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Modified DFA and DCCA approach for quantifying the multiscale correlation structure of financial markets

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HIGHLIGHTS

- US and Chinese stock indices differ in their multiscale auto-correlation structures.
- We investigate the similarity and uniqueness among US and Chinese stock indices.
- Detailed multiscale cross-correlation structures are obtained for four representative samples.
- Vertical and horizontal comparisons are presented for different window sizes.
- New conclusions regarding multiscale correlation structures are obtained.

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ABSTRACT

We use multiscale detrended fluctuation analysis (MSDFA) and multiscale detrended cross-correlation analysis (MSDCCA) to investigate auto-correlation (AC) and cross-correlation (CC) in the US and Chinese stock markets during 1997–2012. The results show that US and Chinese stock indices differ in terms of their multiscale AC structures. Stock indices in the same region also differ with regard to their multiscale AC structures. We analyze AC and CC behaviors among indices for the same region to determine similarity among six stock indices and divide them into four groups accordingly. We choose S&P500, NQCI, HSI, and the Shanghai Composite Index as representative samples for simplicity. MSDFA and MSDCCA results and average MSDFA spectra for local scaling exponents (LSEs) for individual series are presented. We find that the MSDCCA spectrum for LSE CC between two time series generally tends to be greater than the average MSDFA LSE spectrum for individual series. We obtain detailed multiscale structures and relations for CC between the four representatives. MSDFA and MSDCCA with secant rolling windows of different sizes are then applied to reanalyze the AC and CC. Vertical and horizontal comparisons of different window sizes are made. The MSDFA and MSDCCA results for the original window size are confirmed and some new interesting characteristics and conclusions regarding multiscale correlation structures are obtained.

1. Introduction

Economics has become an active research area for physicists, and a number of studies have used statistical mechanics to investigate the nature of an economy. Econophysics [1,2] is the term used to denote the application of statistical mechanics to economic systems. Financial markets represent extremely complex systems with a large number of interacting units that conform to the underlying economic trends. A range of statistical tools have been introduced to investigate financial markets

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as a reflection of economic trends. Auto-correlation (AC) in financial time series and cross-correlation (CC) between financial variables are important features of the dynamics of financial markets [3–12] and are often investigated in the study of such markets.

Many different methods have been used to quantify AC and CC in stock time series. Peters used rescaled range analysis (R/S) to find evidence of long-range AC in several financial markets [13,14]. However, the R/S method is not appropriate for analysis of long-range AC for non-stationary series because of its dependence on extreme values in the samples used and its sensitivity to abnormal values in the series. Peng et al. used detrended fluctuation analysis (DFA) to overcome these disadvantages [15]. DFA has been widely used to detect long-range AC in diverse fields, especially in financial markets [16–19]. CC between stock indices has been investigated using various clustering methods [20–24] and random matrix theory [25–27]. In particular, the spectral properties of CC matrices for price changes have been studied for several stock markets [28–31]. However, these traditional techniques have limitations and cannot provide insight into possible changes in the scaling indices [32]. The detrended CC analysis (DCCA) method was proposed by Podobnik and Stanley for analysis of power-law CC between simultaneously recorded non-stationary time series [33]. DFA and DCCA methods have been used to investigate AC and CC in many previous studies [34–41]. For example, Podobnik et al. suggested a new test for quantifying the statistical significance of CC [39]. Horvatic et al. demonstrated that power-law CC between different simultaneously recorded time series can be accurately quantified in the presence of highly non-stationary sinusoidal and polynomial overlying trends by using DCCA with polynomials of varying order [40]. Podobnik et al. studied the effect of periodic trends on systems with power-law CC and found that periodic trends can severely affect the quantitative analysis of long-range correlations, leading to crossovers and other spurious deviations from power laws [41].

In the previous studies, the DFA and DCCA exponents were estimated as the slope of a variability function $F_{DFA}(s)$ and $F_{DCCA}(s)$, respectively, plotted versus the resolution s on a log–log scale. Although the DFA and DCCA scaling coefficients have been used in a large number of studies, full validation of this approach has not yet been performed. In particular, the ranges for identification of α_1 and α_2 cannot be defined precisely, and are usually determined by visual inspection of data. It is also unknown whether and how external factors alter the ranges for identification of the two coefficients. Moreover, describing AC and CC among financial markets using α_1 and α_2 may be an inadequate oversimplification of a more complex phenomenon, because these correlations might actually consist of a much larger number of scaling coefficients. If this is the case, then a whole spectrum of the local scaling exponent $\alpha(s)$ rather than just two coefficients would be required to describe the correlations accurately. Hence, previous studies on multiscale DFA [42–44] inspired us to propose MSDFA and MSDCCA methods to investigate AC and CC.

The proposed methods are related to multiscale behaviors of time series, which share some common features with and ideas underlying the multifractal versions of DFA and DCCA [45,46]. They all require a multitude of scaling exponents for a full description of the scaling behavior of a time series. They are techniques for determining fractal scaling properties and detecting long-range correlations in noisy, nonstationary time series. However, there are also some differences between them. The multifractal versions of DFA and DCCA describe the global multiscale correlation of time series under continuous scales and focus on the generalized scaling exponent $H(q)$ and multifractal spectrum $f(\alpha)$. By contrast, MSDFA and MSDCCA describe the local multiscale correlation of time series under discrete scales and focus on the spectrum of $\alpha(s)$. There are several MFDCCA versions, including MF-X-DFA [46] based on DCCA [33], MF-X-DMA [47] based on MF-DMA [48] and DMA [49], MF-HXA [50], and MF-X-PF [51]. In spite of successes noted in the literature, multifractal analysis has strict requirements for the data to be investigated and requires basic assumptions such as nonstationarity and an acceptable level of noise in the signal. Multifractal analysis also requires initial assumptions about the presumed time scale of the problem investigated, which may lead to artifacts in some cases. For example, if a crossover falls within the scaling range, the results will be biased. If the scaling range includes only large scales, then information about the fractal properties at small scales may be missed, and these properties might be dramatically different and very interesting. Even if the MF-DFA and MF-DCCA methods are used separately for small and large scales, we would miss analysis of properties within the crossover range, and these properties might be very different from case to case. Hence, we propose MSDFA and MSDCCA methods, which have fewer data prerequisites and initial assumptions, and thus yield a more concise analysis.

In this study, we analyze AC for single stock indices by MSDFA and CC between two different stock indices by MSDCCA for selected US and Chinese indices during 1997–2012. Using secant rolling windows of different sizes, we observe the spectral evolution for AC and CC and make vertical and horizontal comparisons for windows of different sizes.

The remainder of the paper is organized as follows. Section 2 describes the methodology and Section 3 outlines the database used. Section 4 presents the results, MSDFA and MSDCCA analyses, and vertical and horizontal comparisons for secant rolling windows of different sizes. Vertical comparison involves comparing scaling exponent spectra for several time series using the same secant window size. Horizontal comparison involves comparing scaling exponent spectra for the same time series using different secant window sizes. Finally, in Section 5 we draw conclusions and discuss future work.

2. Method

We use the MSDFA and MSDCCA methods because of the limitations and inapplicability of two-coefficient DFA [52] and DCCA methods. We apply MSDFA and MSDCCA to obtain a spectrum of $\alpha(s)$ rather than just two coefficients for more accurate description of AC and CC among stock indices.