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Evolution, structure and dynamics of the Thai stock market: A network perspective

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Abstract. We study 115 stocks from the Thai Stock Market (SET) from 2006 to 2015. The evolution of correlations between stocks is estimated for different periods of world major financial events and the effect of these global financial events on the Thai stock market is studied. A spectral analysis of the correlation matrix based on random matrix theory is done. The evolution and dynamics of threshold networks derived from the correlation matrix are studied. The entropic measure on the eigenvector gives the information contained in each eigenvector which shows that eigenvector on lower side of spectrum are highly localized as compared to higher side of spectrum. The evolution of various topological properties of network are investigated. Thai stock market is found to be less robust during the global financial crisis.

1. Introduction

The recent few decades have shown a growing interest of physicists in economic and financial systems. Economic and financial systems are known as complex evolving systems, with many hidden variables, and unknown interactions governing its structure and dynamics [1–3]. By using the methods and tools from random matrix theory, network theory, and combining with the massive data-sets generated by the financial systems, it is possible to make data-based models to explain the topology, dynamics, and evolution of the complex financial systems [1,3,4]. Random matrix theory which is being successfully used in diverse field including biology, finance, wireless communication, etc. [1,5,6], is used to filter information from statistical noise. Followed by the application of complex network theory to study the topological properties and dynamics of the Thai stock market. The present study is to understand the effect of various world financial events on the structure and organization of the Thai stock market.

2. System and data

The system includes the SET index comprising of 574 stocks. The daily adjusted close price of 574 Thai companies are downloaded from Yahoo finance from 2006 to 2015. Only those companies which were present over the complete period from 2006 to 2015 are considered for analysis, which results in 115 stocks. These 115 stocks are filtered and processed through a series of automated and manual steps. We divide the complete period (2006-2015) into segments of world major financial events and their effect on the Thai stock market is studied. The period is divided into 5 windows comprising of US subprime crisis (Jan 2006- Dec 2007), global financial crisis (Jan 2008- Sep 2009), followed by a calm period (Oct 2009- Dec 2010), European Sovereign debt crisis (Jan 2011- Dec 2012), and Chinese stock market turbulence (Jan 2013- Dec 2015). For each window, the daily logarithmic returns for stock i is defined as $R_i(t) = \ln P_i(t) - \ln P_i(t-1)$, where $P_i(t)$ and $P_i(t-1)$ price of stock i on days t and $t-1$. The normalized log-returns are given by $r_i(t) = \frac{R_i(t) - \langle R_i \rangle}{\sigma_i}$, where σ_i is the standard deviation of $R_i(t)$ over the complete period.

3. Correlation matrix

The cross-correlation matrix is created from log-returns of 115 Thai stocks. The correlation coefficient between the stock i and j is given by $C_{i,j} = \langle r_i(t) r_j(t) \rangle$. The eigenvalues λ_i and eigenvectors $\mathbf{v}_i$ of the correlation matrix are calculated and arranged in an increasing order such that $\lambda_1 < \lambda_2 < \cdots < \lambda_N$ with $N = 115$.

To separate information from noise, we generate an ensemble of random correlation matrices, known as Wishart matrices. The properties of Wishart matrices are well defined and studied in details [7]. The eigenvalue distribution follows the Marcenko-Pastur distribution defined by $P_\lambda = \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}}{\lambda}$, where $Q = \frac{L}{N} > 1$ (L = trading days and N = stocks). The random matrix bounds on the largest and smallest eigenvalues are given by $\lambda_\pm = \sigma^2 \left(1 + \frac{1}{Q} \pm 2\frac{1}{\sqrt{Q}}\right)$ with $\sigma = 1$. For each window and for complete period, the eigenvalue statistics is estimated and is shown in table 1. The number of eigenvalues outside the RMT bounds (lower and upper) increases at the time of crisis (US subprime crisis, 2008 global financial crisis, European sovereign debt crisis, Chinese stock market turbulence) whereas there is a significant decrease in the number of eigenvalues outside the RMT bound for calm period. This observation reflects from the fact that during crisis, the system tends to be more correlated hence diverges from the RMT results. Whereas during the calm period, system is less correlated with a high noise and shows similarity to a random system. The magnitude of the largest eigenvalue also indicate the crisis period, higher magnitude implies a severe crisis. From table 1, we find that during period of the US crisis, 2008 global crisis and Chinese stock market turbulence, the impact on the Thai stock market is higher as compared with the period of the European debt crisis. Hence Thai markets are linked more to the US and Chinese markets than the European markets.

To find the information content of a eigenvector, we define its entropy as $H_i = -\sum_{j=1}^{N} v_i(j)^2 \log_L v_i(j)^2$, where N is the number of stocks and $v_i(j)$ is the j^{th} component of the i^{th} eigenvector. We find that the entropy of eigenvector on the lower side of spectra is smaller as compared to the entropy on the higher side of the spectra. The entropy of the eigenvector corresponding to eigenvalues in bulk ($\lambda_- < \lambda < \lambda_+$) are similar to the RMT results indicating that these eigenvectors are highly plagued with the randomness. The eigenvectors on the lower side of the spectra are highly localized and more informative. The localization is more for 2008 Global financial crisis and Chinese stock market turbulence. Various studies shows that small eigenvectors are important for the system, in the Markowitz theory of portfolio selection they represents the least risky portfolios [8] and in biology, for protein sequence they

Table 1. Comparison of eigenvalue statistics of financial windows with the random system.

	λ_-	λ_+	$\lambda < \lambda_-$	$\lambda > \lambda_+$	L	λ_{min}	λ_{max}
US subprime crisis	0.273	2.184	15	3	504	0.117	22.923
Global financial crisis	0.207	2.387	13	3	387	0.085	21.975
Calm period	0.181	2.478	7	1	349	0.086	17.178
European debt crisis	0.265	2.207	11	2	488	0.128	21.136
Chinese turbulence	0.365	1.948	15	2	734	0.141	20.730
Complete period	0.614	1.479	32	6	2462	0.183	19.086

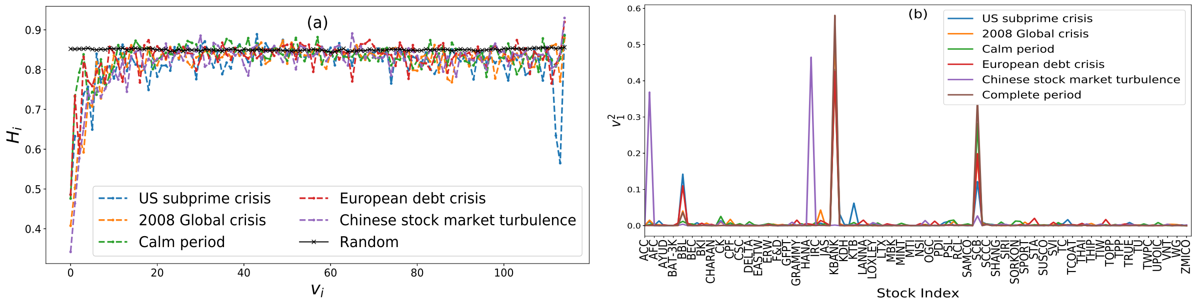

Figure 1. (a) Eigenvector entropy and (b) smallest eigenvector square for each window.

represents the functional sectors [6]. The components of these localized eigenvectors form a sector with very close ties. In the Thai stock market, the smallest eigenvector components for most windows represent the banking sector, i.e most significant interactions are the interactions of banks with each other. For the detailed analysis, we study components of the smallest eigenvector to check the most contributing stocks for each window as shown in figure 1. Smallest eigenvector components shows that the top stocks belong to the banking sector. The most dominating company is the Kasikorn (Kbank) bank for all windows. We observe that the banking sectors become more correlated during the crisis period. The stocks which shows high correlation and contribute the most to smallest eigenvector are Kasikorn bank, Bangkok bank, Siam Commercial Bank and Krung Thai bank. The contribution of stocks changes during Chinese stock market turbulence. During Chinese stock market turbulence telecommunication sector has higher contribution (ADVANC and INTUCH) as compared to the other periods where banking sector dominates.

4. Networks

The threshold network is created from the correlation matrix based on threshold value θ. A threshold network $G(N, E)$ with node (N) and edges $E_{i,j}$ between node i and j is defined by $E_{i,j} = 1$ if $C_{i,j} \geq \theta$ $(i \neq j)$ and 0 otherwise.

We study network at three different thresholds (0.1, 0.25, 0.5) shown in figure 2 which represents three regimes. At low threshold (0.1) shown in figure 2(a), there is a high noise content in the data and system is dominated by noise. With an increase in threshold, the noise decreases in the system. The range of average random correlation is (0.25) shown in figure 2(b), therefore at this threshold the information and noise contributes equally. At a higher threshold (0.5) shown in figure 2(c), the noise is negligible, the system has only those interactions which are significant. We study the evolution of network with threshold and time (windows) to observe dynamics of the system. A network can be mathematically represented by the adjacency matrix (A), which is a square $N \times N$ matrix with element $a_{ij} = 1$, if there is a connection between stocks i and j and zero otherwise. Since the threshold network is undirected therefore the adjacency matrix (A) is a symmetric matrix such that $a_{ij} = a_{ji}$.

4.1. Topological properties

The topological properties of network at different threshold and windows are studied and shown in table 2. We first study the network density which is ratio of the actual number of links to total possible links in the network defined by $\rho_G = 2M/N(N-1)$ where M is the number of actual links and N is the number of nodes in the network. We observe a sharp decrease in the number of edges and density with threshold. The decrease in density is more predominant for the calm period as compared to the crisis period. At 0.25 threshold, the network density is

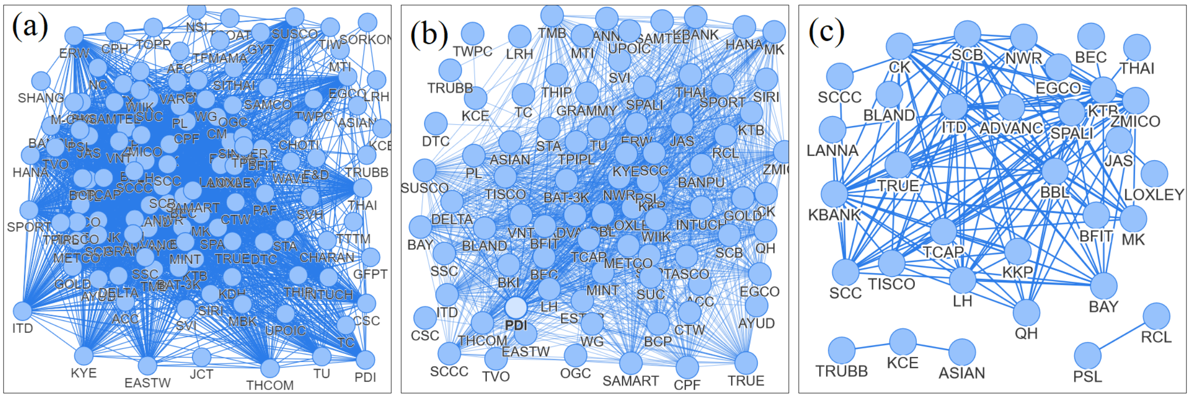

Figure 2. Network of the Thai stock market at thresholds (a) 0.1, (b) 0.25 and (c) 0.5.

significantly high at the time of financial turbulence as compared to calm period. US subprime crisis, global financial crisis and the European debt crisis show higher turbulence.

Table 2. Topological properties of network for each financial windowat different threshold.

	Threshold	US crisis	Global Fin. crisis	Calm period	European debt crisis	Chinese turbulence	Complete period
M	0.10	2998	2876	2685	3663	3890	2619
	0.25	1296	1217	646	1180	1032	930
	0.50	147	127	35	39	30	45
ρ_G	0.10	0.457	0.439	0.410	0.559	0.593	0.400
	0.25	0.198	0.186	0.099	0.180	0.157	0.142
	0.50	0.022	0.019	0.005	0.006	0.005	0.007
$\langle\kappa\rangle$	0.10	0.770	0.722	0.662	0.809	0.829	0.744
	0.25	0.526	0.479	0.386	0.486	0.473	0.429
	0.50	0.160	0.161	0.067	0.082	0.059	0.084

Clustering coefficient is the measure of local connectivity in the network, which quantifies the inter-connectivity between the neighbors of a node. The clustering coefficient of node i is given by $\kappa_i = \frac{2m_i}{n_i(n_i-1)}$, where m_i is number of connections between the neighbors of node i, and n_i is the number of nearest neighbors of i. The term $n_i(n_i-1)/2$ gives the maximum possible connection between neighbors n_i of a node i. The average clustering coefficient over all nodes in the networks is $\langle\kappa\rangle = \frac{1}{N}\sum_{i=1}^{N}\kappa_i$. The average clustering coefficient in the network is a measure of average connectivity in network. We observe that the network is more clustered during the crisis period. European debt crisis and Chinese stock market turbulence shows a high value of clustering at small thresholds. At higher thresholds, US Subprime crisis and 2008 global financial crisis show a high value of clustering coefficient.

Degree of a node is defined as the number of connection it has with all the other nodes in the network. The degree of node i is defined by $K_i = \sum_{i\neq j} E_{i,j}$. There are nodes in the network with a high degree, called hubs. The presence of hubs indicates the scale free nature of the network. To further analyze the network, we create and study the degree distribution of each financial window at different threshold and compare it with the random network (figure 3).

The random degree distribution is created by generating a random graph with same number of nodes and edges as the complete period at that threshold. At low threshold $\theta \leq 2.5$, the degree distribution behaves more like a random network. However at higher threshold the randomness decreases and the system shows a scale free behavior, which is the characteristics of many real world systems [9].

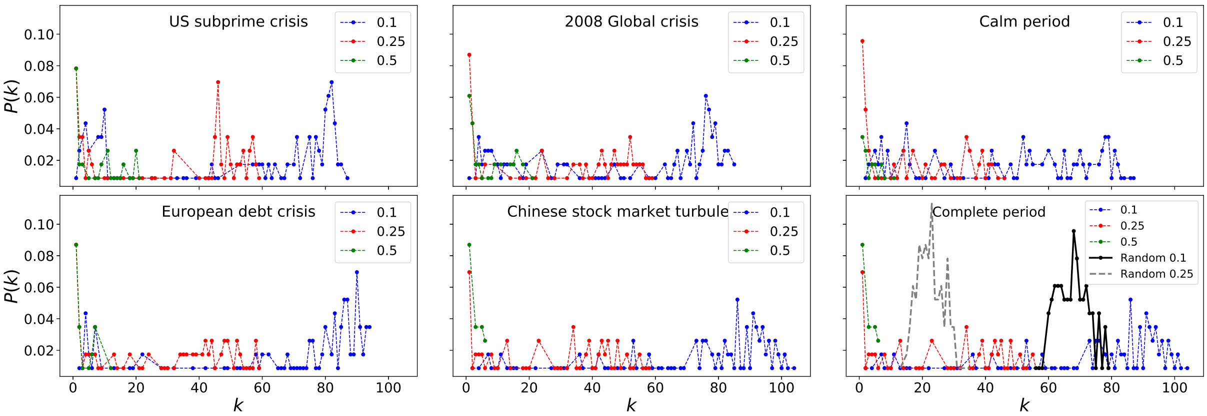

Figure 3. Comparison of degree distribution of the Thai stock market at different financial windows with random at different thresholds.

4.2. Robustness and information flow in the network

The largest eigenvalue (λ_{max}) of the adjacency A is known as the spectral radius of the network. It gives the rate of information flow in the network [10]. A higher value of λ_{max} implies a better communication between nodes in the network. The variation of spectral radius with threshold for different financial windows is shown in figure 4(a). Another quantity of interest is the epidemic threshold τ_c which quantifies the rate of spread of infection in a network [10]. The epidemic threshold is given by $\tau_c = 1/\lambda_{max}$ and is shown in figure 4(b). The rate of spread of contagion is higher for a smaller value of epidemic threshold τ_c, hence a less robust network against the infection. We find that the communication within the network is higher during the 2008 global financial crisis, US subprime crisis and European debt crisis. Hence, the Thai stock market is very prone to failure during these time frames. The highest robustness is found for the calm period and Chinese stock market turbulence. During these time windows the information flow is lower, indicating a lower interaction among Thai stocks.

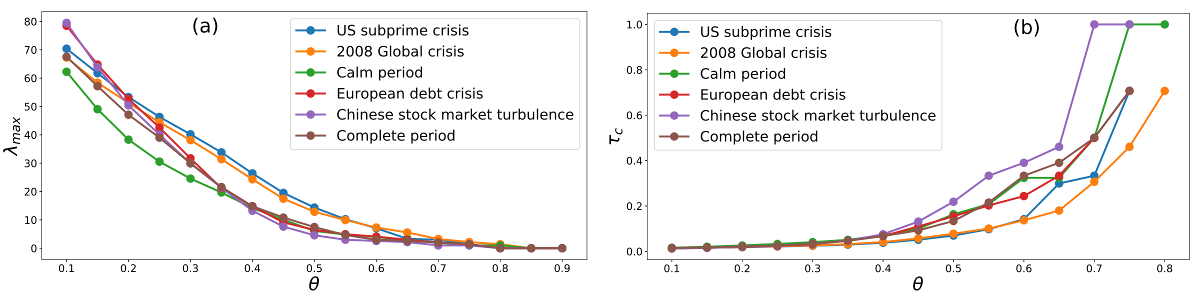

Figure 4. Variation of (a) spectral radius and (b) epidemic threshold with threshold (θ).

5. Results and conclusion

In this work, we discuss a spectral and network method based on the correlation matrix to analyze the Thai Stock market. A correlation matrix is created from the time series data for different financial period and compared with random Wishart matrices. We study the statistics of eigenvalues outside the RMT bounds which shows that during the crisis, there is a significant increase in the number of eigenvalues on the lower side of the spectra. The largest eigenvector is known as the market mode and gives the average behavior of the market as a whole and the components gives contribution of each stock towards the movement of the Thai SET index. Each eigenvector represents a direction which can physically represents a sector (or group of sectors) for example the eigenvector corresponding to the smallest eigenvalue is highly localized which corresponds to the banking sector with highly interacting bank and financial stocks. A threshold-based network is created from the correlation matrix. Thai Stock market shows a scale free degree distribution, which indicates that there are only a few stocks which have higher financial interactions (hubs) where as a large number of stocks have only a few interactions. High value of the clustering coefficient shows that stocks in the Thai stock market are clustered in form of highly interconnected groups (sectors). The spectral radius shows that the Thai stock market is more closely packed during the time of financial crisis hence a better and efficient communication between nodes as compared to the calm period.

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