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Multifractal cross-correlation analysis in electricity spot market

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HIGHLIGHTS

- Electricity price and trading volume series are analyzed by MF-DFA.
- The newly developed MFCCA methodology is applied.
- The cross-correlations disappear on the level of relatively small fluctuations.
- The MFCCA methodology provides more convincing results than MF-DXA.

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ABSTRACT

In this paper, we investigate the multiscale cross-correlations between electricity price and trading volume in Czech market based on a newly developed algorithm, called Multifractal Cross-Correlation Analysis (MFCCA). The new algorithm is a natural multifractal generalization of the Detrended Cross-Correlation Analysis (DCCA), and is sensitive to cross-correlation structure and free from limitations of other algorithms. By considering the original sign of the cross-covariance, it allows us to properly quantify and detect the subtle characteristics of two simultaneous recorded time series. First, the multifractality and the long range anti-persistent auto-correlations of price return and trading volume variation are confirmed using Multifractal Detrended Fluctuation Analysis (MF-DFA). Furthermore, we show that there exist long-range anti-persistent cross-correlations between price return and trading volume variation by MFCCA. And we also identify that the cross-correlations disappear on the level of relative small fluctuations. In order to obtain deeper insight into the dynamics of the electricity market, we analyze the relation between generalized Hurst exponent and the multifractal cross-correlation scaling exponent λ_q. We find that the difference between the generalized Hurst exponent and the multifractal cross-correlation scaling exponent is significantly different for smaller fluctuation, which indicates that the multifractal character of cross-correlations resembles more each other for electricity price and trading volume on the level of large fluctuations and weakens for the smaller ones.

1. Introduction

The power sector has gradually been transformed from an exclusive monopolistic state to a competitive market place after deregulation, which has exposed market players to more uncertainty. Due to the unique nonstorability (outside of hydro) of electricity, electricity price is much more likely to be driven by spot demand and supply considerations

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than any other commodities, with demand in the short-term market being fairly inelastic. As a result, sizable shocks in production or consumption may give rise to the price jumps [1]. Because of the potential instability of the electricity system, many studies concentrate on the correlations and memory characteristics of electricity price in recent years, and most literatures show that the electricity price is strongly non-stationary and the return series are long-range anti-persistent auto-correlations by using different methods, such as rescaled range analysis, detrended fluctuation analysis, periodogram methods, multiscale wavelet approach, Markov switching multifractal model and fractionally integrated autoregressive moving average model [2–7].

Nonlinear auto-correlations or cross-correlations of time series are often grounded on the study of their multifractal structure [8]. There exist many different methods which are applied to characterize the auto-correlations and cross-correlations of data in various area, such as physics [9], geophysics [10], economics [11–14], hydrology [15] and so on. The most popular method is Detrended Fluctuation Analysis (DFA) developed by Peng et al. [16], which can detect the scaling properties of long-range power-law auto-correlation of nonstationary time series. In addition, another robust and powerful technique is Multifractal Detrended Fluctuation Analysis (MF-DFA), which is proposed by Kantelhardt et al. [17]. To quantify the cross-correlations between two non-stationary time series, a new method based on detrended covariance, called Detrended Cross-Correlation Analysis (DCCA) is proposed by Podobnik and Stanley [18], which is the generalization of the fractal auto-correlation (DFA). Subsequently, the multifractal extension (MF-DXA) of the DCCA method was proposed by Zhou [19]. Other closely related methods to deal with multifractal cross-correlations have also been introduced in Refs. [20–26]. Recently, Oswiecimka et al. proposed a novel algorithm named Multifractal Cross-Correlation Analysis (MFCCA) [27], which is a consistent extension of detrended cross-correlation analysis (DCCA). Different from the methods proposed earlier, MFCCA allows to compute the arbitrary-order covariance function of two signals, and at the same time it properly takes care of the relative signs in the signals, which can avoid the limitation of taking modulus [21,28,29] of the cross-covariance function, and properly quantify and detect the subtle characteristics of two simultaneous recorded signals. By means of this new method, we can calculate the spectrum of the cross-correlation scaling exponent λ_q and estimate the scaling properties of the qth order cross-covariance function with respect to the original sign of the cross-covariance.

Therefore, we apply the MFCCA to investigate the cross-correlation properties between the electricity price and trading volume in the Czech electricity spot market. To the best of our knowledge, there are few literatures focusing on the study of the cross-correlations between the electricity price and trading volume. In fact, as a most important index, the trading volume contains much of useful information about the dynamics of price formation, which can help us to understand the behavior of electricity markets. In this paper, first the multifractality of electricity price return series and trading volume variation series are confirmed using MF-DFA. Furthermore, a multifractal cross-correlation analysis between electricity price return and trading volume variation series in Czech electricity spot market is also conducted. We qualitatively analyze the cross-correlations between the series of the electricity price return and trading volume variation employing the statistics proposed by Podobnik et al. [30]. Then, we utilize the MFCCA method to investigate the cross-correlations between the two series.

The organization of this paper is as follows. Section 2 presents the methodology used in this paper and Section 3 is the data description. Section 4 provides the empirical result. We conclude in Section 5.

2. Methodology

2.1. MF-DXA method

Multifractal Detrended Cross-Correlation Analysis (MF-DXA) method was used to quantify the cross-correlations of two different non-stationary time series, which is introduced by Zhou [19] and has been applied in many empirical systems [28,29,31]. The MF-DXA procedure consists of five steps, and the first step is the same as to the traditional DFA procedure. Consider two time series x_k and y_k, where $k = 1, 2, \ldots, N$ and N is the length of the time series.

Step 1: Determine the profile

$$Y(i) = \sum_{k=1}^{i} (x - \langle x \rangle), \qquad Y'(i) = \sum_{k=1}^{i} (y - \langle y \rangle) \tag{1}$$

where $\langle\rangle$ denotes averaging over entire time series.

Step 2: Cut the profile $Y(i)$ and $Y'(i)$ into $N_s = [N/s]$ nonoverlapping segments of equal length s. Since the record length N need not be a multiple of the considered time scale s, a short part at the end of the profile will remain in most cases. In order not to disregard this part of the record, the same procedure is repeated starting from the other end of the record. Thus, $2N_s$ segments are obtained altogether. In practice, it is reasonable to take $10 < s < N/5$.

Step 3: Calculate the local trend for each segment v by a least-square fit of the data. Then we calculate the difference between the original time series and the fits.

Step 4: Calculate the covariance of the residuals in each segment v:

$$f_{xy}^2(s, v) = \frac{1}{s} \sum_{k=1}^{s} (Y_k - \widetilde{Y}_{k,v}) \cdot (Y'_k - \widetilde{Y}'_{k,v}), \tag{2}$$