Network Structure of Financial Market of S&P500 around Financial Crises

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Abstract-The structural change of financial network of S&P 500 around financial crises from 1998-2012 with 6-months' time window is investigated. We construct a planar maximally filtered graph from correlations between companies. We calculate the average shortest path and clustering coefficient of the financial networks to observe the change of the network. We found the higher average shortest path before the crises and decreases over time until market enter calm state. However, the average clustering coefficient decreases in the beginning of the crises and increases with the intense of crises. The change of network structure can identify financial states which can be useful for portfolio investment.

Indexed Terms-Correlation network, financial network, network properties, and planar maximum filtered graph.

I. INTRODUCTION

The research on financial market based on various network methodologies has come to spotlight in the last few years, and after the financial crisis of 2008–2009 it has found more interest in the field. Different models and methods have been developed to extract the features of the network [1, 2]. For example, the topological phase transitions, the power-law property and the hierarchical structure of financial market networks are widely studied. The minimal spanning tree (MST) has been applied to financial markets such as the Dow Jones Industrial Average (DJIA) and S&P 500 [3]. The method of correlation networks has been applied to the structural transition of financial networks during a crisis in a local market [5]. The power law of the degree distribution function in the MST has been observed in the US stock market [6]. The network topology of the German stock market around the global financial crisis 2008 has gained lot of interest in recent years [7].Network structures of financial markets around the financial crisis have been observed to show substantial changes from large fluctuations in market dynamics [7-12].A topological change in the MST has been observed in the Warsaw stock exchange [7, 13].However, Tumminello *et al* have proposed that the planner maximally filtered graph (PMFG)is better option than the MST to construct network because the PMFG always contains the MST [4].The PMFG always contains more information than the MST having less strict topological constraint allowing to keep a larger number of links [4, 16, 17].Some articles also use a threshold method to filter the financial networks but it fails to give a satisfying description of the topological stability [11].Here in this article, we apply a filtering procedure - PMFG to describe the network structure of the financial network and properties of that network to observe the change of the network around the time period of financial crisis.

II. MATERIALS AND METHODS

A. Data Sets

The closing levels of stock indices are the best indicators to give information about the stock market fluctuations in a day. So, we have considered closing stock prices to analyze the US stock market. We analyzed the daily closing prices of 377 stocks from the S&P 500 from 1998 to 2012. These 377 companies survived in the market during this period. Six-months moving time window is considered to calculate the cross-correlations. In these periods, different kinds of crisis have introduced themselves to affect the market. For example, there was the Russian crisis (1998), the September 11 attacks in

2001, the downturn of stock prices from 2000 to 2002 due to the so-called dot-com bubble, the subprime mortgage crisis in 2007, the global financial crisis in 2008, and the European sovereign debt (ESD) crisis in 2011.

B. Correlation Analysis

The daily return of i^{th} stock index on day t, $R_i(t)$, is defined as

$$R_i(t) = \ln[I_i(t)] - \ln[I_i(t-1)], \quad (1)$$

Where $I_i(t)$ is the closing price of a stock index i on day t. The normalized return for the index is defined by

$$r_i(t) = (R_i(t) - \langle R_i \rangle)/\sigma_i. \quad (2)$$

Here σ_i is the standard deviation of time series of the index i and the averages $\langle \cdots \rangle$ are taken over a given time horizon T (approximately 125 days). Then, the Pearson correlation matrix C is calculated from the return time series for 377 stocks over the period T as

$$C_{ij} = \langle r_i(t) r_j(t) \rangle - \langle r_i(t) \rangle \langle r_j(t) \rangle, \quad (3)$$

Which represents the cross correlation between returns for each pair of stock i and j.

C. Planar Maximally Filtered Graph

A planar maximally filtered graph (PMFG) is a weighted planar graph. The minimal skeleton during the formation of MST excludes many links which can leads to loss of valuable information. To minimize this loss of information, Tumninello et al proposed a method by iteratively connecting the most similar nodes until the graph can be strung into a surface having genus g=k. For g=0, it is called Planar Maximum Filtered Graph [4]. The genus is a topologically invariant property of a surface defined as the largest number of non-intersecting simple closed curves that can be drawn on the surface without separating it. Roughly speaking, it is the number of holes in a surface. Simply, the PMFG is the extension of the MST that contains more information. Its sub graphs (cycles) have important relationship to original data. The PMFG has a richer information content than the MST with a larger number of edges (the PMFG has $3p - 6$edges, while the MST has$p - 1$, where p is the number of vertices) and contains of 3- and 4-cliques.

III. RESULT ANALYSIS

A. Average Cross-correlation:

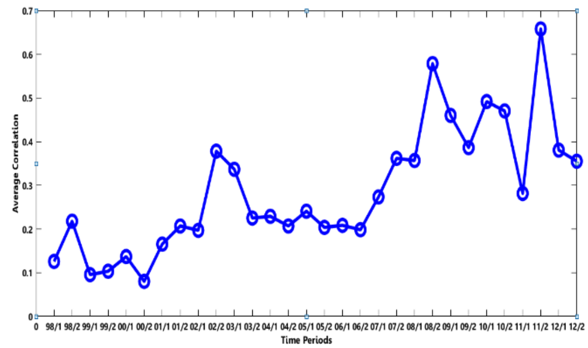


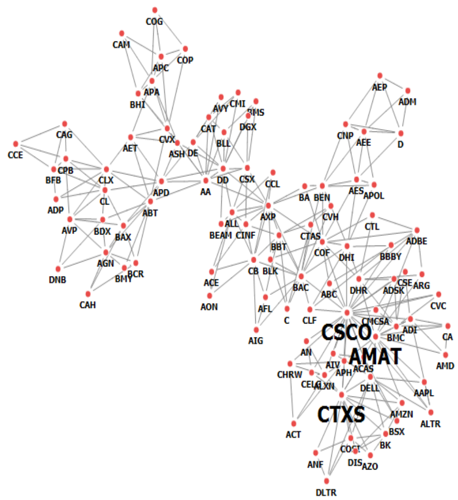
Fig.1 Average Cross-correlation (1998-2012)

In Fig. 1 we present the average cross correlation from year 1998 to 2012. In the 2^{nd} half of 1998, the average correlation is bigger than previous period due to Russian crisis. After the Russian crisis, the correlation is decreased in 1999 and almost unchanged from 2^{nd} half 1999 to 2000. The level of correlation is increased from 2001 to 2002 due to the September11 attack and dot-com bubble. After the dot-com bubble, the correlation is decreased until 2^{nd} half of 2003. No significant change in the average of the correlation was observed in 2004-2006. The level of correlation is increased in 2007-2008 due to the mortgage crisis and global financial crisis. After temporarily stabilizing in 2009, the average of correlation is raised again in 2010-2011 due to European sovereign debt crisis. In 2012, the correlation is decreased again, which implies that the market is going to recover.

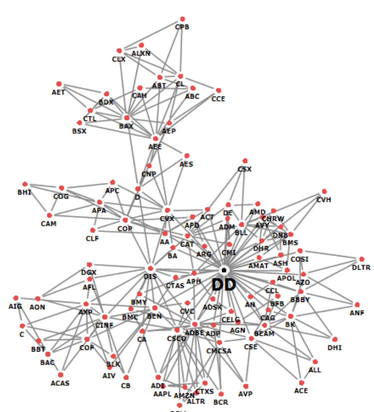
B. Network Structures

We observed the organization of the nodes in the PMFGs during the different crucial time periods of the financial market. In Fig.2 (a) we show the structure of the PMFGs for the last 6 months of year 2000 using 100 nodes. We select 100 nodes to show the structure of network explicitly. The year 2000 is assigned in the beginning of the 'dot-com' bubble.

There is no big cluster near the center of the graph. Rather there are small clusters quite away from each other throughout the network. The significant nodes which make small clusters are Citrix systems (CTXS) and Applied Materials Incorporation (AMAT). They are located in the branch of information technology. This bubble was on companies of communication sector and the hub nodes of the clusters were found on that sector.



(a)



(b)

Fig 2. The PMPG in two selected periods (a) PMFG, 2nd 6 months of 2000, (b) PMFG, 2nd half of 2008

The structure of the PMFGs for the 2nd half of 2008 are drawn in Fig 2(b) where the network structure is remarkably altered. The structures of the PMFGs in these periods are quite different from other periods. There are few dominant nodes in the network. The largest hub node is Du Pont which is included in the sector of material. The secondary hub node is Adobe system Inc (ADBE).

C. Network Properties

Here we have discussed about two network properties of PMFG- Average Shortest Path Length and Clustering Coefficient to observe the change of the network

a) Average Shortest Path Length

The average shortest path length in a network can be expressed as [18]

$$\bar{l} = \frac{1}{N(N-1)} \sum_{\substack{i,j \\ i<j}} l_{ij}\,, \tag{4}$$

Where l_{ij} is the shortest path length between nodes i and j. Fig.3 shows the average shortest path length for PMFG with evolution of time. Three prime crises are shown in three boxes respectively. The mean shortest path lengths for PMFG are higher in the beginning of 'dot-com bubble' which imply that the networks became chain-like. After that, the mean shortest path length decreased and the lowest value is found in the 1st half of 2003 which indicates that a given node can be reached from the other nodes with a very small number of steps and consequently, the networks are clustered. Although, the average shortest path length is decreased during subprime mortgage crisis, it turns up just before global financial crisis. The average shortest path length falls a bit during global financial crisis in 2nd half of 2008, it implies that the networks are not clustered as like as other crises. The mean shortest path length is seen higher value before European sovereign debt crisis and decreased over time. It implies that the companies are making clusters with the intense of crisis. After that, the mean path length of PMFG is almost unchanged.

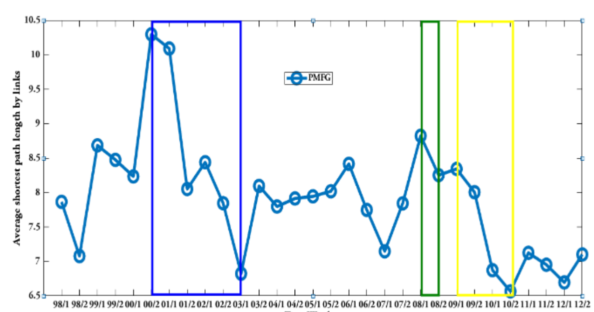


Fig 3: Average Shortest Path Length

b) Clustering Coefficient

The clustering coefficient of a node i is defined as

$$C_i = 2m_i / n_i(n_i - 1) \quad (5)$$

Where n_i denotes the number of neighbors of the vertex i and m_i represents edges between neighbors of the vertex i. The clustering coefficient C_i is equivalent to 0 if $n_i \leq 1$ the average change of clustering coefficient of nodes is observed with evolution of time for PMFG shown in fig.4. The average clustering coefficient became smaller in the beginning of the 'dot-com bubble' and gradually increased over the time. The lower values of clustering coefficient imply that there are small clusters in the network. The peak value is found in the first half of 2003 when 'dot-com bubble' became intense in the market. It implies that the network contains some big groups near to center. The average clustering coefficient became lower before the crises and increased during crises which are shown in fig.4 by solid box.

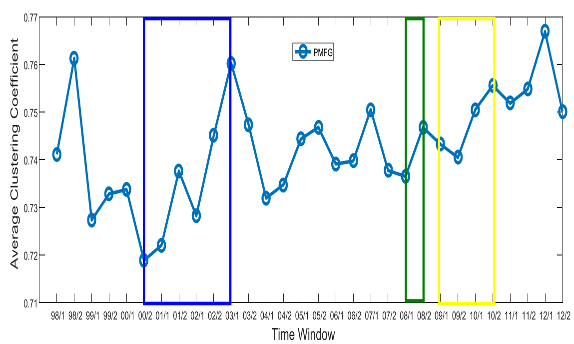


Fig 4: Average Clustering Coefficient

VI. CONCLUSION

The dynamical changes of planar maximally filtered Graph constructed from correlation matrix are observed for S&P500. In the beginning of 'dot-com bubble', the average shortest path is higher which indicate that the network is chainlike. The chainlike structure becomes star like with the intense of crisis seen by lower average shortest path. The average clustering coefficient is lower in the beginning of the crisis and increases until market enter calm state. The drastic change of PMFGs is found during Russian crisis in 1998, around 'dot-com bubble' of 2000 and after global financial crisis. The observation of the network properties can be used to identify the rapid change of the market state which can be helpful to examine the market movement.

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