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Information transfer network of global market indices

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HIGHLIGHTS

- We construct the information transfer network based on the transfer entropy.
- The transfer entropy represents the causality.
- We find that there is a small-world (SW) regime when we remove the edges.
- In the SW regime, the clustering coefficient synchronized with the volatility.
- We compare the results with the topological properties of correlation networks.

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ABSTRACT

We study the topological properties of the information transfer networks (ITN) of the global financial market indices for six different periods. ITN is a directed weighted network, in which the direction and weight are determined by the transfer entropy between market indices. By applying the threshold method, it is found that ITN undergoes a crossover from the complete graph to a small-world (SW) network. SW regime of ITN for a global crisis is found to be much more enhanced than that for ordinary periods. Furthermore, when ITN is in SW regime, the average clustering coefficient is found to be synchronized with average volatility of markets. We also compare the results with the topological properties of correlation networks.

1. Introduction

Due to the availability of large volumes of data amenable to computational analysis, financial systems have been increasingly studied in statistical physics as a part of complex systems in which human activity causes rich interesting phenomena [1,2]. From the empirical studies on financial market data, many interesting universal behaviors which govern the dynamical properties of financial systems have been found [3–5]. Most of those empirical data describe the time evolution of market properties such as price or index. In general the time evolutions of such quantities are irregular and unpredictable. Thus, extracting an essential regularity and universal behavior is not a trivial task. Especially, inferring causal relationship between different time series is very important if the underlying mechanisms are not fully understood. The analysis of complex time series plays an important role in many disciplines such as physics, neuro-science, seismology, and climate science as well as economics [6–9]. In this sense, developing theoretical methods or an efficient way to analyze such time series becomes more important to understand essential properties in various systems.

Studies on financial systems were focused on finding universal properties of financial systems such as (i) the fat-tailed distribution of return, (ii) absence of correlation in the time-series of return, and (iii) long-term correlation in volatility. Such universal properties are relatively well studied, and many stochastic models and agent based models have been

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introduced to uncover the origin of such universal behaviors [1,2]. Especially, understanding the peculiar behavior of volatility is particularly important because the volatility is closely related to the significant events in financial markets such as bubbles and crashes [10–13]. Thus, quantifying such significant economic events is very crucial not only practically but also theoretically. Moreover, the volatility is also known to be closely related to the amount of information that has arrived in the market at a given time and plays an important role in the modeling of the financial systems [1,14,15]. However, the information flow in the financial system during such significant financial events is not yet well understood because of their intrinsic complexities.

Recently, there have been several attempts to investigate the relationship between interacting components in various financial systems using graph theoretical approaches [16–21]. The graph theoretical approaches have provided simple intuitive frameworks to study the underlying properties of financial systems. Since the effect of interaction topology on the observed universal behavior in financial systems is shown to be crucial [22,23], it is important to find the structure of interactions and its topological properties. However, these studies are in general based on the assumption that the interaction between each component of the system is symmetric. For example, since the correlation matrix which is widely used in the analysis of domestic markets with random matrix theory is usually symmetric [24–26], some extensions of such analysis to the studies on global market indices assumed the symmetric interaction [16,17,20]. Thus, the network representation based on such symmetric interaction matrix is generally considered as an undirected network. The assumption of symmetry might give a correct idea to understand the various characteristics observed in financial systems only when the time scale of information flow is smaller than that of the measurement. On the other hand, if the time scale of information flow is large, then the asymmetric relationship between components should be considered due to the causality. The causality is usually measured by the time-delayed mutual information [27] and the delayed cross-correlation [28,29]. But it was shown that the mutual information does not explicitly distinguish the actually exchanged information due to a common history or input signal. In order to improve the measurement of information transfer by excluding those influences, the transfer entropy (TE) was recently introduced [30] and has been widely applied in many disciplines of sciences such as neurosciences [9]. TE is also successfully applied to analyze the information flow in various economical systems [21,31–35].

Therefore, in this paper we investigate the information transfer networks (ITN) for different periods to understand how the information transfer changes when there occur significant economic events. In addition we also study the relationship between the topological property of ITN and volatility. For this purpose, we select 10 global stock indices over the world. The time series of each index is divided into six different periods. Four of them correspond to the periods of significant financial events such as subprime mortgage crisis, and two of them are ordinary periods for comparison. ITN for each period is constructed from the measured TE. By applying the threshold method [17], we show that ITN undergoes a crossover to a small-world (SW) network from the complete graph. The obtained ITN in SW regime is not static, i.e the topology of ITN in SW regime depends on time, which shows a behavior of dynamically evolving temporal network [36–38]. Especially, we find that the SW regimes for the periods of global crisis and bear market become larger than those for ordinary periods. Furthermore, when ITN is in SW regime the behavior of clustering coefficient of ITN coincides with that of the volatility. We also compare the results with that for the correlation networks (CN) for each period.

2. Data set

In order to study how the information transfer between different countries is changed when there are significant financial events, we mainly use 10 major global market indices traded from 01/01/1991 to 31/12/2012. These indices are USA, S&P 100; Japan, Nikkei 225; Hong Kong, HSI; Singapore, STI; Australia, AORD; China, SSE; Swiss, SMI; Germany, DAX30; France, CAC40; and UK, FTSE. Though more global indices would be preferable, using more indices results in a substantial shortening of trading periods due to available data. Because of the differences in national holidays and weekends among the countries, the data are adjusted according to the following rules as suggested by Ref. [17]: when more than 30% of markets did not open on a certain day, the data of the day is removed. On the other hand, if it was fewer than 30%, we keep existing indices and insert the last closing value of index for each unopened market. From the obtained time series of index I, $Y_I(t)$, the return of market index I is defined as [1],

$$R_I(t) = \ln(Y_I(t)) - \ln(Y_I(t - \Delta t)). \tag{1}$$

Here we use $\Delta t = 1$ day.

As an example, $Y(t)$ and volatility $|R_I(t)|$ of S&P100 index are displayed in Fig. 1. The shaded intervals represent the six different periods which are labeled with a number 1–6. Four of them are the periods for significant financial events (periods 3–6 in Fig. 1). For comparison's purpose, two ordinary periods during which any remarkable financial event does not occur (periods 1 and 2 in Fig. 1) are also investigated [39]. The details of the financial events related to each period are listed in Table 1. As shown in Fig. 1(a), during the ordinary periods (periods 1 and 2), $Y(t)$ increases very slowly and the corresponding $|R(t)|$ is relatively small. In contrast to the ordinary periods, in the periods 3–6, $Y(t)$ changes more rapidly, thus $|R(t)|$ becomes large, which are the characteristics of significant financial events.

3. Definition of states

To calculate TE between indices, we first define the state, i_t, of index I at the day t. One of the simplest choices of i_t for a market index I was suggested in Ref. [35] depending on the sign of $R_I(t)$. However, for this binary state, i_t describes only