Finance Research Letters 17 (2016) 97–102

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

# Are stock market networks non-fractal? Evidence from New York Stock Exchange

Zhi-Jian Zeng[a], Chi Xie[a,b,*], Xin-Guo Yan[a], Jue Hu[a], Zhou Mao[a]

[a] College of Business Administration, Hunan University, Changsha 410082, China
[b] Center of Finance and Investment Management, Hunan University, Changsha 410082, China

ARTICLE INFO

*Article history:*
Received 8 December 2015
Revised 4 February 2016
Accepted 8 February 2016
Available online 18 February 2016

*JEL classification:*
G01-Financial crisis
G11-Portfolio choice Investment decisions

*Keywords:*
Econophysics
Stock market
(Non)-fractal
Minimum spanning tree

ABSTRACT

In this paper, we investigate the fractal (non-fractal) property of stock market network by using the edge-covering with simulated annealing method. We choose the daily closing price of 2109 stocks traded on the NYSE during the period from 2011 to 2014 as dataset and construct the network by using minimal spanning tree (MST). The empirical results show that the degree of stocks obeys power-law distribution and the highly connected stocks connect with each other directly, i.e., the stock market network is non-fractal. Our work provides a new perspective on risk management, which can be used in other network-based financial systems.



## 1. Introduction

Recently, the econophysics offers a novel perspective on risk management (Kwapien and Drozdz, 2012). Some of the most interesting research in this field regards the financial markets as complex networks and studies the interaction of their components (Boginski et al., 2005; Mantegna, 1999; Mizuno et al., 2006; Pajevic and Plenz, 2012; Vandewalle et al., 2001; Zhao et al., 2013). In a complex financial market network, financial institutions and their interactions are represented by nodes and edges, respectively. Many attempts are made to reveal the topological property of financial market networks, including the scale-free distribution, the topological phase transition and the hierarchical structure et al. (Cimini, 2015; Harre and Bossomaier, 2009; Song et al., 2011; Vandewalle et al., 2001).

Besides the aforesaid features, the pattern of connectivity between nodes should be clarified in order to deepen the understanding of the topological structure of financial market networks. Self-similarity property on different length scales (i.e., the fractal property) is usually applied to characterize the connectivity between nodes in complex systems (Song et al., 2005; 2006). The idea of fractal is introduced by Mandelbrot, which is applied in various fields of research such as physiology, neuroscience, earth sciences, engineering, biology, and finance (Liu et al., 2014; Mandelbrot, 1967). In particular, fractal analysis is a popular method in risk management which regards the financial prices as time series (Kantelhardt et al., 2002; Lin et al., 2012; Qiu et al., 2011; Zhou, 2009). Nevertheless, whether the financial market networks are self-similar has re-

* Corresponding author at: College of Business Administration, Hunan University, Changsha 410082, China. Tel.: +86073188823890; fax: +86073188823670.

*E-mail address:* xiechi@hnu.edu.cn, xiechi@outlook.com (C. Xie).

http://dx.doi.org/10.1016/j.frl.2016.02.002
1544-6123/

ceived less attention and it is important for the stability of financial systems. Song et al. claim that the hubs (i.e., the nodes with large degree) are dispersed in fractal networks, whereas hubs in the non-fractal networks connect with each other directly (Song et al., 2005). The fractal networks are more robust to the failure of hubs than the non-fractal networks (Song et al., 2006). Yan et al. (2014; 2015) study two networks which consists of the stocks traded on Shanghai Stock Exchange and the component stocks of S&P 500 index respectively, and verify the non-fractal property of both networks. This non-fractal property indicates that the stock market networks are vulnerable to the failure of highly connected stocks. Moreover, the crisis contagions originated from hubs can easily fragment the stock market networks. However, the aforesaid research works only choose a portion of stocks from stock markets as representative for simplification, which is not enough for the aim of probing the fractal (or non-fractal) property of a whole stock market network (i.e., the network contains all available stocks in a market). Further works should be performed to clarify whether the whole stock market networks are non-fractal.

Therefore, in this work, we aim to study the fractal (or non-fractal) property of stock market networks. We construct the stock market network by using minimum spanning tree (MST) which is a powerful tool to investigate financial market networks (Yan et al., 2014; 2015). Then, we adopt the edge-covering with simulated annealing method proposed by Zhou et al. (2007) to explore the fractal (or non-fractal) property of stock market network. By the empirical analysis, we find that the stock market network is non-fractal. In this non-fractal network, the highly connected stocks connect with each other directly. Besides, we exam the degree distribution of stocks by using the toolbox proposed by Clauset et al. (2009). The degree of stocks obeys power-law distribution, which implies that a few stocks are highly connected, whereas the degrees for a large amount of stocks equal to one. In details, less than 5% stocks (i.e., 10 stocks) dominate 32% relationships of the whole market and 67.76% of nodes (i.e., 1429 stocks) have one neighbor.

## 2. Data and methodology

### *2.1. Dataset*

New York Stock Exchange (NYSE) is the world's largest stock exchange market which attracts much attention of researchers and investors.We chose the daily closing prices of stocks of NYSE from January 2011 to December 2014 as dataset, so there are 1009 daily closing price in each time-series. The data is obtained from Yahoo Finance (http://finance.yahoo.com). We fix the length of the time-window to be four years to explore the general trend of long-term mark networks' properties, and at the same time, we retain enough stocks to investigate the non-fractal property of a "complete" stock market networks (Bonanno et al., 2003; Di Matteo et al., 2010; Fiedor, 2014) We remove the stocks with incomplete data during the analyzed period and 2109 stocks are retained in this research. The daily return of stock $i$ on day $t$, $r_i(t)$, is defined as:

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

where $P_i(t)$ is the closing price of stock $i$ on day $t$.

### *2.2. Network construction*

Due to the complexity of stock market networks, there is a general need to filter the networks (Tumminello et al., 2005). For the aim of extracting the useful information, Mantegna (1999) suggests a MST method which can be constructed based on a metric distance matrix. The element of the metric distance matrix, i.e., the metric distance between each pair of stocks is defined as:

$$d_{ij} = \sqrt{2(1-\rho_{ij})}, \tag{2}$$

where $\rho_{ij}$ is the correlation coefficient. We use the Pearson's correlation coefficient (PCC) between each pair of stocks $i$ and $j$, which is given by:

$$\rho_{ij} = \frac{\langle r_i r_j\rangle - \langle r_i\rangle\langle r_j\rangle}{\sqrt{\left(\langle r_i^2\rangle - \langle r_i\rangle^2\right)\left(\langle r_j^2\rangle - \langle r_j\rangle^2\right)}}, \tag{3}$$

where $\langle ...\rangle$ is the average on the trading days of the investigated time period. $\rho_{ij}$ between stocks $i$ and $j$ varies from -1 (completely anti-correlated) to 1 (completely correlated). Due to the properties of the correlation coefficient, the values of metric distance are limited to $0 \le d_{ij} \le 2$.

MSTs can be constructed by several algorithms. We build the stock market network by using Kruskal's algorithm because the algorithm is based on distance matrix. Following the non decreasing order of the metric distance $d_{ij}$, we connect node $i$ and node $j$ if at least one node of the pair has not been connected yet. When there is no node left out, the above processes finish and we obtain a total minimal distance tree which keeps only $N-1$ links out of the original correlation matrix $N(N-1)/2$ links.