



Multifractal detrended cross-correlations between the CSI 300 index futures and the spot markets based on high-frequency data

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HIGHLIGHTS

- The cross-correlation between the CSI 300 index futures and spot markets is discussed.
- Asymmetric multifractal cross-correlation is studied.
- The characteristic of frequency difference of the cross-correlation is investigated.
- Transmission direction of the cross-correlation is further discussed.

ARTICLE INFO

Article history:

Received 17 May 2014

Received in revised form 14 July 2014

Available online 25 July 2014

Keywords:

Multifractal detrended cross-correlation

CSI 300

High-frequency data

Asymmetric

ABSTRACT

The cross-correlation between the China Securities Index 300 (CSI 300) index futures and the spot markets based on high-frequency data is discussed in this paper. We empirically analyze the cross-correlation by using the multifractal detrended cross-correlation analysis (MF-DCCA), and investigate further the characteristics of asymmetry, frequency difference, and transmission direction of the cross-correlation. The results indicate that the cross-correlation between the two markets is significant and multifractal. Meanwhile, weak asymmetries exist in the cross-correlation, and higher data frequency results in a lower multifractality degree of the cross-correlation. The causal relationship between the two markets is bidirectional, but the CSI 300 index futures market has greater impact on the spot market.

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1. Introduction

The China Securities Index 300 (CSI 300), which was launched on April 16, 2010, is the first stock index futures contract in China. The CSI 300 not only fills the gap in Chinese financial futures markets and enriches the financial derivatives, but also helps to avoid market risks and to participate better in the competition of international market. Because the CSI 300 index futures link directly with the CSI 300, an intimate relationship may exist between the two markets.

Although researchers focus on the relationship between the stock index futures and the spot markets, the results they obtained are different. Developed countries launch their stock index futures early, which is why their research achievements

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<http://dx.doi.org/10.1016/j.physa.2014.07.065>

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are fruitful. There are three main viewpoints of the stock index futures. The first perspective addresses that stock index futures can enhance the volatility of the spot market [1–4] because of high leverage, high liquidity, and bidirectional operation in the futures market. Second, the stock index futures are beneficial to increase market depth and market trade efficiency, which can reduce the volatility of the spot market [5–7]. Lastly, transactions have little effect on the stability of the stock market [8–10].

The late introduction of the CSI 300 index futures results in the lack of systematicness in the research on the relationship between the CSI 300 index futures and CSI 300. By using the asymmetric GARCH model, Yang et al. [11] report the strong bidirectional dependence in the intraday volatility of both markets, while the cash market still plays a more dominant role. Li [12] uses the Granger causality test, VECM, impulse response, and variance decomposition method, and finds a co-integration relationship and bidirectional Granger relationship between the two markets. Jia and Jiang [13] report no obvious price guide relationship between the two markets by using the Granger causality test as well.

The existing literatures above mainly refer to traditional measuring methods, such as the GARCH and the VAR models, which show different results and do not reveal multifractality. Fortunately, Wang and Xie [14] use the multifractal cross-correlation method to investigate the multifractal cross-correlation between the CSI 300 futures and the spot markets. However, Wang and Xie [14] investigate only the time-varying multifractality characteristic of the cross-correlation and the relationship between the cross-correlation exponent and the averaged generalized scaling exponent. Therefore, some characteristics of the cross-correlation between the CSI 300 futures and the spot markets have to be further investigated. Among the questions that need to be answered are whether the multifractality is asymmetric or not, what the transmission direction of the cross-correlation is, and whether the multifractal cross-correlation differs at different frequency data.

In 2008, Podobnik and Stanley [15] propose a new method, which is the detrended cross-correlation analysis (DCCA). The DCCA quantifies long-range cross-correlation between two non-stationary time series. Then Zebende [16] proposes the DCCA cross-correlation coefficient, which can calculate the level of cross-correlation between two non-stationary time series. To analyze the multifractal characteristics in two cross-correlated non-stationary signals, Zhou [17] uses the multifractal detrended cross-correlation analysis (MF-DCCA, or called MF-DXA), which combines the ideas of multifractal detrended fluctuation analysis (MF-DFA) and DCCA. Concerning MF-DCCA, there are also several versions including the MF-X-DFA [17] based on the DCCA [15], the MF-X-DFA [18] based on MF-DMA [19] and DMA [20], MF-HXA [21] and MF-X-PF [22]. Since then, the DCCA and MF-DCCA methods have been widely used in the analyses of cross-correlation between two financial series [23–28].

Other than the aforementioned literatures, recent research findings are abundant. Ma et al. [29], Wang et al. [30], and Wang and Xie [31] empirically analyze the cross-correlation between the Chinese stock market and adjacent stock markets, between price returns and trading volumes for the CSI 300 index futures, and between the Renminbi and four major currencies, respectively. Siokis [32], through multifractal analysis of stock exchange crashes, reports that temporal correlations play a substantial role during an extreme event. Zebende et al. [33] establish a well-defined relationship between the long-range auto-correlation exponent and the long-range cross-correlation exponent, which will be accomplished theoretically by differentiating the DCCA cross-correlation coefficient. Podobnik et al. [34] study the long-range cross-correlations for multiple time series, precisely the return time series of the NYSE members.

To our knowledge, only a few studies employ the MF-DCCA method in analyzing the cross-correlation between stock index futures and spot markets, particularly the in Chinese context.

The loss of intraday data due to low-frequency data can skew the results, but high-frequency data can remedy the flaws. Therefore, like Ref. [14], we will investigate the cross-correlation between the CSI 300 index futures and the spot markets based on high-frequency data. Because the results of using artificial data by Jiang and Zhou [18] and He and Chen [35] suggest that (MF-)DCCA and DMCA (for $\theta = 0.5$, MF-DMCA is also named the MF-X-DMA in Ref. [15]) perform better than DMCA ($\theta = 0$ and 1) when the length of time series is long enough (length is longer than 20 000), we choose the MF-DCCA as the empirical method. Moreover, Ref. [14] investigates only the time-varying multifractality characteristic of the cross-correlation and the relationship between the cross-correlation exponent and the averaged generalized scaling exponent. Therefore, our work aims to achieve three objectives. First, we use the MF-DCCA method to analyze cross-correlation between the CSI 300 index futures and the spot markets as a whole, and then investigate the asymmetry of cross-correlation when either of the two markets is going up or going down. Second, we study the changes of cross-correlation for data at different frequencies to reveal the frequency difference characteristic of cross-correlation. Third, we discuss transmission direction of the cross-correlation using time-delay DCCA and the Granger causality test, to make a complete analysis of the relationship between the CSI 300 index futures and CSI 300.

The rest of this paper is organized as follows. Section 2 presents the MF-DCCA and MF-ADCCA methods. Section 3 presents and describes the basic statistical properties of the data. In Section 4, we present the empirical analysis of the cross-correlation between the CSI 300 index futures and CSI 300, including the analysis of asymmetric characteristics, frequency difference, and transmission direction of the cross-correlation. Section 5 draws the conclusions.

2. MF-DCCA and asymmetric MF-DCCA methods

Consider two time series $\{x^{(1)}(t)\}$ and $\{x^{(2)}(t)\}$ of the same length N , where $t = 1, 2, \dots, N$, then the MF-DCCA method can be described as follows:

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