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Finite-size effect and the components of multifractality in transport economics volatility based on multifractal detrending moving average method

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HIGHLIGHTS

- Multifractal characteristics of freight rate returns in MF-DMA analysis.
- Reflection of the fluctuation size on multifractality.
- Quantitative analysis of multifractality to identify the possible source(s) considering the finite-size effect.

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ABSTRACT

Analysis of freight rate volatility characteristics attracts more attention after year 2008 due to the effect of credit crunch and slowdown in marine transportation. The multifractal detrended fluctuation analysis technique is employed to analyze the time series of Baltic Dry Bulk Freight Rate Index and the market trend of two bulk ship sizes, namely Capesize and Panamax for the period: March 1st 1999–February 26th 2015. In this paper, the degree of the multifractality with different fluctuation sizes is calculated. Besides, multifractal detrending moving average (MF-DMA) counting technique has been developed to quantify the components of multifractal spectrum with the finite-size effect taken into consideration. Numerical results show that both Capesize and Panamax freight rate index time series are of multifractal nature. The origin of multifractality for the bulk freight rate market series is found mostly due to nonlinear correlation.

1. Introduction

The study of financial time series has been the focus of intense research by the physics community in the last several years since Mantegna and Stanley [1] introduced the method of scale invariance from the complexity science into the economic systems for the first time. Moreover, new paradigms and a range of complex systems such as nonlinear dynamics and statistical mechanics have been coherently set up and investigated which may produce results relevant for both physics and economics by physicists with a background of economics [2]. Nowadays, some excellent compilations are but not limited to Mantegna and Stanley [3], Bouchaud and Potters [4], Drożdż et al. [5] and Yuan et al. [6] and Grech [7]. It is widely

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acknowledged that the international shipping industry which facilitates 90% of world trade is tightly linked to the global economy, thus various studies are deserved to investigate the dynamicity and volatility of shipping market for investment purposes like any other financial asset or commodity [8–11]. As is generally known, the dry bulk carrier market is more competitive and typical, hence in this paper, the Baltic dry bulk freight rate index, which is considered by the investment community as a leading indicator of economic activity in shipping market [12], is investigated and analyzed.

In general, a fractal is a rough or fragmented geometrical shape that can be subdivided into parts, each of which is (at least approximately) a reduced-size copy of the whole.

Scaling phenomena is found in many systems, from geophysical to biological, thus Mantegna et al. [1] explored the possibility that it also exists in economic systems. A fractal system is usually described by a scale invariant parameter called fractal dimension [13]. Many fractals require a set of parameters to specify such objects are known as multifractals. Several approaches have so far been developed and applied to explore the fractal properties. One is the rescaled adjusted range analysis method by Hurst [14]. The rescaled analysis is difficult to capture long-range correlations of nonstationary series. A new method to investigate the multi-affine fractal exponents and the correlation coefficient is introduced by Castro et al. [15]. Peng et al. [16] proposed detrended fluctuation analysis (DFA) as an alternative approach. Subsequently, DFA is used to test for the presence of long-term correlations in the return intervals [17–20]. But DFA cannot properly describe multi-scale and fractal subsets of time series data though many records do not exhibit a simple monofractal scaling behavior. The definition of multifractality was first introduced in turbulence and it was soon applied to finance because its heavy tails and long-term dependence nature [19]. Weber et al. [21] examined the spectra and correlations of climate data with a novel method called pth-degree DFA where p refers to a real number and for $p = 2$ recover the usual DFA. In this way some of the multifractal time series can be identified. Bacry et al. [22] developed a method for the simplest type of multifractal analysis based on the standard partition function multifractal formalism. This is a highly successful method for the multifractal characterization of normalized and stationary measures, but it has difficulty in giving the correct result for nonstationary time series. The multifractal detrended fluctuation analysis (MF-DFA) introduced by Kantelhardt et al. [23] for the multifractal characterization of nonstationary time series based on a generalization of the DFA method is a remarkable powerful technique. It has so far been applied to various fields of stochastic analysis, for instance, in biophysics [24,25], in geophysics [26,27], applied physics [28,29] and in markets return analysis [30–35]. The detrending moving average (DMA) method is largely used in quantifying the long-term correlations of nonstationary time series both in real world and synthetic ones [36,37]. Considering the moving average function of the original series and based on the moving average method. DMA is highly efficient in obtaining scaling properties. Before long, MF-DMA is first proposed by Gu and Zhou in 2010 which is a further extension of DMA to higher-dimensional versions [38]. They analyzed the multifractal characteristics of Shanghai Stock Exchange Composite Index using MF-DMA method and found that the backward MF-DMA algorithm has a significant advantage over MF-DFA in detecting the scaling exponents with a comparison result presented.

The prime objective of this kind of analysis is to characterize the statistical properties of the time series and have a better understanding of the underlying dynamics mechanism. Moreover, such knowledge might be crucial to tackle relevant problems in finance. For analysts and policy makers, the importance of an accurate forecast of volatility and dynamicity to tasks such as risk management, portfolio allocation, value-at-risk assessment and option cannot be exaggerated [34,39–44]. Henceforth our discussion will be restricted to the time series analysis of dry bulk freight market. Presently the fluctuations of dry bulk freight market become almost impossible to predict its accurate rise or fall. As we know, over 70% of average freight rate changed between the first half year and the second one in year 2008. Sometimes such change is insignificant, for instance in year 2010. Also, freight rate feature of different ship sizes interested us, since the results of Lu et al. [45] is not consistent with that of Kavussanos [46]. He found that larger vessels tend to experience fiercer volatility, whereas Lu et al. reached the conclusion that smaller vessels react to market's shocks more intensively, owing this phenomenon to the complexity of the freight rate market after the year 2003. Whatever may be the reason, the dynamical nature of the dry bulk freight market is quite complex, and one needs to study the time series of price index from all possible angles in order to understand the underlying mechanism.

In this article we apply the MF-DFA technique to characterize the time series of dry bulk freight rate index and the most popular ship sizes of Capesize and Panamax during the period March 1st, 1999 to February 26th, 2015. In order to visualize the recent market pattern after year 2007 with larger fluctuation, we separately analyze the series of period I from Mar 1st 1999 to Feb 21st 2007 and period II from Feb 22nd 2007 to Feb 26th 2015. Various multifractal variables, such as the Hurst exponent, probability distribution of Hurst exponent and multifractal spectrum are calculated. Furthermore, special quantitative analysis is given to identify the possible source(s) of multifractality in these series since the multifractal nature of the original time series results from three components, which are linear correlation, nonlinear correlation and the fat-tailed probability distribution (PDF) components, respectively [47,48]. For this purpose, we analyze a randomly shuffled series whose multifractal nature is caused by the PDF part only, and a surrogate series whose multifractal property is due to the linear correlation and PDF part, corresponding to the original series BCI, through measuring the width of the multifractal spectra [49]. In order to get more accurate estimates of the possible sources of multifractality in BCI series, we apply MF-DMA method which is proven to have a better performance compared with MF-DFA in quantifying the components of multifractal spectrum [38].

The paper is further organized as follows: Section 2 introduces the MF-DFA method and MF-DMA method; Section 3 describes the data; Section 4 discusses the results and the article is summarized in Section 5.

2. Methodology

2.1. The multifractal detrended fluctuation analysis method

Here is a brief introduction of MF-DFA method according to Kantelhardt et al. [23].

The operation of MF-DFA on the series $x(i)$, where $i = 1, 2, \ldots, N$ and N is the length of the series, is as follows. With $\bar{x}$ we indicate the mean value of series $x(i)$.

We assume that $x(i)$ are increments of a random walk process around the average $\bar{x}$, thus the "trajectory" or "profile" is given by the integration of the signal

$$y(i) = \sum_{k=1}^{i}[x(k) - \bar{x}], \quad i = 1, 2, \ldots, N. \tag{1}$$

Next, the integrated series is divided into $N_s = int\,(N/s)$ non-overlapping segments of equal length s. Since the length N of the series is often not a multiple of the considered time scale s, a short part at the end of the profile $y(i)$ may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end. Thereby, $2N_s$ segments are obtained altogether. We calculate the local trend for each of the $2N_s$ segments by a least-square fit of the series. Then we determine the variance

$$F^2(s, v) = \frac{1}{s}\sum_{i=1}^{s}\{y[(v-1)s+i] - y_v(i)\}^2 \tag{2}$$

for each segment v, $v = 1, \ldots, N_s$ and

$$F^2(s, v) = \frac{1}{s}\sum_{i=1}^{s}\{y[N-(v-N_s)s+i] - y_v(i)\}^2. \tag{3}$$

For $v = N_s + 1, \ldots, 2N_s$. Here, $y_v(i)$ is the fitting line in segment v. Then, we average over all segments to obtain the qth order fluctuation function

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

where, in general, the index variable q can take any real value except zero. Repeating the procedure described above, for several time scales s, $F_q(s)$ will increase as s increases. By analyzing log–log plots $F_q(s)$ versus s for each value of q, we determine the scaling behavior of the fluctuation functions. If the series $x(i)$ is long-range power-law correlated, $F_q(s)$ will increase for large values of s as a power-law

$$F_q(s) \approx s^{h_q}. \tag{5}$$

The value h_0 corresponds to the limit h_q as $q \to 0$, and cannot be determined directly by using the averaging procedure of Eq. (4) because of the diverging exponent. Instead, a logarithmic averaging procedure has to be employed,

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s}\ln\left[F^2(s, v)\right]\right\} \approx s^{h_0}. \tag{6}$$

In general the exponent h_q will depend on q. For stationary series, h_2 is the well-defined Hurst exponent H. Thus, we call h_q the generalized Hurst exponent. h_q is independent from q, which characterizes monofractal series. The different scaling of small and large fluctuations will yield a significant dependence of h_q on q. For positive q, the segments v with large variance (i.e. large deviation from the corresponding fit) will dominate the average $F_q(s)$. Therefore, if q is positive, h_q describes the scaling behavior of the segments with large fluctuations; and generally, large fluctuations are characterized by a smaller scaling exponent h_q for multifractal time series. For negative q, the segments v with small variance will dominate the average $F_q(s)$. Thus, for negative q values, the scaling exponent h_q describes the scaling behavior of segments with small fluctuations, usually characterized by large scaling exponents.

Another manner to qualify multifractality in a series is by using the multifractal spectrum $f(\alpha)$. The multifractal spectrum can be obtained using the relationship

$$\tau(q) = qh(q) - 1 \tag{7}$$

and then the Legendre transform

$$\alpha = \frac{d\tau}{dq} \tag{8}$$

$$f(q) = q\alpha - \tau(q) \tag{9}$$

where α is the Holder exponent or singularity strength and $f(\alpha)$ can be used to determine the multifractality level thus a broader curvature indicates a stronger multifractality.

Specifically, let

$$\Delta\alpha = \alpha_{\max} - \alpha_{\min} \tag{10}$$

where $\alpha_{\max}$ and $\alpha_{\min}$ are the maximum and minimum values of α respectively.

The polynomial order m is ordinary valued 1, 2, 3... Corresponding to the MF-DFA algorithms with $m = 1, 2, 3$, MF-DFA, MFDFA2 and MFDFA3 are named separately. And the MF-DFA2 method is utilized in this article to investigate the Baltic Dry Bulk Freight Rate Index

2.2. The multifractal detrending moving average method

Here is a brief introduction to MF-DMA according to Gu and Zhou [38]

Assume there is time series $x(t)$, where $t = 1, 2, \ldots, N$ and N is the length of the series. We construct a new profile

$$y(t) = \sum_{i=1}^{t} x(i) \quad t = 1, 2, \ldots, N. \tag{11}$$

Next, we calculate the moving average function $\widetilde{y}(t)$ of the sequence of cumulative sums in a moving window,

$$\widetilde{y}(t) = \frac{1}{n} \sum_{k=-\lfloor (n-1)\theta \rfloor}^{\lceil (n-1)(1-\theta) \rceil} y(t-k) \tag{12}$$

where n is the size of window, $\lfloor x \rfloor$ is the largest integer but not greater than x, $\lceil x \rceil$ is the smallest integer but not smaller than x, and θ is the position parameter, of which the value varies from 0 to 1. The moving average function $\widetilde{y}(t)$ is calculated over $\lceil (n-1)(1-\theta) \rceil$ data points in the past while $\lfloor (n-1)\theta \rfloor$ data points in the future. There are three special cases with different values of θ. The first case is called the backward moving average, where $\theta = 0$ and $\widetilde{y}(t)$ contains all the past information. The second case $\theta = 0.5$ refers to the centered moving average, in which the moving average function $\widetilde{y}(t)$ is calculated over half past and half future data points. The third case $\theta = 1$ corresponds to the forward moving average, in which $\widetilde{y}(t)$ considers the trend of future data points. In this paper, we consider the backward moving average, where $\theta = 0$, since it has been proved to perform best among the three cases [48].

Then, remove the moving average function $\widetilde{y}(i)$ from $y(i)$ to detrend the series and get the residual sequence $\varepsilon(i)$.

$$\varepsilon(i) = y(i) - \widetilde{y}(i), \tag{13}$$

where $n - \lfloor (n-1)\theta \rfloor \leq i \leq N - \lfloor (n-1)\theta \rfloor$.

Next, we divide the residual series $\varepsilon(i)$ into N_n ($N_n = \lfloor N/n - 1 \rfloor$) segments, which are disjoint and have the same size n, and each segment can be denoted as $\varepsilon_v(i) = \varepsilon(l+i)$ for $1 \leq i \leq n$, where $l = (v-1)n$. The root-mean-square function $F_v(n)$ can be obtained through

$$F_v^2(n) = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_v^2(i), \tag{14}$$

and the qth order overall fluctuation function $F_q(n)$ can be calculated by

$$F_q(n) = \left\{ \frac{1}{N_n} \sum_{v=1}^{N_n} F_v^q(n) \right\}^{\frac{1}{q}}, \quad q \neq 0 \tag{15}$$

$$\ln [F_0(n)] = \frac{1}{N_n} \sum_{v=1}^{N_n} \ln [F_v(n)], \quad q = 0. \tag{16}$$

Then, varying from the values of n, we can find out the power-law relation between $F_q(n)$ and n, which reads

$$F_q(n) \sim n^{h(q)}. \tag{17}$$

Finally, the definitions of multifractal scaling exponent $\tau(q)$ and multifractal spectrum $f(q)$ are similar with that of MF-DFA which have been illustrated above.

3. Data description

Bulk cargo shipping market is not only one of the most important markets of shipping, but also a global bellwether, signaling industrial health wherever it trades, for bulks are mainly used to transport steel, pulp, grain, coal, iron ore,

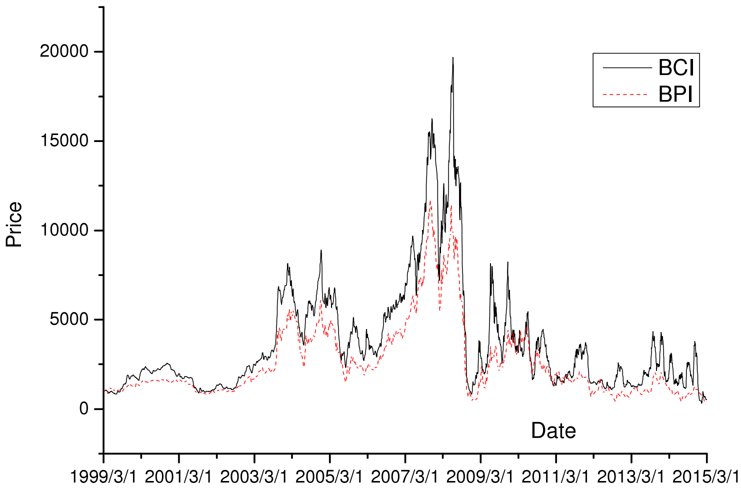

Fig. 1. Baltic dry bulk freight rate.

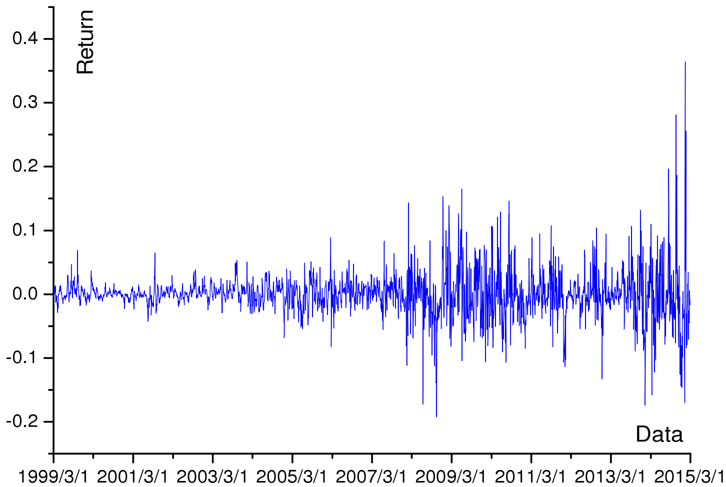

Fig. 2. Logarithmic return of BCI.

ore, bauxite and other daily necessities and industrial raw materials. Therefore, we pay great attention to dry bulk index.

In the analysis, we choose Panamax and Capesize to study the fluctuations in freight rate of dry bulk shipping market since there is an obvious trend of large-scale ship in dry bulk market, and these two kinds of bulks can better reflect the volatility. Baltic Panamax Index (BPI), and Baltic Capesize Index (BCI), which reflect the cost of hiring a vessel across a range of indicative shipping routes, are chosen and analyzed in the following study.

The sample for daily BPI and BCI covers the period from March 1st, 1999 to February 26th, 2015. The time series consists of 3999 observations, a large enough set to engage in multifractal analysis. Fig. 1 is the line graph of BPI and BCI in the sample period. The index curves show sharp fluctuations and the indices underwent intensive changes in the year 2008, when the world financial crisis happened. Fig. 2 plots the BCI daily logarithmic increments (that is, $\ln P(t) / \ln P(t-1)$). Logarithmic returns are used as they are a convenient way to show daily fluctuations in prices. A logarithmic approach fits better in the multifractal methods used while returns often reduce non-stationarities in time series [50–53].

4. Results and discussion

4.1. Multifractal characteristics of bulk shipping market returns

The Hurst exponent defines the monofractal structure of the time series by how fast the overall root-mean-square (RMS) grows with increasing segment sample size (i.e., scale). In the multifractal time series, local fluctuation, RMS, will be extreme large magnitude for segments within the time periods of large fluctuations and extreme small magnitude for segments within the time periods of small fluctuations. The q-order Hurst exponent can be defined as the slopes (Hq) of

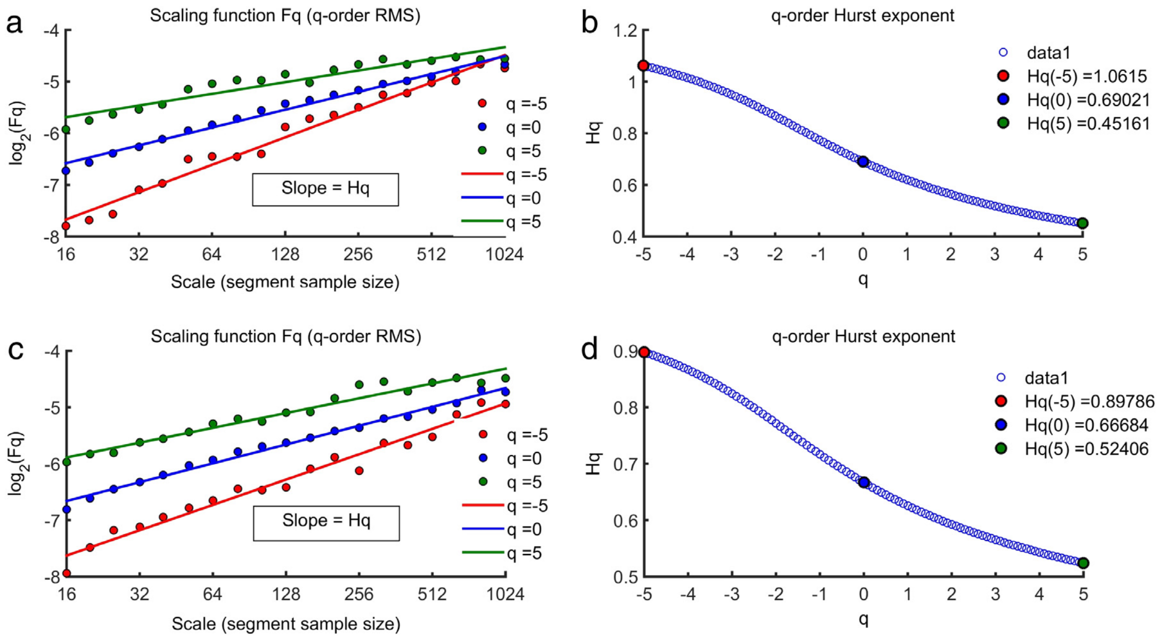

Fig. 3. q-order RMS and q-order Hurst exponent for BCI return and BPI return.

regression lines (q RegLine) for each q-order RMS (F_q). Fig. 3(a) and (c) show that the slopes Hq of the regression lines are q-dependent for the multifractal time series. The difference between the q-order RMS for positive and negative q's are more visual apparent at the small segment sizes compared to the large segment sizes. The small segments are able to distinguish between the local periods with large and small fluctuations (i.e., positive and negative q's, respectively) because the small segments are embedded within these periods. In contrast, the large segments cross several local periods with both small and large fluctuations and will therefore average out their differences in magnitude. The q-order RMS of multifractal time series with increasing q leads to a decreasing Hq for multifractal time series, see Fig. 3(b) and (d). Both BCI and BPI returns are of multifractal characteristics.

4.2. Time-dependent multifractal detrended fluctuation analysis of freight rate fluctuation

The logarithmic return of BCI in Fig. 2 suggests that the fluctuation becomes larger from year 2007 of world financial crisis compared to time series before 2007. Since a coherent understanding of financial fluctuations such as financial crisis is of great significance [46], we separate the total data into two periods: period I from Mar 1st 1999 to Feb 21st 2007 and period II from Feb 22nd 2007 to Feb 26th 2015 in order to analyze the financial crisis's effects on multifractal characteristics of time series. The q-order Hurst exponent Hq is only one of several types of scaling exponents used to parameterize the multifractal structure of time series. The local Hurst exponent Ht in periods with fluctuations of small and large magnitudes is therefore consistent with the q-order Hurst exponent Hq for negative and positive q's, respectively. The advantage of local Hurst exponent Ht compared with q-order Hurst exponent Hq is the ability of Ht to identify the time instant of structural changes within the time series [54]. In studies where the financial phenomenon is perturbed at some time instant, the local Hurst exponent Ht can identify how this perturbation affects the local scale invariant structure of the economic time series. The temporal variation of local Hurst exponent Ht can be summarized in a histogram representing the probability distribution (Ph) of Ht (see Fig. 4 (a) for period I and (c) for period II). The multifractal spectrum ($f(\alpha)$ and α) are shown in Fig. 4(b) for period I and (d) for period II. The multifractal spectrum width $\Delta\alpha$ is employed in this article as a parameter to describe the level of multifractality. The growth of structural differences between the two periods with small and large fluctuations as the multifractal spectrum width becomes larger. Multifractal spectrum of period II is obviously with left truncation, which originates from the leveling of the q-order Hurst exponents for positive q's. The multifractal spectrum width $\Delta\alpha$ in Fig. 4(b) and (d) indicate both BCI return period I and period II are of strong multifractality. The results are consistent with that of Mali and Mukhopadhyay [35].

4.3. Quantitative analysis of multifractal components with MF-DMA method

According to the partition function method of the multifractal analysis [55], the apparent multifractal spectrum can be decomposed into three parts: the nonlinear correlation, the linear correlation and the fat-tailed probability distribution

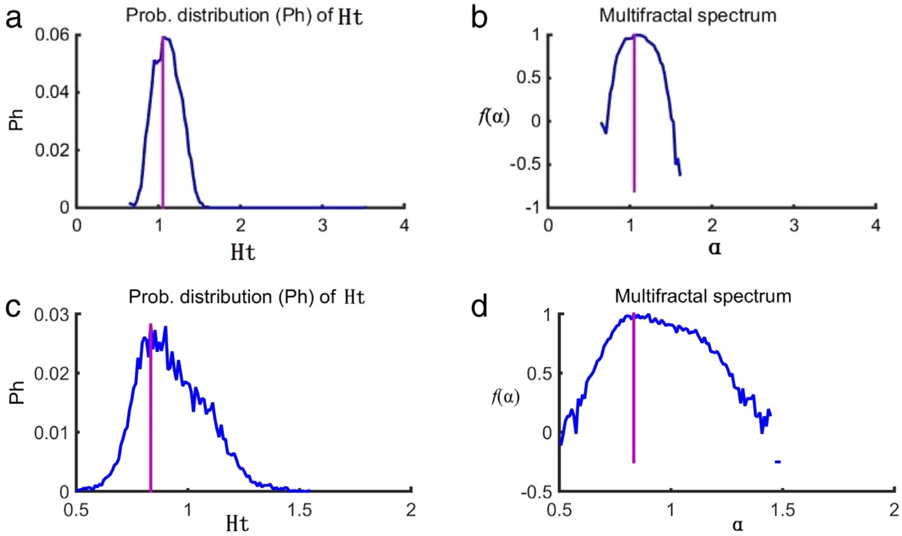

Fig. 4. MF-DFA2 for probability distribution *Ph* of the local Hurst exponents *Ht* and the multifractal spectrum $(f(\alpha), \alpha)$ of BCI return period I and period II.

(PDF), which can be expressed as the following equation,

$$\Delta\alpha = \Delta\alpha_{NL} + \Delta\alpha_{LM} + \Delta\alpha_{PDF}. \tag{18}$$

It is significant to note that both the linear correlation part and nonlinear correlation part are temporal correlations, and the linear correlation part $\Delta\alpha_{LM}$ is caused by finite-size effect [32,56]. Besides it is worthwhile to mention that the linear correlation part $\Delta\alpha_{LM}$ can be also independently calculated using semi-analytic formulas given in explicit form in Ref. [32] that provide general quantitative description of this phenomena. The finite-size effect is defined as a kind of calculation deviation caused by the limitation of sample size. Namely, the smaller the sample size is, the larger the calculation deviation will be. To eliminate the disturbance of the sample size, especially for small sample size ($<$10 000), the linear correlation part need to be calculated and excluded from the effective multifractality, thus the effective multifractality $\Delta\alpha_{\text{eff}}$ which includes the nonlinearity part $\Delta\alpha_{NL}$ and the PDF part $\Delta\alpha_{PDF}$ can be acquired.

In order to accurately describe the multifractality spectrum, it is necessary to make a quantitative analysis to both remove the linear correlation part due to the length of the time series (consists of 3999 observations) and decompose the other two effective parts [57]. The quantitative analysis can be reached by constructing two new time series: the shuffled time series and the surrogated time series.

The shuffled time series can be constructed by random shuffling of the given series. For this procedure, the temporal correlations will be destroyed yet the probability distribution will not be altered [38].

The surrogated time series referred above can be generated by two steps. The first step is to make the surrogated time series owns the same probability distribution as the original time series of volatility, which can be realized through transformation method [58]; the second step is to introduce linear correlations in the surrogated time series by using an improved amplitude adjusted Fourier transform (IAAFT) algorithm [57]. For detailed steps of constructing the surrogated time series, readers can refer to the paper [47].

The numerical results are shown in Fig. 5. As shown in Fig. 5, we know that the multifractality caused by the fat-tailed probability distribution part is $\Delta\alpha_{PDF} = 0.045$, the total multifractality is $\Delta\alpha = 0.695$, and the multifractality caused by linear correlation and PDF parts are $\Delta\alpha_{LM} + \Delta\alpha_{PDF} = 0.326$, then we can get the non-linear correlation part contributes $\Delta\alpha_{NL} = 0.369$ to the multifractality, the effective multifractality $\Delta\alpha_{\text{eff}} = \Delta\alpha_{PDF} + \Delta\alpha_{NL} = 0.414$.

Therefore, a qualitative conclusion can be easily drawn that the multifractality is generated mostly from non-linearity correlation and a little from a fat-tailed probability distribution function of the values in the BCI series.

5. Conclusion

Multifractal nature of (i) BCI return and (ii) BPI return time series during the period March 1st, 1999 to February 26th, 2015, has been investigated in terms of the multifractal detrended fluctuation analysis. For better understanding of the rapidly increasing and fluctuating market trend over the last few years we divide BCI return series into two: period I from Mar 1st 1999 to Feb 21st 2007 and period II from Feb 22nd 2007 to Feb 26th 2015. Original BCI return series, corresponding to a randomly shuffled and a surrogated series are analyzed. Multifractal observables, such as the local Hurst exponents *Ht*, probability distribution *Ph* of *Ht* and singularity spectrum $(f(\alpha), \alpha)$ for all the series, are extracted and are fitted (whenever possible) to the series. The following conclusions can be drawn from our analysis.

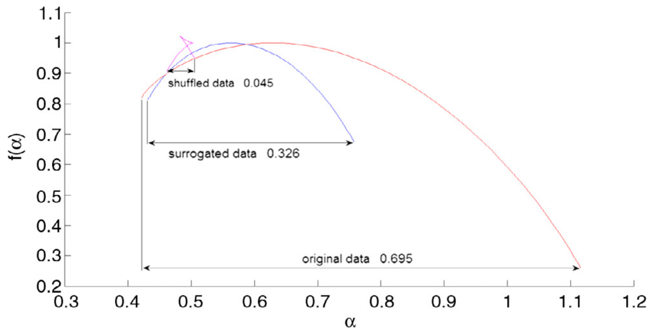

Fig. 5. MF-DMA for the BCI's multifractal spectra of three time sequences.

The MF-DFA fluctuation functions for all the analyzed time series of BCI return and BPI return nicely follow the scaling law, as is expected for a multifractal series. The generalized Hurst exponent spectra corresponding to the original series are found to be order dependent. The nature of $f(\alpha)$ spectra investigated by MF-DMA method is consistent with the fact that multifractality of BCI return time series is generated mostly from non-linearity correlations of the small and large fluctuations and a little from a fat-tailed probability distribution function of the values in the series. The growth of structural differences between the two periods with small and large fluctuations as the multifractal spectrum width becomes larger. Multifractal spectrum of period II is obviously with left truncation, which originates from the leveling of the q-order Hurst exponents for positive q's. BCI return series of both periods I and II are of strong multifractality.

It is obvious that the dry bulk freight rate market series are multifractal. The multifractal spectrum describes the singularity content of the dry bulk freight rate market series, and the width of the multifractal spectrum ($\Delta\alpha$) can be used to estimate the strength of multifractality as well. The volatility of the dry bulk freight rate increases with the increasing of the value of $\Delta\alpha$, which indicates the larger strength of multifractality and greater risk of the market. The conclusion can be used to give a rough evaluation of the market risk, and make some help for the market risk management.

However, some factors like division of freight rate series and abrupt events will radically change the multifractal features. Further research may be done to study the influence that various factors have on the MF-DFA method in order to improve its accuracy. As the major origin for multifractality is long-range time correlation, forecast for dry bulk freight rate market may be for future research. It would not only allow better specifying freight rate pattern but also be helpful in assessing the asset values of bulk carriers and catering for profitable investment strategies.

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