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Understanding the multifractality in portfolio excess returns

Cheng Chen, Yudong Wang *

School of Economics and Management, Nanjing University of Science and Technology, Xiaolinwei Street 200, Xuanwu District, Nanjing 210094, China

HIGHLIGHTS

- The multifractality in portfolio excess returns has not been considered in the literature.
- The significant multifractality is revealed via MF-DFA.
- The multifractality is mainly attributed to long-range dependence.
- The cross-correlations between portfolio and market returns are multifractal.

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ABSTRACT

The multifractality in stock returns have been investigated extensively. However, whether the autocorrelations in portfolio returns are multifractal have not been considered in the literature. In this paper, we detect multifractal behavior of returns of portfolios constructed based on two popular trading rules, size and book-to-market (BM) ratio. Using the multifractal detrended fluctuation analysis, we find that the portfolio returns are significantly multifractal and the multifractality is mainly attributed to long-range dependence. We also investigate the multifractal cross-correlation between portfolio return and market average return using the detrended cross-correlation analysis. Our results show that the cross-correlations of small fluctuations are persistent, while those of large fluctuations are anti-persistent.

1. Introduction

The efficient market hypothesis of Fama [1] advocates that the current financial asset prices can respond quickly to the new information and therefore market investors have rare chance to get excess returns. However, more and more researchers find that capital markets do not work efficiently as EMH depicts but like a complex system. Many phenomena such as long-term reversal effect [2], momentum effect [3] and some other stylized facts that are pervasive in both developed and emerging market also reflect that investors can get excess return if they could find the law hidden in the market. These studies all bring big challenges to the EMH.

In the area of econophysics, a wide range of methods have been developed to test for EMH by examining the independence of financial asset returns. Peng et al. [4] propose the detrended fluctuation analysis (DFA) when studying the autocorrelations of molecular chains in deoxyribonucleic acid (DNA). Then Kantelhardt [5] extend DFA to the multifractal form and introduce a multifractal detrended fluctuation analysis (MF-DFA). MF-DFA is widely employed to reveal the existence of multifractality in the capital markets which again highlights the fact of market inefficiency. For example, Onali and Goddard [6] investigate the performance of Italian stock market, and the evidence shows that the market is multifractal.

* Corresponding author.
E-mail address: wangyudongnj@126.com (Y. Wang).

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Narouzzadeh and Rahmani [7] find the multifractal temporal dependence in Iranian rial–US dollar exchange rate using MF-DFA, also indicating that the exchange market is inefficient.

The interdependence or cross-correlation which suggests that a variable can predict the other variable also implies the market inefficiency. Podobnik and Stanley [8] extend the DFA to bivariate case and design a new algorithm for cross-correlation, named detrended cross-correlation analysis (DCCA). This method can be used to effectively detect cross-correlation between two non-stationary time series. Until now, DCCA has been the most popular method for cross-correlation. For example, Dutta et al. [9] employ DCCA and find the strong cross-correlations between exchange rates and stock markets in India. Sequeira Jr. et al. [10] also use the DCCA and find that the cross-correlations between the Brazilian stock and commodity markets are stronger than what would be expected from simple combinations of auto-correlations of individual series. Wang et al. [11] quantitatively investigate the cross-correlations between Chinese A-share and B-share markets using the method of DCCA, and point out that the cross-correlations are strongly multifractal in the short-term and weakly multifractal in the long-term. Dutta et al. [12] consider that the cross-correlation coefficients can be linked with the stability of the market, and the market is more stable when the two series are more heavily correlated. In addition, the DCCA method has been also used in some other related papers [13–18].

Moreover, the sources for multifractality are investigated from several aspects, such as the long-range correlation and the fat-tailed distribution. Barunik [19] compute the generalized Hurst exponents of different financial time series including the stock market indices, interests and exchange rates and finds that the major reason for formatting their multifractal characteristics lies in the fat-tailed distribution. Wang [20] shows that long-term dependence is the primary cause of the multifractal phenomenon of the NASDAQ stock market.

Although the multifractality in financial markets has been studied extensively, in this paper we revisit this topic by contributing to the literature in two aspects. First, we focus on the excess returns, rather than the nominal returns in most studies since investors are usually more concerned about the return in excess of risk-free rate. For most investors, one of the important reasons for choosing stocks instead of riskless Treasury bill is that they have chance to get higher return as the compensation of undertaking the higher risk. If the return that investors get from the stock market is even lower than the risk-free rate, then they would only buy the Treasury bill and undertake no risk. Furthermore, we investigate the multifractality in portfolio returns, instead of returns of individual stocks or market index. The motivation is from the market segmentation theory which suggests that investors always pay attention to only a fraction of stocks and portfolio diversification theory which argues that investing in a basket of assets performs better than investing in an individual asset. We detect the multifractality in returns of portfolios formed by rules of size and book-to-market ratio via a multifractal detrended fluctuation analysis (MF-DFA). We also find the source of multifractality to further understand the origins of portfolio uncertainty. Second, we investigate the long-range cross-correlations between portfolio returns and market returns using the well-known detrended cross-correlation analysis (DCCA). This has important implications for asset pricing. For example, if returns of portfolio and market index are long-range cross-correlated, the classical Capital Asset Pricing Model (CAPM) which implies short-term contemporaneous correlated behavior is not suitable to capture their relationships.

The remainder of this paper is organized as follows: Section 2 provides the methodology. Data description is provided in Section 3. Section 4 shows the empirical results. The last section concludes the paper.

2. Methodology

In this section, we will give a brief description about the multifractal detrended fluctuation analysis (MF-DFA) and its bivariate extension, i.e., multifractal detrended cross-correlation analysis (MF-DCCA). These two methods have been considered powerful tools in analyzing multifractality in autocorrelation and cross-correlation, respectively.

2.1. Multifractal detrended fluctuation analysis

Traditional detrended fluctuation analysis (DFA) can only be used to detect the mono-fractal characteristics of the time series. Kantelhardt [7] extend the DFA method to the multifractal form and propose the new method known as the multifractal DFA (MF-DFA). The MF-DFA algorithm can be described as follows:

Step 1. Consider one time series, $\{x_t,\ t = 1, \ldots, N\}$, where N is the length of the series. Then we describe the "profile" and get a new series,

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

where $\bar{x}$ denotes the average over the whole time series.

Step 2. Divide the profile $\{y_k\}_{k=1,\ldots,N}$ into $N_s \equiv int(\frac{N}{s})$ nonoverlapped 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 may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end of the profile. In this way, $2N_s$ segments are obtained altogether. Following the suggestion of Peng et al. [4], we set $10 < s < N/5$.