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Characterizing emerging European stock markets through complex networks: From local properties to self-similar characteristics

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ABSTRACT

We investigate the properties of the returns of the main emerging stock markets from Europe by means of complex networks. We transform the series of daily returns into complex networks, and analyze the local properties of these networks with respect to degree distributions, clustering, or average line length. We further use the clustering coefficients as quantities describing the local structure of the network, and approach them by using multifractal analysis. We find evidence of scale-free networks and multifractality of clustering coefficients.

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1. Introduction

Complex networks are a recent technique through which complex systems can be more deeply understood. The appeal of complex networks comes from the fact that they allow the study of different and complex systems in a way in which classical graph theory cannot be applied. The research so far has extended classical graph theory by developing statistical tools to study the topological properties of these complex networks at a local or global scale; see, for example, Albert and Barabasi [1], da Costa et al. [2], and Newman [3]. More recently, there has been a growing interest in approaching financial time series from the perspective of complex networks; see Refs. [4–8].

In this paper, we propose the study of several key stock market indices from Central and Eastern Europe, namely the main stock market indices from the Czech Republic, Hungary, and Poland, in the context of complex networks. These markets have been studied not only less from the perspective of standard statistical and econometrical methods, as Bubak et al. [9] have noted, but also much less from the perspective of methods from econophysics. Notable exceptions are the papers by Jagric et al. [10] and Domino [11]. We derive complex networks from the series of daily returns of the selected stock market indices, and analyze the local properties of the resulting networks, such as degree distributions or clustering. Taking the clustering coefficients as measures, we further analyze them with respect to the presence of self-similarities.

2. Methodology

The literature on how a time series can be transformed into a complex network is rapidly growing. Donner et al. [12] summarized the research done to date, pointing to the existing contributions on this topic. Among the main methods used to derive complex networks from time series we can enumerate the transition network, the cycle network, the correlation network, the visibility graph, the k-nearest-neighbor network, or recurrence networks. In this paper, we follow the approach by Xu et al. [13]; see also Refs. [14,15] for related research.

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After we derive the complex network from the time series we use, we compute the usual statistics for a complex network. Following Ref. [16], we further study the self-similar characteristics of the local features of the network. In this sense, we consider the clustering coefficient of a node as a quantity describing the local structure of the network. We analyze the series of clustering coefficients through multifractal detrended fluctuation analysis. We briefly describe below this method that we use in the paper.

There are a number of techniques to derive the multifractal spectrum of a time series, some based on wavelets, and others based on detrended fluctuation analysis (MFDFA, hereafter). MFDFA is a well-established technique due to Kantelhardt et al. [17].

In this paper, we use a modified version of MFDFA by including empirical mode decomposition, EMD hereafter. The introduction of EMD-based MFDFA can be traced back to Qian et al. [18]. The development assumes that the first two steps of the MFDFA remain the same. In the third step, instead of a polynomial detrending, specific to detrended fluctuation analysis, EMD is used to decompose the series; see Ref. [19] for a presentation of the method. The approach used in this paper is described below, following Ref. [18].

Assume that we have a time series $x(t)$ $t = 1, \ldots, N$. The first step implies the construction of the profile, which is basically a cumulative sum of the time series:

$$u(t) = \sum_{i=1}^{t} x_i, \quad t = 1, \ldots, N. \tag{1}$$

In the second step, the new series from step 1, $u(t)$, is partitioned into N_s segments of equal size s, which are disjoint, with $N_s = [N/s]$. We can denote each segment by u_v, with the property that

$$u_v(i) = u(l + i) \quad \text{for } 1 \leq i \leq s, \tag{2}$$

where l is given by the following formula: $l = (v - 1)s$.

In step 3, the MFDFA approach uses detrending based on a polynomial fitting. However, in EMD-based MFDFA, for each segment u_v obtained in the second step, an EMD-based local trend is obtained, $\tilde{u}_v(i) = r_n(i)$, from which the residuals are extracted:

$$\varepsilon_v(i) = u_v(i) - r_n(i), \quad 1 \leq i \leq s. \tag{3}$$

The other two remaining steps are unchanged. In the fourth step, the residuals from step 3 are used to determine the detrended fluctuations function $F(v, s)$ for each segment u_v, as given below:

$$[F(v, s)]^2 = \frac{1}{s} \sum_{i=1}^{s} [\varepsilon_v(i)]^2. \tag{4}$$

From this, one can compute the qth-order overall detrended fluctuation by averaging all the segments as follows:

$$F_q(s) = \left\{ \frac{1}{N_s} \sum_{v=1}^{N_s} [F(v, s)]^q \right\}^{\frac{1}{q}}, \tag{5}$$

where q can take any real value except $q = 0$. In the latter case, the formula is given by

$$F_0(s) = \exp\left\{ \frac{1}{N_s} \sum_{v=1}^{N_s} [F(v, s)] \right\}. \tag{6}$$

The last step implies the determination of the power-law relation between the detrended fluctuation function $F(s)$ and the timescale s. In order to obtain it, one varies the variable s:

$$F_q(s) \sim s^{h(q)}, \tag{7}$$

where $h(q)$ is the generalized Hurst index.

From this, for each value of q, one can determine the corresponding $\tau(q)$ function:

$$\tau(q) = qh(q) - D_f, \tag{8}$$

where D_f is the multifractal spectrum.

One should add that the DFA-based local Hurst exponent is obtained for the moment $q = 2$, and thus it is a particular case of MFDFA.

3. Results and discussion

3.1. Data used

The data consist in daily returns of main stock market indices in the Czech Republic, Hungary, and Poland. The data were used in US dollar denominated values. The data for the Czech Republic consists in daily observations for the PX index

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