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Network Approach to Capture Co-movements of Global Stock Returns

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Abstract

This research aims at developing a network-based index to investigate the change in the level and evolutionary pattern of comovement in the global stock markets. A correlation-based stock market network has been constructed for major stock markets in North America, Europe, and Asia. The behavior of key metrics of the networks such as edge density, clustering coefficient, power-law exponent, length of the Minimum Spanning Tree (MST), and the largest eigenvalues of the correlation matrices have been analyzed. We propose network-based comovement indices derived from standard metrics in the literature for regional and global stock markets to capture the level of comovements of stock returns in the market. Further we analyze these comovement indices using non-parametric statistical methods to test for any significant variation in these indices during the crisis phase compared to those during a phase of stability. The collapse of Lehman Brothers in the United States in September 2008 that triggered a global stock market crisis has been used as an example to demonstrate the potential use of the proposed indices in capturing the dynamic behavior of the stock markets. The study reveals the presence of regional influences on the network dynamics. It also unearthed the emergence of a global pattern in the dynamics of comovement indices around the onset of the crisis confirming interdependence of the global stock markets. The findings provide empirical evidences of statistically significant drift in the mean of the comovement index and presence of non-randomness in the evolutionary behavior of the comovement indexes of the stock market networks about the period of crisis. The findings of this research would be useful in identifying early warning signals of a financial crisis.

Keywords: Network, Spanning Tree, Cross-correlation, Stock Market, Financial Crisis, Efficient Market Hypothesis

1. Introduction

Understanding the behavior of stock markets is a puzzle that attracted research interests leading to development of various theories and methodologies over decades. One of the important theories for understanding the behavior of stock markets is the Efficient Market Hypothesis (EMH). According to this hypothesis, the stock markets are unbeatable as all the relevant information are incorporated and reflected in the prices of stocks leaving no room for any systematic way to make superior gains in the stock market. The EMH may be true in the ideal scenario of all the investors being rational, well informed, and homogeneous in their decision making. But, in reality the scenario may be different as they may be irrational, have incomplete or even disparate information, and may adopt heterogeneous decision rules based on their individual interpretation of the market condition. Consequently, the EMH has also been contested by several researchers. There are evidences in the literature for and against EMH. The EMH failed to explain extreme events such as huge single-day fall in stock markets that may not reflect the change in the true fundamental value of the stocks. Such phenomenon is observed because the stock markets are affected due to factors including social, technological, economic, political, and even idiosyncrasies of investors and other stakeholders. There are a large number of heterogeneous interacting elements in the stock market leading to complex interactions that influence the observable behavior of stock prices and stock market indexes. This led to another school of thought that considers the stock market as a complex adaptive system to understand its behavior (Mauboussin 2002; Yalamova 2009). Understanding the behavior of such a complex system is difficult because of the presence of non-linearity and heterogeneity in the local actions of the large number of agents and their interaction with the environment leading to the emergent global system level behavior (Cilliers 1998; Yang & Shan 2008).

Network modeling using the graph theoretic concepts has been used in the literature to capture the interactions among components of different types of complex systems and subsequently to study the behavior of the complex system using the growth and evolution of such networks (Leskovec 2008). Network approach and associated topological measures have been used in studying several real world phenomena including the social networking for locating experts and facilitating collaborations in a large community (Newman 2003; Kim *et al.* 2007; Gabaixa *et al.* 2007 ; Newman 2008; Cetorelli & Peristiani 2009). The behavior of financial markets also reflects the consequences of interaction among human agents in the market trying to maximize their own gains. These interactions give rise to complexities in the global behavior of financial market. The networking effect among stock markets offers us a better understanding of how people from different countries have access to information about events and how their reactions to those events affect the financial market. A network analysis based approach helps in revealing the internal structure of stock markets and their evolution over time. This in turn helps in identifying integrated as well as segmented stock markets for international diversification of portfolio as well as for improving the global financial system.

Representation of stock markets data using a network and the properties of the network topology of US and Chinese stock market have been studied in (Boginski *et al.* 2006), (Huang *et al.* 2009). It has been shown (Tse *et al.* 2010) that the US stock market netwok obtained from price returns has scale-free degree distribution for sufficiently large value of the threshold for the correlation coefficients and this property has been exploited to propose a degree-based index as an indicator of market performance. Other related studies on network topology of Brazilian, Korean and Indian stock market have been reported in (Tabak *et al.* 2009), (Jung *et al.* 2006),(Pan & Sinha 2007). The concept of networks has been successfully applied to study the behavior of Korean (Kim *et al.* 2007), Chinese (Huang *et al.* 2009) and Brazilian (Tabak *et al.* 2009) stock markets.

The interdependence between financial markets and behavior of stakeholders across the globe has been investigated in the literature. The role of behavioral biases of investors in determining opening prices of index futures contracts has been discussed in (Fung *et al.* 2010) by considering market maturity effect, calm-down effect, and recency effect. The relationship between stock price synchronicity and joint control of firm activities due to interlocking directorates have been studied in (Khanna & Thomas 2009). The stock market behavior of Middle East and North Africa region using variants of CAPM model have been investigated to find how these markets are integrated with the world market (Cheng *et al.* 2010). They have shown that the herding behavior of retail investors and sentiment of foreign investors caused bubbles in the stocks of construction companies in Taiwan. The recent global financial crisis originated in the US financial market but had huge impact on global stock markets and financial institutions worldwide. The linkage between complex structure of global stock markets and associated factors responsible for the observed complexity in their behavior can hardly be overemphasized.

The behavior of individual stock is normally monitored using a time series data and tracking such data becomes very difficult as the number of stocks to monitor increases. Literature suggests that the network based approach would be a viable option to study the complex interrelationship between the stock markets by presenting the information hidden in the huge volume of time-series stock market data in a manageable fashion.

Known studies found in the literature on network based models have mostly focused on the static behavior of the stock market networks with scopes limited only to regional stock markets. To the best of our knowledge, the network approach has not been used for any comparative study of the evolutionary behavior of the stock market networks of different countries let alone the detection of the onset of a global financial crisis. This paper attempts to contribute towards the development of a network based model for studying the behavior of the market around a financial crisis. The emergent system level behavior of the comovement in correlation between the daily returns of the stocks in the stock markets around the globe has been studied. To this end, a correlation based stock market network has been constructed to capture the comovement in the correlation between returns of the stocks for selected stock markets from North America, Europe, and Asia around the recent financial crisis during 2008-09. The aim was to look for the presence of patterns that can be construed as an early warning signal of a stock markets crisis in the horizon. Our objective in this paper is two-fold. First, to quantify and measure the systemic risk due to the comovement in the correlation between stock returns in the regional and the global stock markets and second, to investigate whether there is any significant anomaly in the dynamics of stock market networks of the world economy that may serve as an early warning signal for a crisis.

The rest of the paper is organized as follows. Section 2 addresses the relevance of this research against early warning systems for a financial crisis. Section 3 defines some key metrics used in our study and proposes the network representation of stock market. Section 4 describes the real life data used in this study. Section 5 describes the methodology to derive stock market networks and to study the dynamics of the networks. Section 6 presents the empirical results and their significance. Section 7 draws concluding remarks.

2. Early Warnings of Financial Crisis

Financial crises often occur due to poor economic fundamentals reinforced by the panic in the minds of investors that amplifies its severity. Collective results of trading decisions made by individual stakeholders in the stock markets, views of analysts, and media reports of market related events often influence market sentiments that get manifested in the decisions of other stakeholders. Such interpretation and speculation about market condition lead to herding behavior among the investors who prefer to go by general consensus seemingly emerging from others' decision rather than making an informed rational decision on their own (Chiang *et al.* 2010b). Due to this unpredictable complex behavior of investors, the stock markets keep experiencing several ups and downs and occasionally face severe crisis situation leading to various other cascading effects that impact economic growth. Financial crises may also arise due to anomalous behavior of various agents in the financial systems to make individual gains without bothering about the global consequences of such behavior. Major reasons of stock market crisis discussed in the literature (Johansen *et al.* 2000; Haldane 2009; Yalamova 2009; Bunda & Zorzi 2010) include the following:

1. Self-reinforcing behavior of noise traders to imitate their local neighbors' decision to buy or sell often reaches to a certain critical point, when all noise traders may place sell order simultaneously leading to a market crash.
2. Rule based trading and herd behavior among investors due to information cascade
3. The weaknesses of the regulatory financial systems in managing large inflows of foreign investments
4. Excessive credit granted to the larger firms for longer period often creating a false impression of public safety net
5. Tendency of over-lending due to large capital inflows and prevailing apprehensions about sudden stop of such funds in future
6. Accumulation of credit encourages the financing of unproductive activities or excessive consumption giving a false perception of economic boom
7. Spillover risks of fictitious regional boom to the world economy

Financial crises originating in one region often spread to other regions indicating some interconnectivity among the regions. The global impact of recent financial crisis originated in the US clearly points to higher level of interdependence in the global financial markets. Such interdependence gives rise to systemic risk that normally arises due to occurrence of some random shock in a financial system and subsequent propagation of the shock to the rest of the system through various mechanisms and transmission channels (Martinez-Jaramillo *et al.* 2010). The transmission of such shocks may be either due to interdependence between the economies or purely as a contagion. But the presence of contagion effect during financial crises has been contested in the literature as (Forbes & Rigobon 2002) have shown that high level of market comovements is normally due to interdependence and not due to the contagion effect if the correlation coefficients are corrected for the heteroskedasticity bias. Whatever may be the reason, the impact of financial crises is so disruptive and global, researchers put continuous effort to identify early warning signals from past financial crises (Bussiere & Fratzscher 2006; Davis & Karim 2008; Son *et al.* 2009; Sun & Li 2009; Roy & Sarkar 2010). Regulators try to take lessons from the past to devise effective policy guidelines to prevent any future crises (Haldane 2009; OECD 2009).

Policy makers need to understand the linkage and coupling strength between various markets of world economy to assess systemic risk and device effective policies to avoid or reduce the impact of financial crises. There is a lack of reliable measures of such systemic risk. Therefore, a reliable measure for assessing systemic risk of stock markets is one of the key concerns of policy makers and financial regulators for risk management, decision making, and to avoid any crisis. There is an immense need to find some key metric that shows significant deviation in its behavior during a crisis from its normal course and can be used for raising an alarm for any probable financial crisis. Existing approach to developing EWS based on time series data do not capture the networking effect of correlation between stocks in stock markets. Therefore, we have devised a network-based approach and proposed a proxy for systemic risk derived from the comovement in the stock returns that can be used as an early warning signal. A network model helps in capturing interdependence between the stocks in a better way and hence it is likely to give a better insight on how the information is visualized and interpreted in the investors mind. In this paper the linkage between sudden change in the network topology and financial crisis has been established providing some empirical evidence for anomaly in the dynamics of stock market networks during a financial crisis.

The empirical evidence presented in this paper strongly signifies that apart from economic fundamentals synchronization of investors' behavior around the globe is responsible for amplification of any shock in the financial network and its spread to global markets. If the level of such amplification increases beyond some threshold level it may lead to a financial crisis.

3. Network Representation of Financial Market

In order to investigate the change in the correlation patterns we have employed six metrics namely, the mean correlation coefficient, the largest eigenvalue of the correlation matrix, the edge density of the stock market correlation network, the clustering coefficient, the power-law exponent (γ), and the length of Minimum Spanning Tree (MST). These metrics have been used to capture the comovement in the returns of the stocks. We shall now explain the rationale behind the use of these metrics. The construction of the proposed stock market correlation network that makes use of these metrics is also given.

3.1 Mean Correlation Coefficient

The distribution of correlation coefficients of returns of stocks gives us an idea about how the stocks of a particular market move together. This distribution for the US market has been shown to remain stationary over different time periods (Boginski *et al.* 2006). We are interested in testing if the distribution remains stationary for the entire eight years from 2002 to 2009 or if there is any change in the distribution of correlation coefficients around the onset of a financial crisis. The mean of the correlation coefficients corresponding to different time periods would be able to capture any drift in the distribution pattern and hence would be used as a metric to study the evolutionary behavior of the stock markets.

3.2 Eigenvalue of the Correlation Matrix

A random behavior in the stock returns can be tested using the random matrix theory (RMT). It has been shown that for a return correlation matrix computed for n stocks with T time records in the limit of $T,n \to \infty$ and $Q = (T/n) \geq 1$, the noise in the estimation of correlation matrix is greatly reduced and the eigenvalue spectral density of the random correlation matrix is given by:

$$\rho(\lambda) = \frac{Q}{2\pi\lambda}\sqrt{(\lambda_{\max} - \lambda)(\lambda - \lambda_{\min})} \quad \text{......(1)}$$

where $\lambda_{\min}^{\max} = 1 + 1/Q \pm 2\sqrt{1/Q}$ .... **(2)**

The two values $\lambda_{\max}$ and $\lambda_{\min}$ give the upper and lower bounds of the eigenvalue of a random matrix respectively. Generally, the largest eigenvalue of the correlation matrix (C) for stock returns in any stock market is significantly larger than what is specified by these bounds for a random matrix. The largest eigenvalue captures the market wide economic information that affects all the stocks in that particular market. The contribution of the market to the information content of the matrix is given by (Garas & Argyrakis 2007):

Market effect $= \lambda / trace(C) = \lambda / n$ .... **(3)**

The market effect as defined in Equation 3 would be used as a metric to study the evolutionary behavior of the stock markets. We are interested in testing if the market effect captured by the largest eigenvalue matches with the other metrics computed using topological properties of the networks thus providing an evidence of similarity of information captured using the eigenvalue and the network topologies.

3.3 Stock Market Correlation Network

We propose a network representation of a stock market by representing the stocks as nodes in a graph and the interrelationship between the stocks as edges. Let G(V, E) be a graph where V is the set of nodes representing the stocks and E is a set of edges denoted by a set of pairs (Vi,Vj). A pair (Vi, Vj) $\in$ E iff ρ(Vi, Vj) $\geq\theta$, where, ρ(Vi, Vj) is the measure of similarity between nodes Vi and Vj and θ is a threshold parameter used to define a link connecting nodes Vi and Vj of the graph. We have used correlation between the daily returns of two stocks as a measure of similarity. One can have any other measures of similarity such as volatility; liquidity etc. as well in the proposed framework. Let the number of elements, i.e. cardinality of set V and set E be denoted by N and M respectively. Thus, N is the total number of stocks in the network and M is the number of edges in the network representing the number of stock pairs having correlation between their daily returns greater than or equal to the value of the threshold θ. Maximum number of edges possible in a network with N nodes is equal to N*(N-1)/2. We shall explain briefly the core concepts and the definitions of the network metrics used in this paper such as edge density, clustering coefficient and the exponent of the power-law followed by the degree distribution of the network.

Edge density: The edge density of a network is a measure of degree of connectivity in the network and is defined as the ratio of actual number of edges in the network to the maximum number of edges possible (Boginski *et al.* 2006).

Edge density = M / (N*(N-1)/2) ……………………………………………………………….. **(4)**

Clustering coefficient: The clustering coefficient of a network is defined at the node level as well as at the network level (Boginski *et al.* 2006). This represents how densely the nodes are clustered together. Let the k_i be the number of nearest neighbor of node *i* i.e. the nodes directly connected with node *i* and m_i be the actual number of edges between its nearest neighbors. k_i is also known as the degree of node *i*. Clustering coefficient of node *i* (CC_i) is defined as the ratio of the actual number of edges between its nearest neighbors to the maximum number of edges possible between the nearest neighbors and the clustering coefficient of the network (CC_N) is defined as the average of the clustering coefficients of all the nodes of the network.

$CC_i = m_i / (k_i*(k_i-1)/2)$. …………………………………………………………………… **(5)**

$$CC_N = \frac{1}{N}\left(\sum_{i=1}^{N} CC_i\right) \quad \text{……………………………………………………………………….} \quad \textbf{(6)}$$

An example network as shown in Figure 1 with nine nodes and seventeen edges is being used to explain the computation of edge density and the clustering coefficients. The edge density = 17 / ((9 x 8)/2) = 0.47. The clustering coefficients for the nodes and the entire network are shown in Table 1.

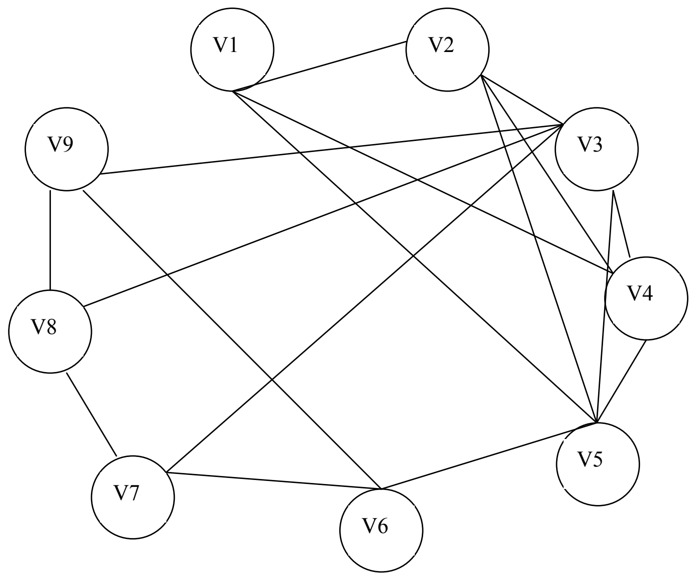

Figure 1: Network Representation of Stock Market

Table 1: Clustering coefficient of nodes and of the network

Nodes/Network	**Number of nearest neighbors (degree k_i)**	**Number of edges between the neighbors**	**Computation**	**Clustering coefficient**
Node V1	3	3	3/ (3*2/2)	1
Node V2	4	4	4 / (4*3/2)	0.67
Node V3	6	3	3 / (6*5/2)	0.33
Node V4	4	5	5 / (4*3/2)	0.83
Node V5	5	5	5 / (5*4/2)	0.5
Node V6	3	0	0/ (3*2/2)	0
Node V7	3	1	1/ (3*2/2)	0.33
Node V8	3	2	2/ (3*2/2)	0.67
Node V9	3	1	1/ (3*2/2)	0.33
Network			(1+2*0.67+3*0.33+0.83+0.5+0)/9	0.52

Power-law exponents (γ): The number of edges connected to a node in a network is known as the degree of the node. For sufficiently high value of threshold θ, the degree distribution of the stock market network has been shown to follow power law given by:

$$P(k) \propto k^{-\gamma} \text{ i.e. } \ln P(k) = -\gamma \ln k + c \quad \text{..........} \quad \textbf{(7)}$$

where *P(k)* is the probability of a node having degree equal to *k* and *ln* is the natural logarithm and *c* is a constant (Boginski *et al.* 2006). This shows that $\ln P(k)$ is linearly related to $\ln k$. Therefore, the power-law exponent γ can be estimated from the slope of the $\ln P(k) \;\; vs \;\; \ln k$ curve. The slope of the $\ln P(k) \;\; vs \;\; \ln k$ curve is negative and hence the value of the exponent γ is positive. If the value of γ is large, the number of nodes with large number of connections in a network would be fewer and vice-versa. The inverse of γ may be interpreted as a measure of propensity of a node to form connection with another node. If γ decreases, the value of its inverse γ^{-1} increases. This implies that the tendency of the network to have an increased number of nodes with denser interconnections. Therefore, we expect a significant decrease in the value of γ at the time of crisis capturing a behavior that even those stocks behaving independent of others during normal time start showing tendency to flock together at the time of crisis.

3.4 Minimum Spanning Tree (MST)

A correlation based network captures all the information about the network but it may contain significantly large number of edges that may lead to increased complexity in understanding the interrelationship between the nodes and visual representation of the network. Therefore, researchers have used Minimum Spanning Tree (MST) to reduce the full network into a simpler network that helps in getting better visual insights but definitely at a cost of loosing some essential information originally captured in the full correlation based network (Tse *et al.* 2010). An MST is a graph in which all the n nodes are connected with (n-1) edges in such a way that the sum total of the distances between the nodes is minimum. Prim's algorithm has been used to construct the MST for the stocks of all the stock indexes as well as for all the stocks taken together. The distance metric d_{ij} between stock *i* and stock *j* used for constructing the MST is computed from the correlation ρ_{ij} between stock *i* and stock *j* using the transformation as follows:

$$d_{ij} = \sqrt{2(1-\rho_{ij})}, \qquad 0 \le d_{ij} \le 2, \quad \text{..........} \quad \textbf{(8)}$$

A higher value of ρ_{ij} implies a lower value of d_{ij} and vice versa (Garas & Argyrakis 2007). The length *L* of an MST is given by the sum of all the distances l_{ij} between the nodes *i* and *j* connected by an edge in the MST.

$$L = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} l_{ij} \quad \text{..........} \quad \textbf{(9)}$$

Where $l_{ij} = d_{ij}$ if the nodes i and j are connected directly in the MST, and $l_{ij} = 0$ otherwise. Therefore, the inverse of the MST length (L^{-1}) is a proxy for the level of integration as implied by the correlation between the stock indices. The inverse of MST length i.e. L^{-1} would be used as a metric to study the evolutionary behavior of the stock markets. We shall now explain about the data used in our study.

4. Data Description

The daily closing prices for the stocks that are components of major stock indexes of ten countries US, Canada, UK, Germany, France, India, Japan, Thailand, Taiwan, and China for eight years from January 2002 to December 2009 have been used for reporting the findings of this research. We have chosen this period to study the behavior of the stock market networks before and after the collapse of Lehman Brothers in America that triggered stock market crisis around the world. Indexes having large number of member stocks were chosen so that we can have larger sample of stocks to study the network behavior. Both the Shanghai and the Shenzhen stock markets of China have been included in the study to compare their evolutionary behavior. Indices S&P500 and NASDAQ Bank from US have been included to compare their evolutionary behavior and the existence of any similarity. The data were downloaded from the Bloomberg terminal on 16th Feb 2010. As a pre-processing step due to missing data, only those stocks were selected that were traded over the entire period of eight years and had very few missing data points. If some data points are missing the price is assumed to remain the same as of the previous trading day. Few data points for some particular day have been removed from some stock indexes if the data for corresponding day was missing in other stock indexes to properly align the data sets of all the markets. Finally, for all the stocks from the ten countries there are 2087 data points for the entire period of eight years. The number of stocks from each stock index along with corresponding country considered in this study is shown in Table 2.

Table 2: Number of stocks for each country

S. No.	Country	Stock Index	Number of stocks
1	India	NSE CNX 500	315
2	China	Shenzhen Composite	441
3	China	Shanghai Composite	486
4	Japan	Nikkie225	195
5	Canada	SP/TSX Composite	147
6	US	S&P 500	425
7	US	NASDAQ bank	243
8	France	SBF250	187
9	Germany	HDAX	67
10	UK	FTSE350	250
11	Thai	Thai Stock exchange	252
12	Taiwan	Taiex	435

5. Methodology

To compare the behavior of the stocks across the market we need to define a similarity metric between two stocks considering various parameters such as return, liquidity, volatility etc. of stocks. One of the measures of similarity to compare the two stocks widely reported in literature is the correlation between the daily returns of the two stocks as shown below. The logarithmic return $R_i(t)$ of the instrument *i* over the one-day period from $(t-1)$ to *t* is given by

$$R_i(t) = \ln\left(\frac{P_i(t)}{P_i(t-1)}\right) \qquad \textbf{(10)}$$

Where $P_i(t)$ denote the price of the instrument *i* on day *t* and the correlation coefficient between instruments *i* and *j* is given by the standard formula (Boginski *et al.* 2006).

$$C_{ij} = \frac{\langle R_i R_j \rangle - \langle R_i \rangle \langle R_j \rangle}{\sqrt{\left\langle R_i^2 - \langle R_i \rangle^2 \right\rangle \left\langle R_j^2 - \langle R_j \rangle^2 \right\rangle}} \qquad \textbf{(11)}$$

where $\langle R_i \rangle$ represents the average return of the instrument *i* over a specified time period T consisting of say, N days i.e. $\langle R_i \rangle = \frac{1}{N}\sum_{t=1}^{N} R_i(t)$.

Therefore, C_{ij} is dependent on the specified time period T. An edge connecting stocks *i* and *j* is added to the graph if C_{ij} is greater or equal to a specified threshold (θ). The connection between two stocks implies that the prices of these stocks fluctuate similarly over specified time period and the degree of similarity is defined by the chosen value of *threshold*. A correlation based stock market network model has been derived and various key metrics as discussed in section 3 have been computed. We have used six metrics namely the mean correlation coefficients, the largest eigenvalue of the correlation matrix, the edge density of the stock market correlation network, the clustering coefficient and the power-law exponent (γ), and the length of Minimum Spanning Tree (MST) to capture the comovement in the returns of the stocks. Subsequently, the dynamics of the network structure has been studied using various overlapping but shifted time series to investigate the anomaly in the evolution of topological properties of such networks. MATLAB and Microsoft Excel tools were used for the analysis of data and presentation of the results. Since we have a maximum of n = 486 stocks (Shanghai Composite index) from any stock index, we have taken T = 500 trading day data for computation of the correlation matrix to reduce the noise in the correlation matrix as per the condition of $Q = (T/n) \geq 1$ as discussed in section 3.2. In order to study the dynamics of the network structure, the data set was partitioned into 80 periods of length 500 days each with each consecutive period obtained by sliding the sampling window by 20 data points (trading days). For this, 2080 data points (500+20*79) were used out of 2087 data points. The start and end date for some selected periods in (MM/DD/YYYY) format is shown in Table 3.

The correlation matrices and the distribution of correlation coefficients for all the stock markets for all the 80 periods as mentioned above have been computed. In order to examine whether the largest eigenvalue of the correlation matrix for all the stock markets considered in our study are significantly larger than what is specified by the bounds given by Equation 2 for a random matrix, the $\lambda_{\max}$ and $\lambda_{\min}$ have been computed for random correlation matrices of the size n equal to the number of stocks corresponding to various stock indexes as shown in Table 4. The corresponding largest eigenvalues (lowest among the eighty values for the eighty periods) of the correlation matrix of stock markets are also given in Table 4. We clearly observe that the largest eigenvalue of the correlation matrix for all the stocks markets are significantly larger than what is specified by these bounds for a random matrix.

Table 3: Periods with associated start and end date

Period No	For 500-day period			Period No	For 500-day period	
	Start date	End date			**Start date**	**End date**
1	1/2/2002	12/2/2003		66	12/27/2006	11/25/2008
10	9/11/2002	8/10/2004		67	1/24/2007	12/23/2008
20	6/18/2003	5/17/2005		68	2/21/2007	1/20/2009
30	3/24/2004	2/21/2006		69	3/21/2007	2/17/2009
40	12/29/2004	11/28/2006		70	4/18/2007	3/17/2009
50	10/5/2005	9/4/2007		75	9/5/2007	8/4/2009
60	7/12/2006	6/10/2008		76	10/3/2007	9/1/2009
61	8/9/2006	7/8/2008		77	10/31/2007	9/29/2009
62	9/6/2006	8/5/2008		78	11/28/2007	10/27/2009
63	10/4/2006	9/2/2008		79	12/26/2007	11/24/2009
64	11/1/2006	9/30/2008		80	1/23/2008	12/22/2009
65	11/29/2006	10/28/2008				

Using the correlation matrices, the stock market correlation networks were constructed and various metrics such as mean correlation coefficient, edge density, clustering coefficient, inverse of the power law exponent (γ), market effect on the stocks captured by the largest eigenvalue of the correlation matrix, and the inverse of the MST length have been computed. The evolutionary behavior of the metrics has been studied to investigate the presence of any peculiarity around the transition from tranquil period to crisis period to get more insight into the evolution of the network structure during the crisis. The observations on their behavior would be explained in Section 6. To bring all the metrics on equal footing for comparison, all the six metrics were normalized using their mean and standard deviations. A sufficiently large historical data was needed to estimate the mean and the standard deviation for this purpose and the same were assumed to be equal to the mean and the standard deviation of the eighty values of the metrics corresponding to the 80 periods of observation as shown in Table 5 and Table 6 respectively in Section 6. These values of the mean μ_{metric} and the standard deviation σ_{metric} of the metrics were used to normalize the metrics using the formula for normalization as:

The normalized value of a metric $Z_{\mathbf{metric}}$ = (Actual value of the metric- μ_{metric})/ σ_{metric} ………..**(12)**

We define a stock market comovement index (SMCI) as the average value of these six normalized metrics for a particular stock market.

i.e. $\text{SMCI} = \frac{1}{6}\sum_{i=1}^{6} Z_{metric_i}$ …………………………………………………………………… **(13)**

We also define a global stock market comovement index (GSMCI) as a weighted average of the stock market comovement indexes for all the (n= 12) stock market indexes.

i.e. $\text{GSMCI} = \sum_{i=1}^{n} SMCI_i * w_i$ ……………………………………………………………..…… **(14)**

Table 4: Bounds on the eigenvalue of random matrices and the largest eigenvalue of the correlation matrices

Stock Index	n	Q= T/n (T = 500 for all)	$\lambda_{\max}$ for Random Matrix	$\lambda_{\min}$ for Random Matrix	$\lambda_{\max}$ for Correlation Matrix
India_NSE CNX 500	315	1.5873	3.2175	0.1958	55.5239
China_Shenzhen_Comp	441	1.1338	3.7603	0.2346	126.5139
Japan_Nikkie225	195	2.5641	2.6390	0.1478	64.8800
Canada_SP/TSX Comp	147	3.4014	2.3784	0.1236	14.0665
US_S&P 500	425	1.1765	3.6939	0.2301	95.6911
UK_FTSE350	250	2.0000	2.9142	0.1716	43.1849
France_SBF250	187	2.6738	2.5971	0.1440	20.6257
Germany_HDAX	67	7.4627	1.8661	0.0718	15.0467
China_Shanghai_Comp	486	1.0288	3.9438	0.2465	143.3502
Thai Stock exchange	252	1.9841	2.9239	0.1724	24.9059
Taiwan_Taiex	435	1.1494	3.7355	0.2329	83.6410
US_NASDAQ bank	243	2.0576	2.8803	0.1687	37.3098

The weights w_i used for this computation were taken as the ratio of the number of stocks in a particular market to the total number of all the stocks taken together i.e. 3443. If a significant number of stock market comovement indexes show an increase in their value at some period of time, then this would be reflected in the global stock market comovement index and may be treated as a signal for greater synchronicity in the market. This can also serve as one of the measures of systemic risk in the global stock market. Since the distribution of the comovement indexes are not known a priori and also we don't have sufficiently large data set to estimate their distribution, we resort to non-parametric methods to study their behavior around the onset of the financial crisis using the comovement indexes for all the markets for 80 periods. Wilcoxon Rank Sum Test was conducted for all the twelve stock markets to test whether there is significant increase in the mean of the comovement index value before and after the Lehman Brother's collapse. The two-tail run test was performed to test for non-randomness in the evolutionary behavior of the stock market comovement indexes at the onset of a financial crisis. We have also proposed an approach adapted from control chart type analysis for capturing an early warning signal from the dynamics of the global stock market comovement index. The evolutionary behavior of the normalized metrics and the comovement indexes and other results would be discussed in Section 6.

6. Empirical Results and Discussion

In this section we shall discuss the empirical results obtained in this study.

6.1. Evolution of Mean Correlation Coefficient

The distribution of correlation coefficient has been computed for all the stock markets and for all the 80 periods as discussed in section 5. We observed that the distribution of correlation coefficient of stocks do not remain stationary for the entire period of eight years but shifts towards right significantly for some periods. The distribution of US S&P 500 stocks for some selected periods has been shown in Figure 2. This shift has been observed for the periods corresponding to post Lehman Brothers collapse. This captures the phenomenon of increase in the correlation between the stock returns during a financial crisis. The overall shape of the distribution remains similar to normal distribution curve but it has fat tail i.e. significantly large proportion of correlations lie on the tails. We expect the distribution of correlation coefficients in the post crisis phase to be significantly different compared to its long run values. To make a comparison, the descriptive statistics of correlation coefficients have been computed for all the ten countries using all the 2087 data points of the full eight year data set as given in Table 5. Figure 3 shows the evolution of the mean correlation coefficient all the stock markets. A drift in the mean correlation coefficient for almost all the countries has been observed at period number 64 compared to the long-run mean given in Table 5. The period number 64 represents a 500 day period corresponding to 11/1/2006 to 9/30/2008 as given in Table 3. New data set in this period compared to the previous period (i.e. Period Number 63) corresponds to 9/3/2008 to 9/30/2008. Therefore this drift in mean correlation can be attributed to some event occurring during 9/3/2008 to 9/30/2008. This clearly captures the occurrence of some critical event during 9/3/2008 to 9/30/2008 that affected the global stock market. This coincides with the period corresponding to the event of Lehman Brothers filing for bankruptcy in the US on September 15, 2008.

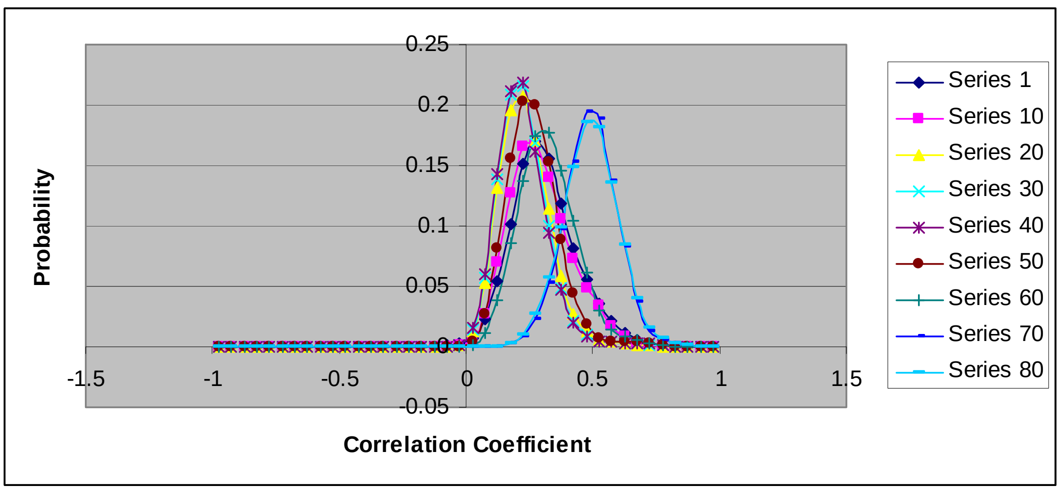

Figure 2: Distribution of correlation coefficient for the US Stock Market

Table 5: Descriptive statistics of correlation coefficients for eight year data set

Stock Index	Mean	Std. Dev	Skewness	Kurtosis	Max	Min	First Quartile	Median	Third Quartile
NSE CNX 500	0.2633	0.0699	0.5022	3.9357	0.7610	0.0404	0.2152	0.2595	0.3059
Shenzhen_Comp	0.4091	0.0937	-0.6281	3.5699	0.8108	0.0033	0.3544	0.4216	0.4746
Nikkie225	0.4195	0.1009	-0.3080	3.0672	0.8841	0.0870	0.3554	0.4310	0.4914
SP/TSX Comp	0.1908	0.1127	1.3754	6.1120	0.8628	-0.0376	0.1131	0.1673	0.2475
S&P 500	0.3663	0.1022	0.7068	4.0277	0.9021	0.0026	0.2948	0.3546	0.4259
FTSE350	0.2693	0.1160	0.7890	4.0245	0.8554	-0.0103	0.1849	0.2559	0.3389
SBF250	0.1678	0.1193	1.1350	4.0288	0.7667	-0.0839	0.0782	0.1366	0.2278
HDAX	0.3025	0.1125	0.9448	4.0164	0.7833	0.0525	0.2208	0.2817	0.3600
Shanghai_Comp	0.4177	0.0883	-0.4285	3.6758	0.8309	-0.0247	0.3631	0.4274	0.4786
Thai Stock exchange	0.0868	0.0951	1.5818	6.2135	0.8006	-0.2086	0.0203	0.0579	0.1293
Taiex	0.2978	0.0946	0.2769	3.4386	0.8202	-0.0244	0.2367	0.2908	0.3572
US_NASDAQ bank	0.1496	0.1971	1.3027	3.3386	0.7909	-0.1525	0.0196	0.0626	0.1863

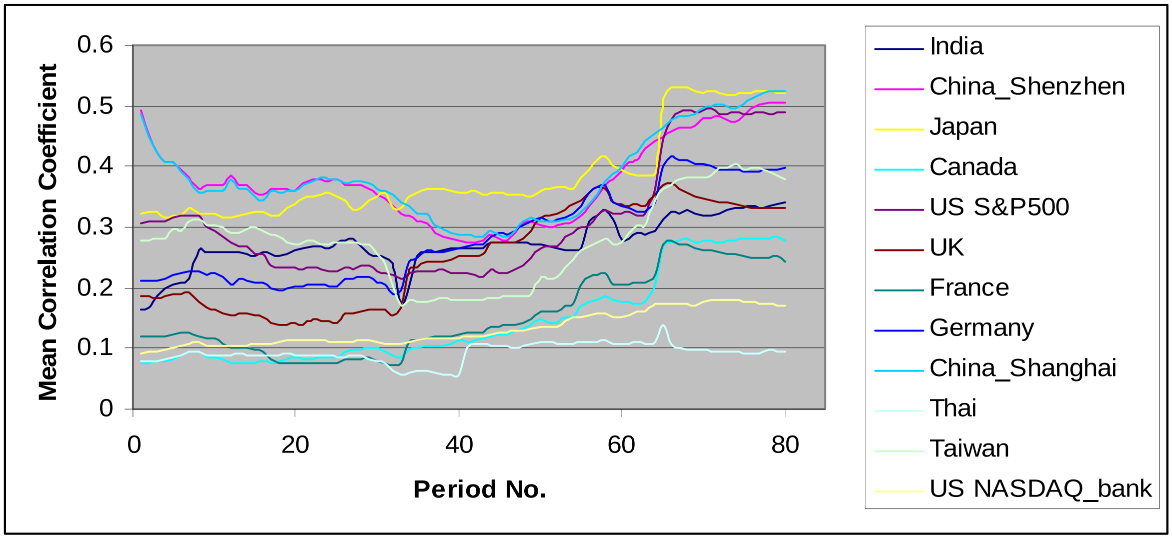

Figure 3: Drift in Mean Correlation Coefficient at the onset of financial crisis

6.2. Evolution of Metrics

As explained earlier the edge density is a measure of how densely the nodes of a network are connected i.e. a higher edge density means relatively more number of stocks are showing comovements in the correlations in the market. This metric can be used to detect the turbulence in the stock market network because if due to any shock in the stock market that may trigger a financial crisis, the stocks start showing comovements, it can be easily captured by a sudden drift in the edge density of the network. Edge density of a network is dependent on the value of the threshold (θ) chosen for the correlation coefficient in constructing the network. The variation of edge density of the stock market networks of the ten countries for various values of θ has been studied and it was observed that the edge density decreases with an increase in the value of threshold θ and tends to saturate as θ increases beyond 0.5. Further, we investigated the evolutionary behavior of edge density for different values of threshold θ and observed a drift in edge density corresponding to period number 64 for all the three values of θ equal to 0.3, 0.4, and 0.6. This signifies that the drift in the edge density is observed for a reasonably broad range of threshold values and for most of the stock markets at the onset of the financial crisis. Therefore, we have selected the value of the threshold θ as 0.6 for our study. The edge density for most of the markets shows very small variation except during August 2008 to October 2008 and subsequently remain high till recent time. This drift in the edge density can be used to detect increased level of comovement in the stock markets at the time of a crisis.

A drift is observed in the clustering coefficient of the networks as well corresponding to the period number 64 signifying increase in the comovement of stocks locally. The ratio of the largest eigenvalue to the trace of the matrix gives a measure of market effect on the stock markets returns. This captures the proportion of variation that can be attributed to the market effect. A drift is observed in the value of the market effect as well corresponding to the period number 64 signifying an increase in the market effect at the time of crisis. Similar drift is observed in the inverse of the power-law exponent γ i.e. $(\gamma)^{-1}$ as well corresponding to the period number 64 signifying that the more nodes of the network tend to have denser connections. This shows that during the financial crisis even those stocks behaving independent of others starts showing tendency to flock together. As discussed earlier, the distance between nodes of an MST is a monotonically decreasing function of the correlation between the nodes. At the onset of crisis, the correlation between the stocks tends to increase, and hence the distance between the nodes in the MST tends to decrease. Therefore, the overall length of the MST tends to shrink. A drift is observed in the value of inverse of the MST length as well corresponding to the period number 64 capturing the shrinking of the MST length at the time of crisis. The mean and the standard deviation of all the six metrics computed from the eighty values of the metrics corresponding to the 80 periods of observation are shown in Table 6 and Table 7 respectively to normalize all the six metrics using equation 12. Table 6 clearly reveals that the value of the clustering coefficient is relatively more compared to corresponding edge density for all the markets. This shows that local clustering of edges and hence the comovement of stocks connected with each other is more prominent than the overall comovement of all the stocks. This may be due to the fact that stocks from same economic sector are more likely to move together than that from other sectors.

Table 6: Mean of important metrics

Stock Index	Mean Correlation Coefficient	Edge Density	Clustering Coefficient	Inverse Power-law Exponent	Market Effect using Eigenvalue	Inverse MST Length
India_NSE CNX 500	0.2722	0.0022	0.0685	0.4845	0.2858	0.0031
China_Shenzhen_Comp	0.3765	0.0560	0.2949	1.5534	0.3940	0.0026
Japan_Nikkie225	0.3845	0.0677	0.3243	1.6357	0.3990	0.0060
Canada_SP/TSX Comp	0.1454	0.0083	0.1399	0.6945	0.1714	0.0065
US_S&P 500	0.3080	0.0373	0.3362	1.3897	0.3212	0.0027
UK_FTSE350	0.2509	0.0168	0.2089	1.0816	0.2816	0.0041
France_SBF250	0.1535	0.0056	0.0812	0.6856	0.1964	0.0049
Germany_HDAX	0.2839	0.0242	0.1494	0.7858	0.3170	0.0151
China_Shanghai_Comp	0.3834	0.0585	0.3260	1.7626	0.3988	0.0024
Thai Stock exchange	0.0924	0.0017	0.0522	0.5840	0.1434	0.0035
Taiwan_Taiex	0.2783	0.0082	0.2096	0.7174	0.2951	0.0024
US_NASDAQ bank	0.1319	0.0400	0.2038	2.3796	0.2308	0.0038

Table 7: Standard Deviation of important metrics

Stock Index	Mean Correlation Coefficient	Edge Density	Clustering Coefficient	Inverse Power-law Exponent	Market Effect using Eigenvalue	Inverse MST Length
India_NSE CNX 500	0.0405	0.0023	0.0471	0.2067	0.0407	0.0001
China_Shenzhen_Comp	0.0687	0.0793	0.2157	1.4060	0.0704	0.0002
Japan_Nikkie225	0.0731	0.1069	0.1952	1.7050	0.0716	0.0006
Canada_SP/TSX Comp	0.0741	0.0094	0.0933	0.3650	0.0741	0.0006
US_S&P 500	0.0966	0.0515	0.1561	0.5965	0.0952	0.0003
UK_FTSE350	0.0829	0.0114	0.0897	0.2781	0.0767	0.0003
France_SBF250	0.0669	0.0065	0.0587	0.3063	0.0623	0.0003
Germany_HDAX	0.0750	0.0250	0.1175	0.4333	0.0664	0.0011
China_Shanghai_Comp	0.0719	0.0826	0.2023	1.5161	0.0723	0.0002
Thai Stock exchange	0.0158	0.0011	0.0172	0.2316	0.0211	0.0001
Taiwan_Taiex	0.0699	0.0092	0.1037	0.2009	0.0685	0.0001
US_NASDAQ bank	0.0280	0.0399	0.1267	2.1762	0.0461	0.0002

6.3. Global Stock Market Comovement Index

All the six normalized metrics show similar behavior as shown in Figure 4. It provides empirical evidence on the existence of shared information content about the market wide information in these metrics derived from the network structure and the correlation matrix. We, therefore, consolidate these metrics into a single stock market comovement index (already defined in section 5). The stock market comovement indexes for all the twelve markets have been computed as the average value of these six metrics and the values are shown in Figure 5. The dynamics of emerging market networks show relatively more fluctuations (noisy patterns) compared to that of developed countries. The Thai Stock market crashed on Dec. 19 2006 after the central bank introduced stringent capital control measures. The comovement index of Thai markets captures this event very well. Subsequently, the global stock market comovement index was computed as a weighted average of all these twelve normalized metrics as shown in Figure 6. The weight used for this computation was computed as the ratio of the number of stocks in an individual market to the total number of all the stocks taken together i.e. 3443. Figure 6 clearly shows an increase in the value of the global stock market comovement index at period number 64; this may be treated as a signal for increased level of synchronicity in the global stock markets. This can also serve as one of the measures of systemic risk in the global stock market.

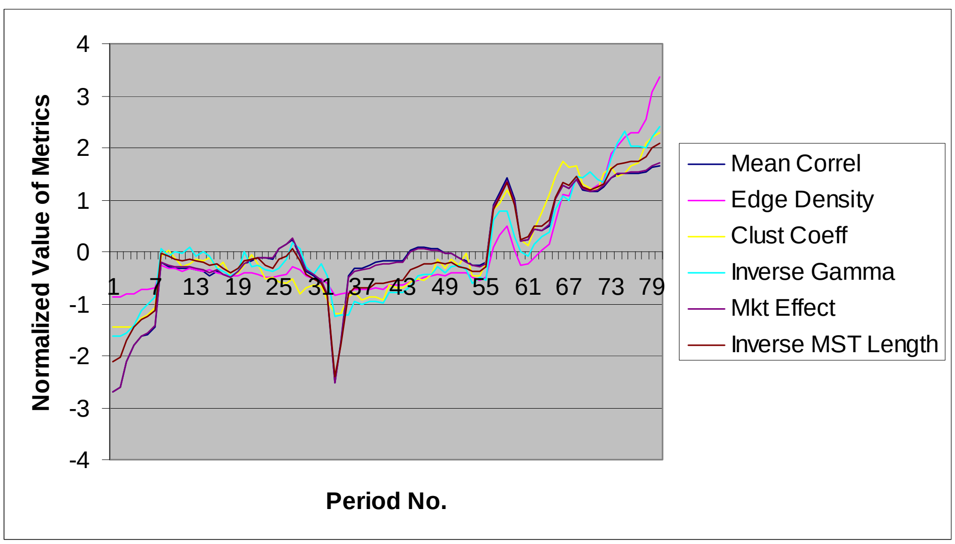

Figure 4: Behavior of the six normalized metrics for Indian stock market

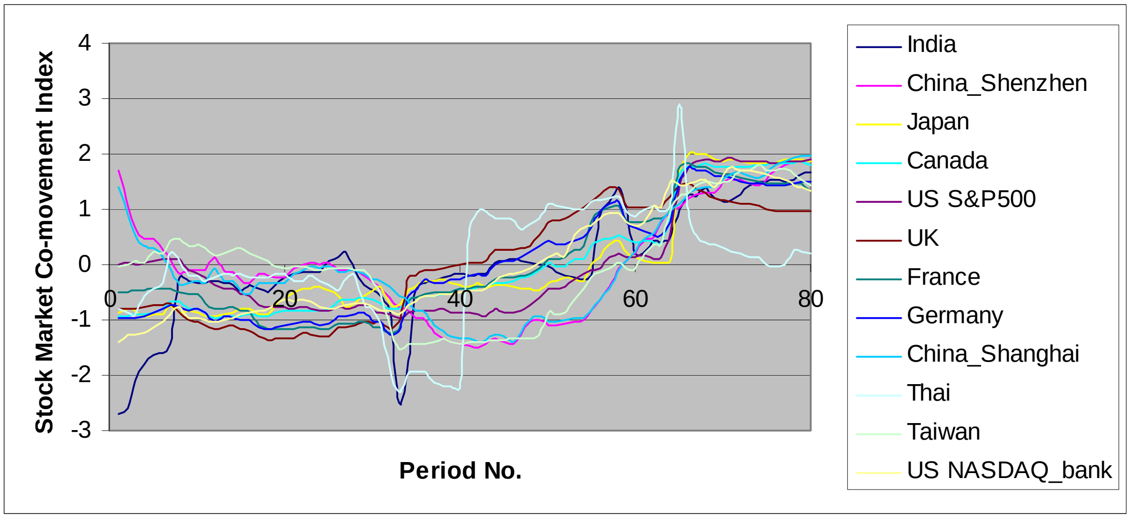

Figure 5: Stock market comovement index for all the twelve markets

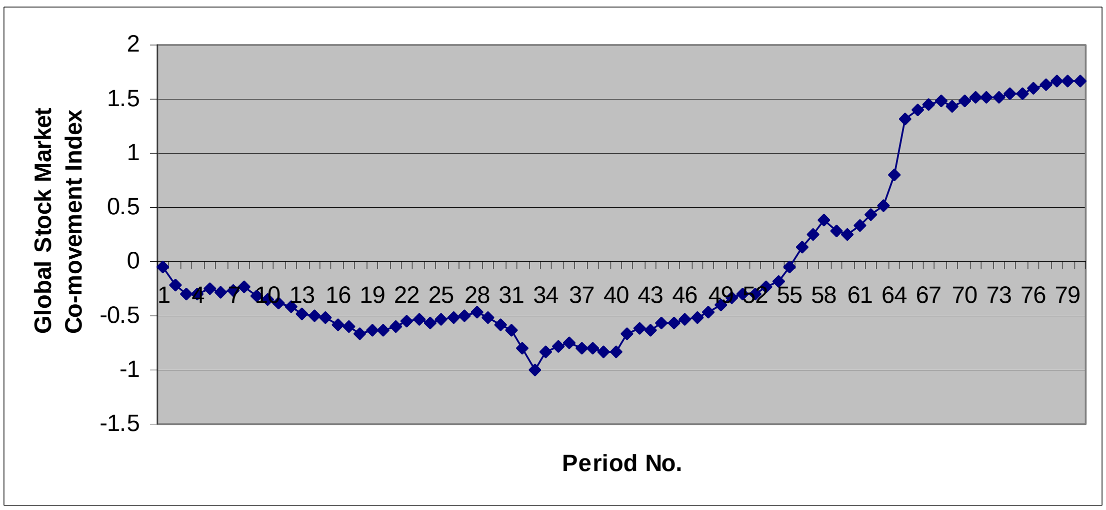

Figure 6: Global stock market comovement index

6.4. Wilcoxon Rank Sum Test

Wilcoxon Rank Sum Test was conducted for all the twelve stock markets to test whether there is significant increase in the mean of the comovement index value before and after the Lehman Brother's collapse and we found a significant drift in the mean for 10 out of 12 markets analyzed. The null hypothesis that the mean comovement index has not increased significantly after the event has been rejected at a very high level of significance. Sample size of both population 1 (before the event) and population 2 (after the event) is 16 each. The result of the test along with the p-value is shown in Table 8. UK and Thai market do not show any significant change in the mean. This may be either because these markets were unaffected by the event or had a very high level of comovements even prior to the Lehman Brother's event.

Null Hypothesis: Ho: $\mu 1 \geq \mu 2$
Alternate Hypothesis: H_1: $\mu 1 < \mu 2$

Level of Significance: 0.001

Table 8: Wilcoxon Rank Sum Test for increase in the mean of the comovement index

Stock markets	Lower Critical Value	Z Test Statistic	*p*-Value	Conclusion
India	-1.64485	-4.63574	1.78E-06	Reject
Schenzhen	-1.64485	-4.78649	8.49E-07	Reject
Japan	-1.64485	-4.56036	2.55E-06	Reject
Canada	-1.64485	-4.78649	8.49E-07	Reject
US	-1.64485	-4.7488	1.02E-06	Reject
UK	-1.64485	-0.41458	0.339225	Do not reject
France	-1.64485	-4.33423	7.31E-06	Reject
Germany	-1.64485	-4.56036	2.55E-06	Reject
Shanghai	-1.64485	-4.78649	8.49E-07	Reject
Thai	-1.64485	3.015113	0.998716	Do not reject
Taiwan	-1.64485	-4.78649	8.49E-07	Reject
NASDAQ_bank	-1.64485	-4.52267	3.05E-06	Reject
Average	-1.64485	-4.78649	8.49E-07	Reject

6.5. Run test

The comovement indexes for all the markets for 80 periods have been used to perform non-parametric two-tail run test to investigate for non-randomness in their behavior. We observed that the non-randomness in the evolutionary pattern of market networks increases after the crisis using the run test at a level of significance (Alpha) = 0.05 for number of runs n = 10, 12, 14, and 16. The following standard procedure has been followed for the run test for all the twelve stock markets.

Null Hypothesis H_0: The sequence of size n is random
Alternate Hypothesis H_1: The sequence of size n is not random

1. For a run of size n, we coded the data to A and B according to the following rule:
If (index > the median of the n index data points), code as "B", else code as "A".
2. n1 = count the number of A in the range n of run of A & B, n2 = n-n1, n1 = min(n1,n2).
3. Look into the run test table for finding critical number of runs corresponding to n1 and n2.
4. Reject Ho if the number of runs is not within the lower and upper critical value of runs and mark the result for that particular market as "Non-random".
5. Count the number of "Non-random" result in the group of 12 stock markets for all the periods to observe the evolutionary pattern.

Figure 7 shows the number of "Non-random" evolutionary patterns out of the twelve markets for each period as a result of run test performed using a run size n = 12 i.e. 12 previous data points. It is evident from the figure that post Lehman brothers collapse the evolutionary behavior of the comovement indexes shows an increases in non-randomness across the globe leading to all the twelve markets showing non-random evolutionary pattern for period no. 71 which is a result of the run test for data corresponding to period no. 60 to 71. This includes the period no. 64 when the Lehman Brother filed for bankruptcy. This clearly shows that post the Lehman Brother event the markets started moving in sync across the globe and hence increasing non-randomness in their behavior.

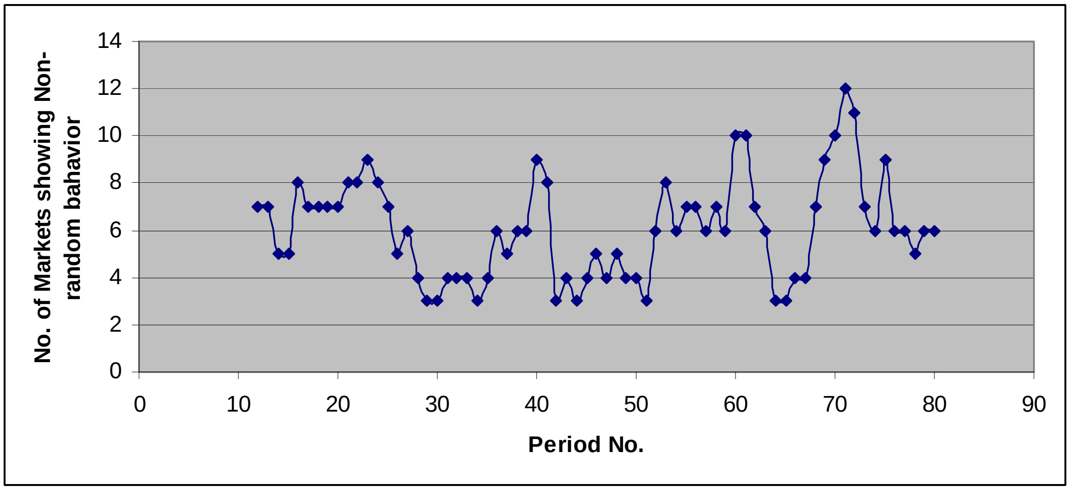

Figure 7: Non-randomness in the comovement index, for run size n = 12

6.6. Evidence on Regional Influences on the Network Dynamics

In order to provide evidence on regional influences on the network dynamics the similarity in the evolutionary behaviour of the stock market comovement indexes has been observed. The evolutionary patterns of the two Chinese stock market comovement indexes have shown considerable similarity as shown in Figure 8 but they behave differently compared to other market comovement indexes. The two US stock market comovement indexes corresponding to indices S&P500 and NASDAQ Bank have shown relatively different evolutionary patterns as shown in Figure 9. This was expected as S&P500 contains stocks from various sectors but the NASDAQ Bank Index has stocks of banks only. In order to depict the regional influences on the network dynamics visually, Minimum Spanning Tree (MST) has been constructed for the global stock market comprising all the stocks from all the twelve stock markets using the Pajek software (Batagelj & Mrvar 2009). The MST was generated using all the 3443 stocks collectively from all the twelve stock indexes and the stocks of different indexes are assigned different colors as shown in Figure 10. The MST clearly shows that the stocks from different stock indexes and countries tend to form separate clusters.

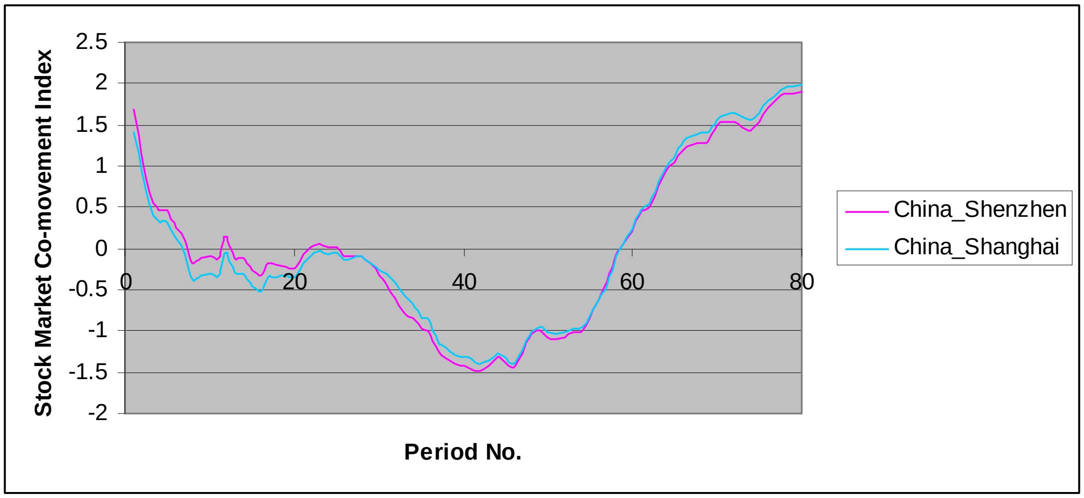

Figure 8: Evolution of Chinese Stock Market Networks

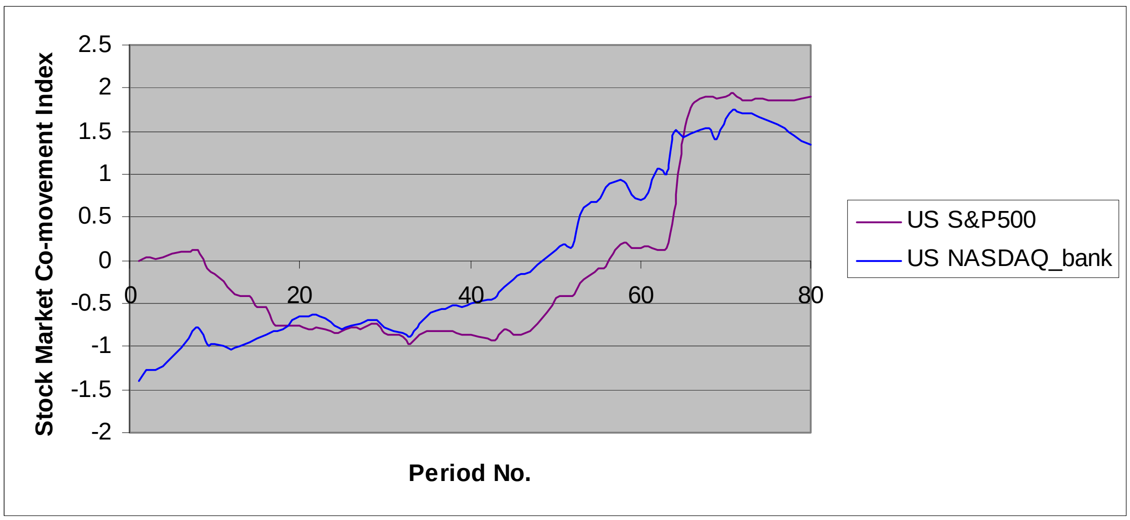

Figure 9: Evolution of US Stock Market Networks

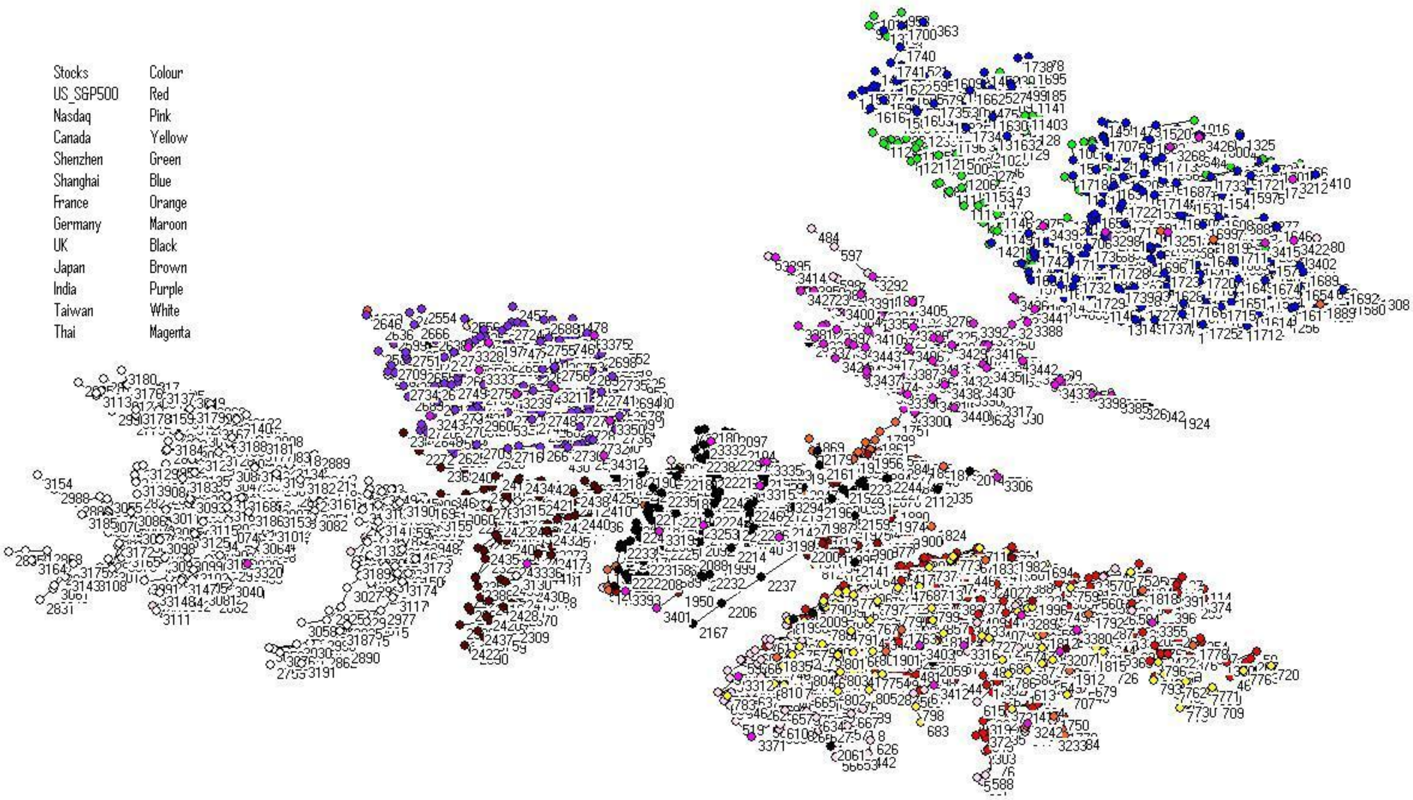

Figure 10: Minimum Spanning Tree (MST) for the global stock market using all the 3443 stocks

6.7. Capturing an Early Warning Signal

We propose an approach adapted from control chart type analysis for capturing an early warning signal from the dynamics of the global stock market comovement index. Figure 11 shows the global stock market comovement index along with the mean and mean + twice the standard deviation of the historical data available for global stock market comovement index as computed using its tranquil period values. We have used the historical data available for the index till the period before the onset of the crisis as tranquil period data i.e. from period no.1 through period no. 63 but it can be estimated from any other larger data set for the tranquil period. The line corresponding to the mean + twice the standard deviation may be used as a threshold line and whenever the global stock market comovement index crosses this line; we may raise an early warning signal for a financial crisis. Another approach may be to compute the mean and the standard deviation dynamically as the moving average and standard deviation of the index with gradually increasing window size by keeping the starting point of the window fixed. In effect, this is the historical mean and standard deviation using all the historical data available for the index till that point of time. This mean and standard deviation can be used to device a modified control chart with up-to-date mean and standard deviation as shown in Figure 12. Here again, we may raise an alarm when the value of the global stock market comovement index increases beyond the sum of the mean and twice the standard deviation signifying an anomalous pattern in their evolution.

Another way to look for the warning signal may be to monitor the change in the global stock market comovement index. Figure 13 shows the change in the global stock market comovement index (GSMCI) along with the sum of the mean and twice the standard deviation of the change in the index. The figure clearly shows an anomalously large change in the index at the onset of the crisis. Therefore, this measure can be used to identify dislocation in the stock market network structure and onset of stock market crisis.

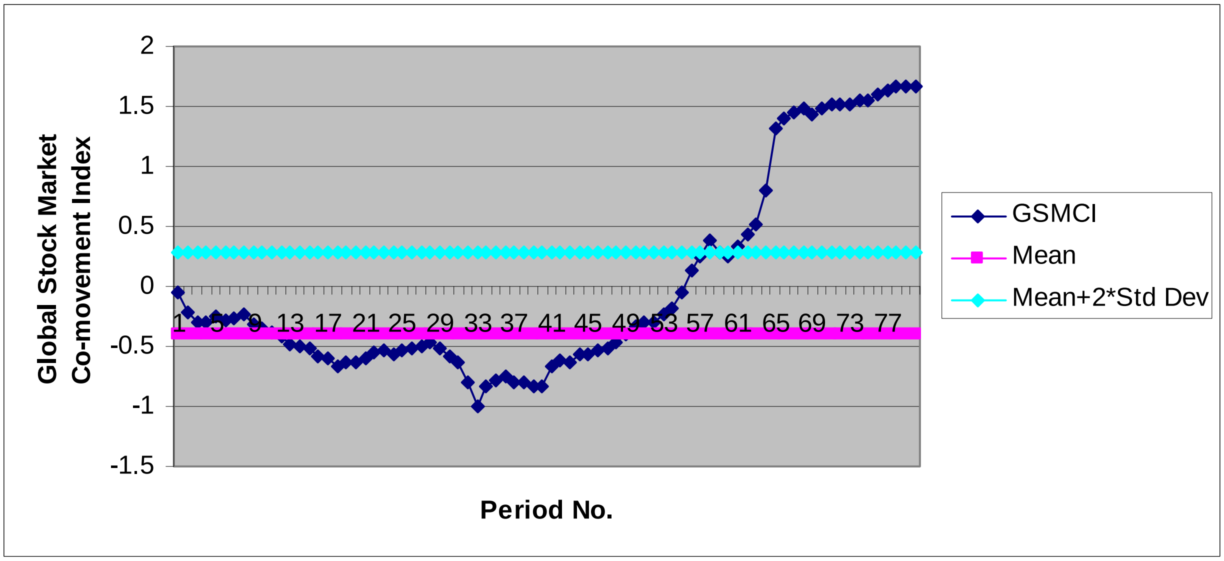

Figure 11: Control chart for capturing an early warning signal

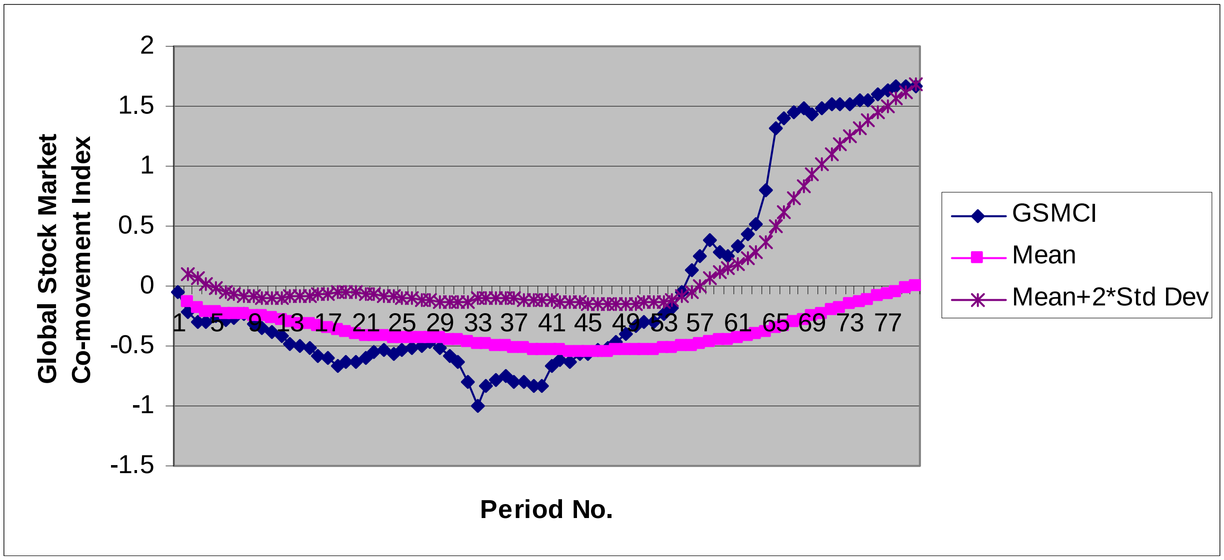

Figure 12: Modified control chart for capturing an early warning signal

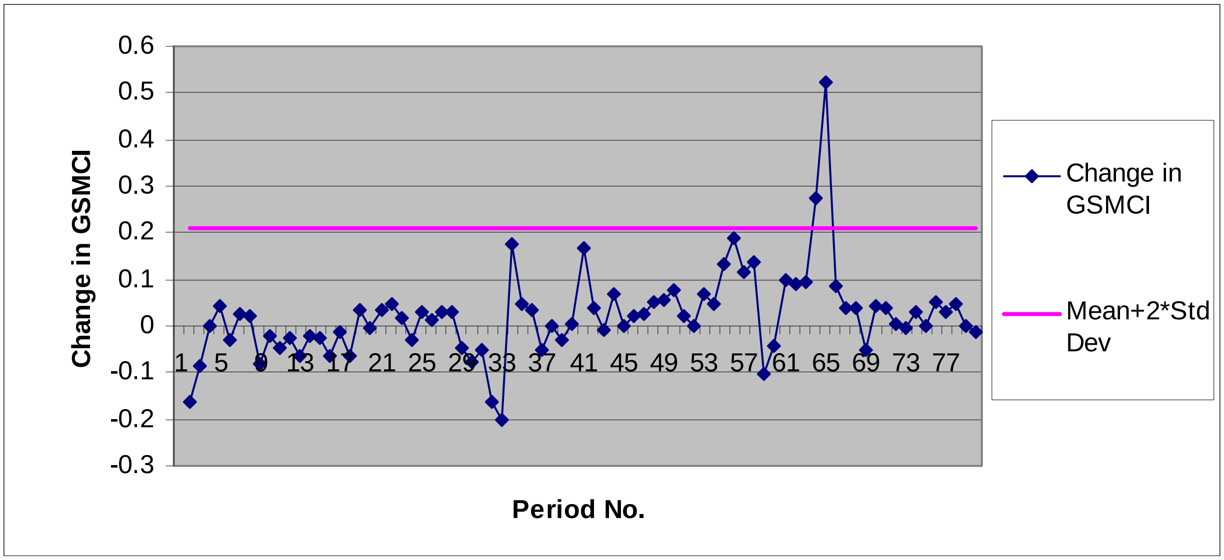

Figure 13: Change in global stock market comovement index

7. Conclusion

A network approach has been used to investigate the impact on the comovement of stock returns of global stock markets following the collapse of Lehman Brothers in America. We have captured anomalous patterns in the evolution of the stock market correlation networks of ten important North American, European, and Asian countries representing developed and emerging economies. Our study confirms the presence of regional influences due to shared information on the network dynamics as both the Chinese stock markets (Shenzhen and Shanghai) show very close similarity in their evolutionary behavior. It also provides empirical evidence on regional influences on the network dynamics and depicted the same visually by constructing the Minimum Spanning Tree (MST) for the global stock market. This study strongly reveals the synchronization of comovements in the stock returns as an emergence of global pattern in the dynamics of the international stock markets in case of extreme events such as the onset of a financial crisis. A global stock market comovement index has been proposed that may serve as a measure of systemic risk due to the comovement of stock returns in the stock markets across the globe and can be used to assess the intensity of impact of any extreme event on the global stock markets. It has established that post any extreme events such as collapse of Lehman Brothers; these comovement indexes show a statistically significant non-randomness in their evolutionary behavior as well as statistically significant shift in the comovement index after the collapse of Lehman Brothers. Existence of such global trend showing significant deviation from the long-run behavior of the network across all stock markets around the collapse of Lehman Brothers shows potential for its use as one of the early warning signals for a financial crisis. The dynamics of emerging market networks show relatively more fluctuations (noisy patterns) compared to that of developing countries.

This study does have some limitations as we have taken only twelve stock markets to estimate the global stock market comovement index. A larger set of different stock indexes across the globe may give a better estimate of the global stock market comovement index. Since the stocks of same sector cluster together, a study of network dynamics of sector indices from across the globe may provide more insights into how the various sectors behave at the onset of financial crisis. A better measure of comovements in the stock returns as well as more accurate estimation of correlation matrix using GARCH model may help forecasting the network behavior to improve crisis prediction capability. Studying the pattern of link formation in the stock market network would provide useful information about the internal structure of the stock market. Such understanding of the internal structure of the stock market system would be crucial for risk management, investor communication and crisis management. The study may also help policy makers to improve regulations in the market and in devising corrective actions using these early warning signals.

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