to 2009.11.20. In order to catch the characteristics before and after 1996, and before and after 2005, it is necessary to take out the time series related to pre and post 1996 and pre and post 2005 as well. Therefore, four periods are required. For the computation of multifractality, 1024 data are used for each period. The features of these periods are analyzed and the relationships among them are figured out correspondently so as to find out whether there are significant changes before and after 1996, and before and after 2005. Totally, 5120 observations are obtained.

6.2 Results

From table 2, it can be seen that the p-value (0.46) is higher than the conventional critical values (0.10, 0.05 or 0.01), which means that the coefficient is not significant. This indicates the null hypothesis of linearity is strongly rejected for the time series. Table 3 shows a p-value (0.000) close to zero, meaning that the coefficient is significant. It can be induced by model fitting that the Shanghai Stock Market moves in a nonlinear process. Further, as shown in table 4, the nonlinearity is fully detected by BDS test. Thus, it is reasonable to apply the nonlinear time series theory to the Shanghai Stock Market.

According to the analysis of the multifractality, different characteristics can be found between pre-1996 and post-1996, and between pre-2005 and post-2005 as well. In our numerical experiments, the calculation of the singularity and singularity spectrum for each interval of 1024 trading days (about 4 years) is

Table 2： Linear model fitting

Dependent Variable: Y				
Method: Least Squares				
Sample (adjusted): 2 4096				
Included observations: 4095 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000478	0.000364	1.312964	0.1893
Y (-1)	-0.011472	0.015608	-0.734997	0.4624

Table 3： Nonlinear model fitting

Dependent Variable: Y				
Method: ML-ARCH (Marquardt) -Normal distribution				
Included observations: 4095 after adjustments				
GARCH=C(3)+C(4) *RESID (-1)^2				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000656	0.000238	2.753164	0.0059
Y (-1)	-0.016262	0.002642	-6.154112	0
Variance Equation				
C	0.000337	3.19E-06	105.8825	0
RESID (-1)^2	0.470701	0.018099	26.00654	0

Table 4： BDS test

BDS Test for Y				
Sample: 1 4096				
Included observations: 4096				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.029187	0.001611	18.11478	0
3	0.058241	0.002559	22.76229	0
4	0.080834	0.003046	26.5417	0
5	0.094289	0.003173	29.71254	0
6	0.100964	0.00306	32.99764	0

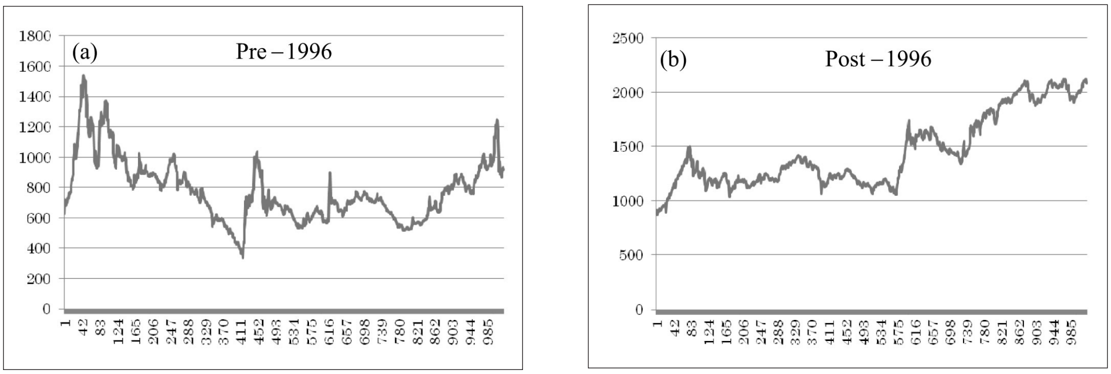

Figure 1: time series plot (pre-**1996** and post-**1996**)

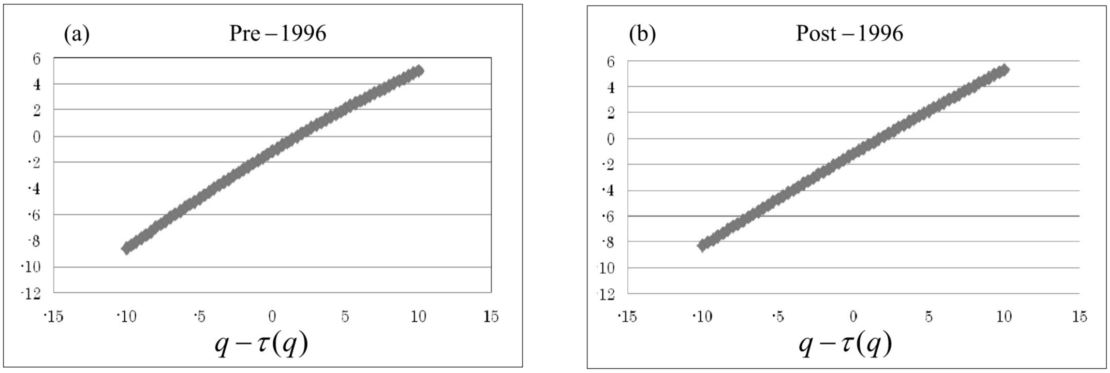

Figure 2: $q-\tau(q)$ plot (pre-**1996** and post-**1996**)

conducted. The multifractal characteristics are included in the figures (figure1 to figure 6.)

Figure 1 shows the original data series for pre-1996 and post-1996. It can be observed that time series before and after 1996 fluctuate in different ways. Figure 2 presents $q-\tau(q)$ plots of the two periods. According to the fractal theory, if $\tau(q)$ fits a non-linear curve, the time series bears multifractality. On the other hand, if the line of $\tau(q)$ is straight, the time series bears mono-fractality. As seen in figure2(a), the $\tau(q)$ is a non-linear function of q , which provides an evidence for the presence of multifractality. While looking at figure 2(b), the $q-\tau(q)$ plot is a slight deviation from linearity, which means the multifractality is weak. Figure 3 shows the $\alpha-D(\alpha)$ plots of the series pre-1996 and post-1996. Based on the multifractal theory, the difference between $\alpha_{\max}$ and $\alpha_{\min}$ (denoted as $\Delta\alpha$) is a statistics to examine the strength of the multifractality. The wider the difference, the stronger the strength of multifractal. From figure 3(a) and figure 3(b), the width of α for the series post-1996 is smaller than that of series pre-1996, which indicates as well that the multifractality is weaker after 1996. Therefore, it can be concluded that after the new policy implemented in 1996, the market became less active than before, the effect for the reform was not found.

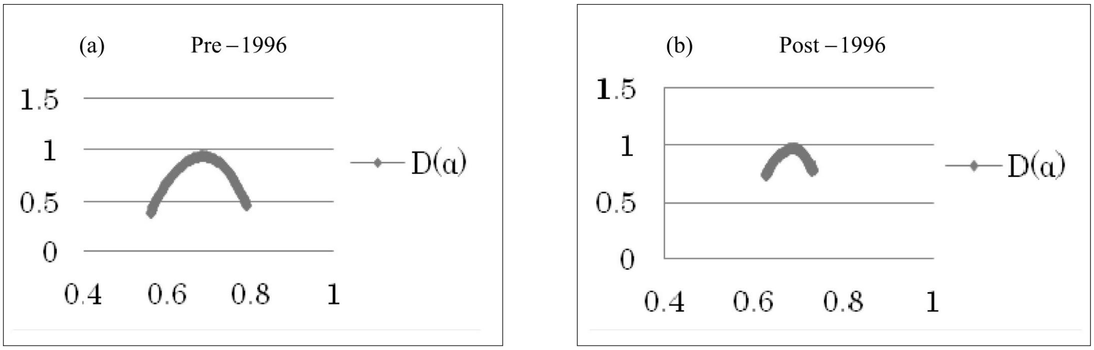

Figure 3: $\alpha - D(\alpha)$ plot (pre-**1996** and post-**1996**)

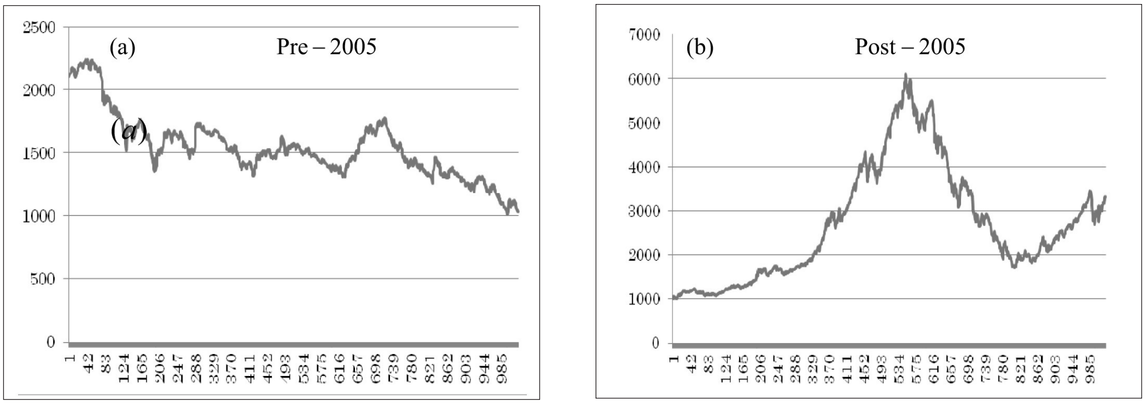

Figure **4**: time series plot (pre-**2005** and post-**2005**)

The multifractal results pre-2005 and post-2005 are shown in figure 5 and figure 6. Figure 4 only displays the original time series for these two periods. It can be observed that fluctuation for the two time series before and after 2005 went in different status. Figure 5 presents $q-\tau(q)$ plots of the two time series. As explained in the above paragraph, if $\tau(q)$ can be fitted well to a non-linear curve, the time series is considered to bear multifractality. Contrarily, if the line of $\tau(q)$ is a straight line, the time series holds mono-fractality. As seen in figure 5(a), the $\tau(q)$ is approximately expressed by a linear function of q, which means multifractality does not exist in the series pre-2005. While checking figure 5(b), the $q-\tau(q)$ plot is found deviated from linearity, which is a hallmark for the presence of multifractality. Furthermore, figure 6 shows that the width between $\alpha_{\max}$ and $\alpha_{\min}$ for the series post-2005 is much larger than that of series pre-2005, which means that the multifractality is stronger after 2005. Consequently, it can be concluded that the new policy launched by Chinese government in 2005 was effective and the stock market became more active and tending to a market-oriented one.

Beside the results included in the figures, table 5 presents the calculation results of the value of

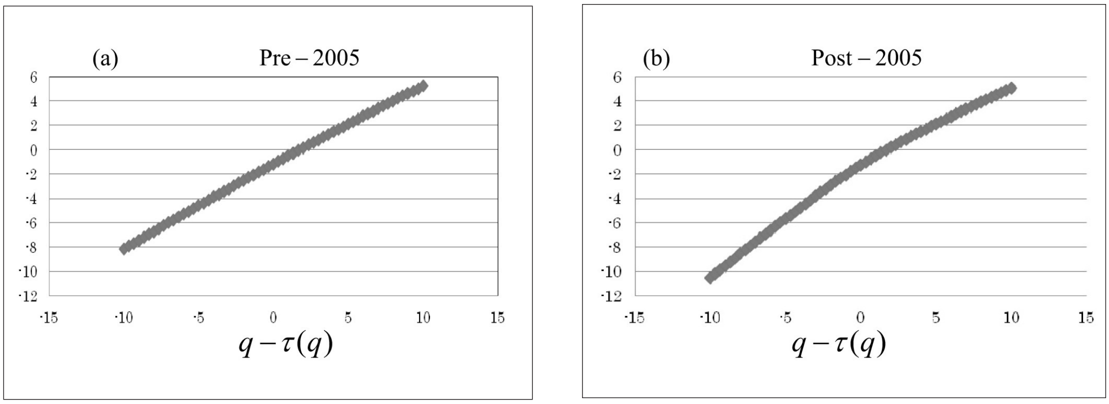

Figure 5: $q-\tau(q)$ plot (pre and post **2005**)

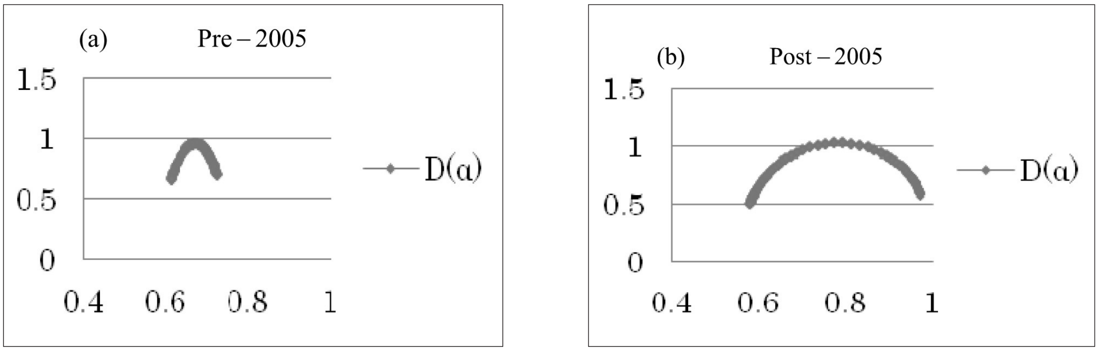

Figure 6: $\alpha-D(\alpha)$ plot (pre-**2005** and post-**2005**)

Table 5 : Singularity width

Period / α	pre-1996	post-1996	pre-2005	post-2005
$\alpha_{\min}$	0.560456046	0.626462646	0.609660966	0.578157816
$\alpha_{\max}$	0.792079208	0.729972997	0.722772277	0.969706059
$\Delta\alpha$	0.231623162	0.103510351	0.113111311	0.391548243

singularity width $\Delta(\alpha)$s for the four series. It can be seen from the table that the $\Delta(\alpha)$s for the period post-1996 and that of pre-2005 are very small, which can confirm that the multifractility for these two periods are weak. On the other hand, the $\Delta(\alpha)$s for the periods of pre-1996 and post-2005 is found larger. In particular, $\Delta(\alpha)$ for the period of post-2005 is obviously the largest. These results are consistent with those shown in the figures (figure 1- figure 6). Consequently, the Shanghai Stock Market fluctuated more conservatively after the 1996 reform but after the new policy enforced by the Chinese government in 2005, it began to perform quite differently than ever before. The market is considered to have started shifting from a centrally-controlled market to a market-oriented one.

7. Conclusion

In this paper, the linear and nonlinear model fitting has been conducted to detect the nonlinearity of the Shanghai Stock Market. As a result, the nonlinear model fits but the linear model does not. To make further confirmation, the nonlinearity test - BDS test - is conducted and confirms the nonlinearity result detected by using model fitting. This finding proves that the Shanghai Stock Market follows a nonlinear process.

From the results of the multifractal analysis, it is obvious that the multifractality for the period post-1996 and pre-2005 is weak and the mono-fractal property can be considered. This means the market moved conservatively without high fluctuation even after the stimulation reform conducted by the Chinese government. This status kept for a long time. From 2005, the market began to bear the multifractality. It can be concluded that the Shanghai Stock Market has its own characteristics without big changes for a long time even if some legal regulations were enforced. From 2005, the market began to bear the multifractality, which means the new reform enforced by the government gave a great impact on the market. It can be concluded that the market began to show the changes since 2005, which means that it is clearly changing to be more market-oriented and presents an on-going trend toward globalization.

The contribution of this study is on applying model-fitting and nonlinearity test to detect the nonlinearity before utilizing the nonlinear theory - multifractal theory - to analyze the time series. Most works showed that the process of detecting and testing the nonlinearity is not conducted before employing the nonlinear analysis theory. It is supposed that the multifractal theory may not be employed if the time series is actually linear. Therefore, we consider that it is necessary to make sure whether it is linear or nonlinear before making use of multifractal theory. In additon, wavelet theory based multifractal theory is rarely applied in financial data analysis despite its wide use in Physics, Medical Sciences, and Engineering. This study has applied this multifractal analysis to the Shanghai Stock Market and showed effective results that can help draw efficient policies with respect to the China's Stock Market.

8. Future research

In this paper, the nonlinearity is detected and tested by model fitting and BDS test. It is proved powerfully that the Shanghai Stock Market possesses a nonlinear feature. It is known that there are other powerful statistical tests for detecting nonlinearity. Our next work is to focus on nonlinearity tests with different approaches. Moreover, figuring out the structural changes in time series is important to analyze the real financial data. Using the multifractal theory to detect the structural changes in time series is another research topic. Furthermore, our future research will be conducted on the comparison of the four important markets: the London Stock Market, the New York Stock Market, the Tokyo Stock Market and the Shanghai Stock Market.

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