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Asymmetric multifractal scaling behavior in the Chinese stock market: Based on asymmetric MF-DFA

Guangxi Cao [a,b,c,*], Jie Cao [a], Longbing Xu [c]

[a] School of Economics and Management, Nanjing University of Information Science & Technology, Ningliu Road 219, Nanjing 210044, PR China

[b] Department of Economics and Related Studies, University of York, York YO10 5DD, UK

[c] School of Finance, Shanghai University of Finance and Economics, Guoding Road 777, Shanghai 200433, PR China

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ABSTRACT

We utilized asymmetric multifractal detrended fluctuation analysis in this study to examine the asymmetric multifractal scaling behavior of Chinese stock markets with uptrends or downtrends. Results show that the multifractality degree of Chinese stock markets with uptrends is stronger than that of Chinese stock markets with downtrends. Correlation asymmetries are more evident in large fluctuations than in small fluctuations. By discussing the source of asymmetric multifractality, we find that multifractality is related to long-range correlations when the market is going up, whereas it is related to fat-tailed distribution when the market is going down. The main source of asymmetric scaling behavior in the Shanghai stock market are long-range correlations, whereas that in the Shenzhen stock market is fat-tailed distribution. An analysis of the time-varying feature of scaling asymmetries shows that the evolution trends of these scaling asymmetries are similar in the two Chinese stock markets. Major financial and economical events may enhance scaling asymmetries.

1. Instruction

The presence of multifractality suggests the inefficiency [1–6], volatility predictability [7], crash predictions [8,9], and complexity [10–12] of the market. Multifractal analysis has been widely applied in stock markets [13,14] to investigate the intermittent nature of turbulence. Multifractal detrended fluctuation analysis (MF-DFA) [15], which is based on detrended fluctuation analysis (DFA) [16], is widely used to detect long-range autocorrelations and multifractality in stock markets for nonstationary time series [17,18]. Numerous studies have analyzed multifractality in the Chinese stock market [19–25], but relatively few have focused on the asymmetry of multifractal scaling behavior. Even though a small number of studies [26] have focused on this field, researchers usually investigate the different correlation features by categorizing the period of stock markets into bull and bear, in which the sample division is subjective. Thus, studying asymmetric correlation in the entire sample interval is necessary. This study intends to fill this research gap.

Correlation asymmetry affects portfolio diversification, risk management, and policymaking [27]. The presence of asymmetric correlation in the stock market is not surprising because of the expected asymmetric response to economic news. Recent studies suggest that asymmetric correlations exist in stock returns [28–30]. Ang and Bekaert [31] utilized a two-regime-switching model to determine the connection between low returns and high correlation. Longin and Solnik [28] define a new concept called "exceedance correlation" and find a high correlation between large negative returns and

* Corresponding author at: School of Economics and Management, Nanjing University of Information Science & Technology, Ningliu Road 219, Nanjing 210044, PR China. Tel.: +86 25 58695638.

E-mail addresses: caoguangxi@yahoo.com.cn, caoguangxi@nuist.edu.cn (G. Cao).

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zero correlation between large positive returns. Ang and Chen [29] use an exceedance correlation test and show that an asymmetric correlation exists in different types of domestic portfolios. Hong and Zhou [32] propose a model-free method and confirm that asymmetry exists in the United States stock market. These methods can detect the presence of asymmetric correlations. However, these methods depend on assumptions, such as model and threshold value selection.

Alvarez-Ramirez et al. [33] extended the DFA in 2009 by developing asymmetric DFA (A-DFA) method to explore the asymmetries in the scaling behavior of time series. We call the A-DFA method "A-MFDFA" in this paper because A-DFA can analyze multifractal scaling behavior. The A-MFDFA method can not only assess multifractality in different correlations but can also detect the asymmetry of scaling behavior in time series with uptrends and downtrends. Alvarez-Ramirez et al. show that different scaling properties exist if the signal trend is positive or negative. However, Alvarez-Ramirez et al. only show intuitively the relationship between asymmetric behavior and intrinsic correlations. They also discuss only the skewness of data distribution in their samples rather than the origins of asymmetric behavior.

Our work aims to achieve three objectives. First, we apply A-MFDFA to explore the existence of asymmetric multifractal scaling behavior in the Shanghai and Shenzhen stock markets. Second, we discuss the source of asymmetric multifractal scaling behavior by comparing the estimated results of the original data with those of shuffled and surrogated data. Third, we apply rolling windows method to investigate the time-varying feature of scaling asymmetries in the Chinese stock market. The results show that the degree of multifractality in the Chinese stock market with uptrends is stronger than that in the Chinese stock market with downtrends. Correlation asymmetries are stronger in large fluctuations than in small fluctuations. Long-range correlations are the main source of multifractality when the market has uptrends, whereas fat-tailed distribution is the main source of multifractality when the market has downtrends. In particular, the main source of multifractal scaling behavior in the Shanghai stock market is fat-tailed distribution, whereas that in the Shanghai stock market are long-range correlations. The multifractality in the Shenzhen stock market is induced by long-range correlations, whereas that in the Shenzhen stock market is related to fat-tailed distribution. The evolution of scaling asymmetries is similar in the two Chinese stock markets. Major financial and economic events may enhance these asymmetries.

The rest of the paper is organized as follows. Section 2 introduces the A-MFDFA method. Section 3 presents the basic statistical properties of the data. Section 4 provides an empirical analysis of the proposed method, and Section 5 concludes the paper.

2. A-MFDFA method

Let $\{x(t)\}$ be time series $t = 1, 2, \ldots, N$, where N is the length of the series; thus, the A-MFDFA method can be summarized with the following steps.

Step 1: We construct the profile as

$$y(j) = \sum_{t=1}^{j}(x(t) - \bar{x}), \quad j = 1, 2, \ldots, N, \tag{1}$$

where $\bar{x} = \frac{1}{N}\sum_{t=1}^{N} x(t)$.

Step 2: We divide the time series $\{x(t)\}$ and its profile $\{y(t)\}$ into $N_n = \mathrm{int}(N/n)$ non-overlapping subtime series of n lengths. A short part of the profile will remain in most cases because the record length N does not have to be a multiple of the considered time-scale n. This procedure is repeated starting from the other end of the record to consider the remaining part of the record. Thus, $2N_n$ segments are obtained. Let $S_j = \{s_{j,k}, k = 1 \ldots, n\}$ be the jth subtime series of length n and $Y_j = \{y_{j,k}, k = 1, \ldots, n\}$ be the integrated time series (i.e., profile) in the jth time interval, $j = 1, 2, \ldots, 2N_n$. Thus, in the jth segment, $k = 1, 2, \ldots, n$, we have

$$s_{j,k} = x((j-1)n + k), \qquad y_{j,k} = y((j-1)n + k), \tag{2}$$

for $j = 1, 2, \ldots, N_n$ and

$$s_{j,k} = x(N - (j - N_s)n + k), \qquad y_{j,k} = y(N - (j - N_s)n + k), \tag{3}$$

for $j = N_s + 1, \ldots, 2N_n \cdot 5 \le n \le N/4$ is traditionally selected based on the recommendations of Peng et al. [16].

Step 3: For each subtime series $S_j = \{s_{j,k}, k = 1 \ldots, n\}$ and its profile time series $Y_j = \{y_{j,k}, k = 1, \ldots, n\}$, we compute the corresponding local least-squares line fits $L_{S_j}(k) = a_{s_j} + b_{s_j}k$ and $L_{Y_j}(k) = a_{Y_j} + b_{Y_j}k$, where k represents the horizontal coordinate and $i = 1, 2$. The fits $L_{S_j}(k)$ and $L_{Y_j}(k)$ represent the linear trends for the jth subtime series S_j and its integrated time series Y_j, respectively. The linear fit $L_{S_j}(k)$ is used only to discriminate via slope b_{S_j} whether the trend of the subtime series S_j is positive or negative. The linear fit $L_{Y_j}(k)$ is used to detrend the integrated time series Y_j. We determine the fluctuation functions

$$F_j(n) = \frac{1}{n}\sum_{k=1}^{n}(y_{j,k} - L_{Y_j}(k))^2 \tag{4}$$

for each segment $j = 1, 2, \ldots, 2N_n$.