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Stock market as temporal network

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HIGHLIGHTS

- Time evolving stock markets have been analyzed by using temporal network representation.
- The temporal centrality has been used as portfolio selection tool.
- The well performed portfolios have proved the effectiveness of the temporal centrality measure.

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ABSTRACT

Financial networks have become extremely useful in characterizing the structures of complex financial systems. Meanwhile, the time evolution property of the stock markets can be described by temporal networks. We utilize the temporal network framework to characterize the time-evolving correlation-based networks of stock markets. The market instability can be detected by the evolution of the topology structure of the financial networks. We then employ the temporal centrality as a portfolio selection tool. Those portfolios, which are composed of peripheral stocks with low temporal centrality scores, have consistently better performance under different portfolio optimization frameworks, suggesting that the temporal centrality measure can be used as new portfolio optimization and risk management tool. Our results reveal the importance of the temporal attributes of the stock markets, which should be taken serious consideration in real life applications.

1. Introduction

The correlation-based network has become an effective tool to investigate the correlation of complex financial systems [1,2]. Different methods have been proposed to probe the complex correlation structures of financial systems including the threshold method, the minimum spanning tree(MST) [3], the planar maximumly filtered graph(PMFG) [4] and a strand of other methods [5–11]. The common aim of all correlation-based networks is to seek for a sparse representation of the high dimensional correlation matrix of the complex financial system. Unlike other eigenvector-based methods (e.g., the principal

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component analysis) which decompose the variance of the system into a few dimensions, the correlation-based methods directly map the dense correlation matrix into sparse representation. The easy implementations and straightforward interpretations of those methods make them quite popular in complex system analysis, especially for complex financial systems.

Recently, the correlation-based network has been used for portfolio selection in which some risk diversified portfolios are constructed based on a hybrid centrality measure of the MST and PMFG networks of the stock return time series [12]. It is well known that the financial system has its own temporal property which makes it extremely hard or even impossible to forecast. Thus if we want to construct our portfolio in a proper way, we have to consider the temporal attribute of the financial system.

In this work, we study the correlation-based networks of stock markets by using the temporal network approach. Specifically we have analyzed the temporal evolution of three major stock markets of the world, namely, the US, the UK and China. Based on a centrality measure of temporal network, we also construct some portfolios that consistently perform the best under two portfolio optimization frameworks. Our work is the first research that incorporates the temporal network method into the study of complex financial system. The temporal evolution of the topological structures can be used to access the information of market instability. The effectiveness of the temporal centrality measure in portfolio selection depicts the importance of the temporal structure for the stock market analysis. The remainder of the paper is organized as follows: Section 2 gives the data description and the methodology we use through the paper. Section 3 presents the main results of the paper including the topology analysis of the stock markets and the applications to the portfolio optimization problems. Section 4 provides our conclusion.

2. Data and methodology

2.1. Data

Our datasets include the daily returns of the constitute stocks of three major indexes in the world: S&P 500 (the US), FTSE 350 (the UK) and SSE 380 (China). After removing those stocks with very small sample size, we still have 401, 264, and 295 stocks for the three markets, respectively. In the S&P 500 dataset, each stock includes 4025 daily returns from 4 January 1999 to 31 December 2014. The FTSE 350 stocks include 3000 daily returns in the period between 10 October 2005 and 26 April 2017. The SSE 380 stocks consist of 2700 daily returns from 21 May 2004 to 19 November 2014.

2.2. Cross-correlation between stocks

We use the logarithm return defined as

$$r_i(t) = \ln p_i(t+1) - \ln p_i(t), \tag{1}$$

where $p_i(t)$ is the adjusted closure price of stock i at time t. We then calculate the cross-correlation coefficients among all the return time series at time t by using the records sampled from a moving window with length Δ. Then the similarity between stocks i and j at time t can be evaluated with the traditional Pearson correlation coefficient,

$$\rho_{ij}^{t,\Delta} = \frac{\langle R_i^t R_j^t \rangle - \langle R_i^t \rangle \langle R_j^t \rangle}{\sqrt{\left[\langle R_i^{t^2} \rangle - \langle R_i^t \rangle^2\right]\left[\langle R_j^{t^2} \rangle - \langle R_j^t \rangle^2\right]}}. \tag{2}$$

Here Δ is the moving window length, and $\langle \ldots \rangle$ represents the sample mean of stocks i and j in the logarithm return series vector $R_i^t = \{r_i(t)\}$ and $R_j^t = \{r_j(t)\}$. Thus we have a $N \times N$ matrix $\mathbf{C}^{t,\Delta}$ at time t with moving windows Δ days, and N is the number of stocks. The entries of the matrix $\mathbf{C}^{t,\Delta}$ are Pearson correlation coefficients $\rho_{ij}^{t,\Delta}$. The moving window widths are $\Delta = 500$ days for S&P 500 and $\Delta = 300$ days for both FTSE 350 and SSE 380. The moving window widths are chosen to make the correlation matrix non-singular(with $\Delta \geq N$). With moving window width Δ, we shift the moving window with 25 days step, thus we obtain a strand of correlation matrices for three markets. Finally we have 142 correlation matrices for S&P 500, 109 correlation matrices for FTSE 350 and 97 correlation matrices for SSE 380, respectively.

2.3. PMFG network of stock market

Since the dense representation given by the cross-correlation matrix will induce lots of redundant information, thus it is very hard to discriminate the important information from noise. Here we employ the planar maximally filtered graph(PMFG) method [4] to construct sparse networks based on correlation matrices $\mathbf{C}^{t,\Delta}$. The algorithm is implemented as follows,

(i) Sort all of the $\rho_{ij}^{t,\Delta}$ in descending order in an ordered list l_{sort}.

(ii) Add an edge between nodes i and j according to the order in l_{sort} if and only if the graph remains planar after the edge is added.

(iii) Repeat the second step until all elements in l_{sort} are used up.