

Effects of Financial Crises on Threshold Network of World Stocks and Commodity Markets

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Abstract: The core focus of the study is to investigate the impact of European crises on commodity and world stock market indices. To investigate the impact during and after crisis, the technique of threshold has been applied to make a complex network from the cross-correlations of the returns of 46 daily time series comprising of 23 global stock market indices and 23 commodity futures from 2010 to 2014. The networks are fragmented with the increase of threshold and the study detects a sturdy association between commodities and stock indices at high threshold during severe crisis of 2011. The dynamic of inter-links between two groups at threshold 0.1 show dissimilar behavior with the dynamic of inter-degrees of individual group of commodities with stock indices. The change of intra-degrees among individual groups of stock and commodities demonstrates that the effect of Cypriot crisis in first half of 2013 on financial indices is more shocking than those of commodity futures. The dynamic of clustering coefficient identifies that Asian financial indices and index of agricultural sector under commodity market are more responsive during as well as after crises. Finally, we propose a definition to measure the states of the network artifact. Identifying the dynamic movement of market state and network structure can be useful as an early warning of upcoming crisis and portfolio investment.

Keywords: World Stock Market, Commodities Market, Threshold Network, Cross Correlation, Dynamic Network Structure

1. Introduction

The world has been experienced of different financial crises mainly for securitization, deregulation, lack of good governance, banking panics, real estate bubble and mark-to market etc. And these financial crises result in creating unemployment, crashing stock market, slowing economic growth, flouting financial structures and initiating the way to depression even trough. Financial and commodity market of an economy have been ruthlessly affected by their financial crises both during and after the crises period.

At the very beginning of 2010 the Europe has been experienced sovereign debt crisis mainly considering the reasons of property bubble, slower government response and differences in fiscal policy among Euro zone countries etc. The countries, such as Greece, Spain, Ireland, Portugal, and Cyprus situated in periphery of euro zone have been affected

harshly. Without taking financial support from the outside party, these countries became unable to repay their government debt. To pay the debt, they took the help of some financiers such as the European Central Bank (ECB), the International Monetary Fund (IMF) and the European Financial Stability Facility (EFSF). To recover the European sovereign debt crisis, seventeen member countries of European union to create the EFSF in 2010. Again in 2012–2013 Cypriot financial crisis vibrated the euro zone. This crisis results from the banking panics of Cypriot. Basically the involvement of Cypriot banks to over-leveraged local property results in such crisis.

Nowadays, modern economy partially depend on commodity markets since markets are mature and highly developed institutions. The rules of efficient market hypothesis is also followed by commodity markets showed by Fama (1970). However, still no research has been done about the interaction of both markets together.

The study aims to investigate the impact of financial crises on commodity market as well as financial market, degrees of correlation between both markets along with the correlation among intra companies and the cross-correlations between commodity future and financial market at different thresholds.

In this study, the technique of threshold is applied to cross-correlations of the logarithmic change of prices of world commodity and financial market together from 2010 to 2014 to observe the degrees of correlation between both markets along with the correlation among intra companies and observe network stability after sovereign debt crisis. The continuous movement of network structure and topological properties is used to identify the market state of each group. Moreover, a definition has been opposed to measure the dynamic change of the networks which can be used to imagine the market movement.

The rest of the paper is organized as follows: section two reviews of literature; section three discusses the methodology that contains data analysis, correlation analysis threshold network analysis, topology dynamics, and network stability. Section four presents results and discussions and section five conclude the paper with some proposals where one can imagine the market movement.

2. Literature Review

Many researches have been done on capital and commodity markets to extract information about states of the market, portfolio investment and risk management, and the correlation and network structure of financial assets [1-7]. Nowadays commodity play a very important role in the modern economy. Commodities follow the rules of the efficient market hypothesis as like as stocks, currencies, and others [1]. However, still no research has been done about the interaction of both markets together. Our focus is to observe the degrees of correlation between both markets along with the correlation among intra companies. It is well known that the intense of correlation depend on different kinds of effects such as globalization, crisis, bubble, information flow etc [8, 9, and 19]. The correlation coefficients of stock or commodity price returns can be used to obtain threshold network, minimal spanning tree (MST) and planar maximally filtered graph (PMFG)[8-15]. The financial networks are constructed from the relation of the cross-correlations between two indices for short and long time series. The network structures of financial indices are altered due to shock of the crisis or external affects. The structural changes of global and local market are observed in the recent studies [14-16]. Qiu et al study the statistical properties of the dynamic network to investigate the temporal correlations of the topology time series [8]. They also focus on the dynamic effect of the thresholds on the network structure and network stability. Song et al used three and six-month window to observe the dynamics of stock market indices running throughout the world [16]. They showed that the structure of PMFG constructed from mutual information between two stocks is changed during big crash. The states of global indices over time is identified by applying principal

component analysis to the correlations of the returns of the world stocks [20]. The MST approach is applied to daily yield rates of 10 years government bonds on nineteen EU countries and worldwide finance and commodity market. The result showed the germination of MST network and the stable connection of financial assets of similar type over time [21]. MST technique has been used to explain the urgency of commodity market and price movements of commodities [17, 25, 26]. The groups of commodities identified according to their sectors and observe their network topologies.

3. Methodology

3.1. Data Analysis

The daily closing prices of 23 world stock market indices placed throughout the world and 23 commodity futures indices from 2010 to 2014 have been used to analyze the data. In the sample periods the world has observed different financial crises that affect the market resulting reorganization of financial structures. The whole index and commodity futures are given in Appendix. Six-month time window is fixed for the study. The data are collected from yahoo finance [24]. To construct cross-correlation matrix with equal time span, public holidays haven't been considered to analyze data. That day hasn't been considered to analyze our data when 60% companies of the markets are inactive on that day. For fully inactive market in a particular day, the last closing price of those markets that haven't active for that day has been considered. Thus, all the indices at the same date have been taken to examine and that data have been filtered, such as prior studies by Kumar (2012), and Sandoval (2012). The daily returns for the indices have been investigated, each containing approximately 128 records for half year.

3.2. Correlation Analysis

To observe the overall picture of commodity and stock markets, volatility and correlation have been calculated from the change of prices of both indices. The daily logarithmic return has been calculated as follows:

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

where $I_i(t)$ is the closing price of index i on day t .

To notice the fundamental interaction among the indices, the normalized return for index i is calculated as

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

where σ_i is the standard deviation of the stock index time series i . Then, we calculate the equal time cross-correlation at time T (approximately 128 days) from the normalized return of two indices by [Nobi (2014)]

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

The average cross-correlations are shown in Figure 1 in the section 4.

3.3. Threshold Network

The threshold networks (TN) are constructed assigning a threshold value to cross-correlations coefficient- referenced by Qiu (2010), Kumar (2012), Nobi (2014), Huang (2009), Namaki (2011), Nobi (2017). In the threshold network, a node (V) represents a distinct index and the links (E) represent the connection between two indices weighted by the cross-correlation coefficient between the two indices of a given time period. In the threshold network, an undirected link adds nodes i and j if the correlation coefficient C_{ij} is greater than or equal to the threshold θ . Therefore, the size of the formation of the cluster and the set of links of the cluster among the nodes depend on the value of the thresholds. We construct correlation networks of both indicators at different thresholds shown in Figure 2 in the section 4.

3.4. Topology Dynamics

The topological properties of a complex network are usually described by the clustering coefficient, the average degree and the cross correlation of degrees. We investigate the topology dynamics with evolution of time.

3.4.1. Change of Mean Degree with Time

The degree of the vertex i is defined by $k_i = \sum_{j \neq i} e_{ij}$, which is the total number of connections in the network, where $e_{ij} = 1$ if the vertices i and j are connected and $e_{ij} = 0$ otherwise [9, 14]. We estimate the number of intra-links in stock indices or commodity futures and the number of inter-links between the stock indices and commodities is shown in Figure 3 in section 4.

3.4.2. Change of Clustering Coefficient with Time

The clustering coefficient of a vertex i is defined as [9, 19]

$$C_i = 2m_i/n_i(n_i - 1) \quad (4)$$

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 change of clustering coefficient of a vertex is observed with evolution of time at threshold 0.1. The clustering coefficient depends on edges and neighbors of the vertex used by [9, 19]. The threshold network is highly clustered during the crisis. As a result, a vertex carries higher clustering coefficient during crises while lower clustering coefficient during calm state. Hence, the financial state of each index can be identified by the movement of clustering coefficient. To denote the dynamic state of each index, the change of the clustering coefficient of each index between two time periods has been defined as

$$\Delta C(t_2, t_1) = C(t_2) - C(t_1) \quad (5)$$

where C is the number of links of each index in a period.

The financial states of a market is identified by Figure 4 shown in section 4.

3.5. Network Stability

Financial network is highly impressionable to the external

information. So, by measuring the network similarity, one can envisage the market movement which can be expedient for risk management and portfolio investment. Network resemblance can be measured by Jaccard index where only the similar links with the same pair of nodes between TNs are considered [9]. The weight of the links is neglected when one calculate Jaccard index. We propose that a dynamic network is stable when the weight of a link does not change in two consecutive threshold networks. We investigate the similarity of the networks in the observation time window. The network similarity is measured as

$$S = (W_c)/W \quad (6)$$

where, $W_c = \sum_{i,j+1}^N (TN_{t_2}(i, j) - TN_{t_1}(i, j))$ and $W = \sum_{i,j+1}^N (TN_{t_2}(i, j) + TN_{t_1}(i, j))$ where $TN_{t_1}(i, j)$ is the weight of the link between the node i and j in the time t_1 .

If the value of S is near to 0, we can say that two networks are almost similar. When the value of S is near to 1, the network is completely dissimilar and it implies that market is going to crisis state. For the negative value of S , the network is also dissimilar. But, it implies that market is going to calm state.

4. Results and Discussion

Figure 1 shows the average cross-correlations whose trend is decreasing in the sample period with the exception of dramatic change in the crisis period. The transition of the average cross-correlation is seen during 2010, 2011 and 2013. The study observe the sharp increase of average cross-correlation during the first half of 2010 and the last half of 2011 respectively. During the crisis, the indices interact strongly while in calm state the indices interact weakly each other. In the period from 2010 to 2014, the average cross-correlation has been decreased approximately 64%. This decrease implies that world financial and commodity market is going to recover from sovereign debt crisis.

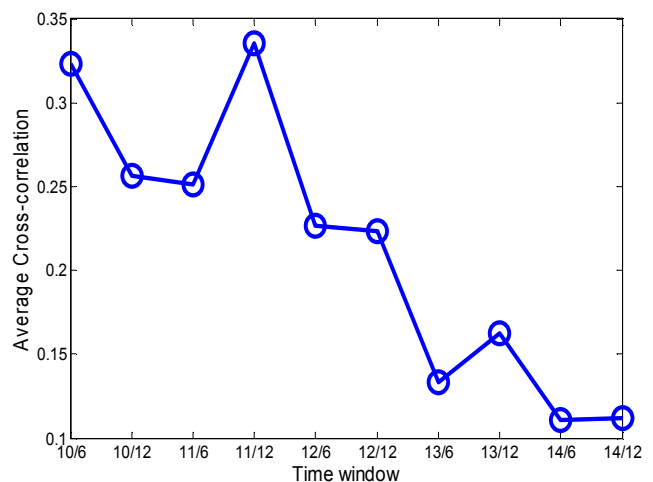


Figure 1. Cross- correlation in different time windows. Each value in horizontal axis (year/month) corresponds to each 6-month period.

We have constructed correlation networks of both indicators (commodity and financial) at different thresholds. At threshold $\theta = 0.1$, a giant cluster of both indicators is observed in figure 2. The commodity indicators start to disconnect from giant cluster at threshold $\theta = 0.2$. With the increase of threshold more nodes have been detached. The rate of disconnection of agriculture nodes from largest cluster is higher than other indices. At threshold $\theta = 0.5$, only energy and three metal commodities (Palladium, Platinum and Copper) make strong association with financial indices during crisis. At threshold

$\theta = 0.6$, Palladium interacts strongly with the financial indices of Hongkong and Singapore while Crude oil has strong connection with the index of United Kingdom during crisis. Two groups are disconnected fully from one another from threshold $\theta = 0.7$. The commodity indicators construct clusters separately by the sectors of metal, energy and agriculture. The financial indicators construct a big cluster. The financial indicators begin to disconnect from big cluster at threshold $\theta = 0.6$ during crisis.

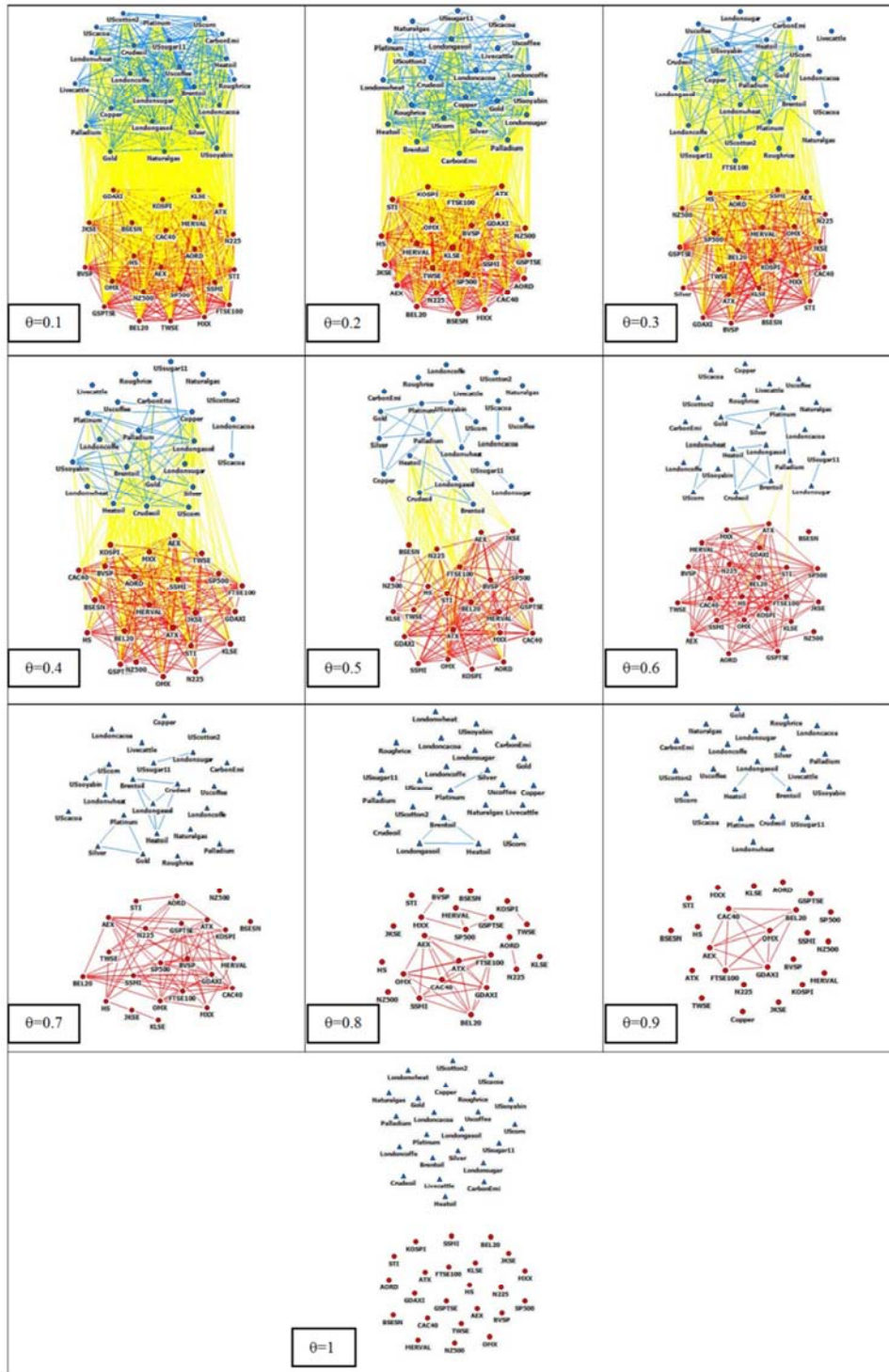


Figure 2. Threshold networks for the last half of 2011 are drawn from the threshold 0.1 to 1 respectively.

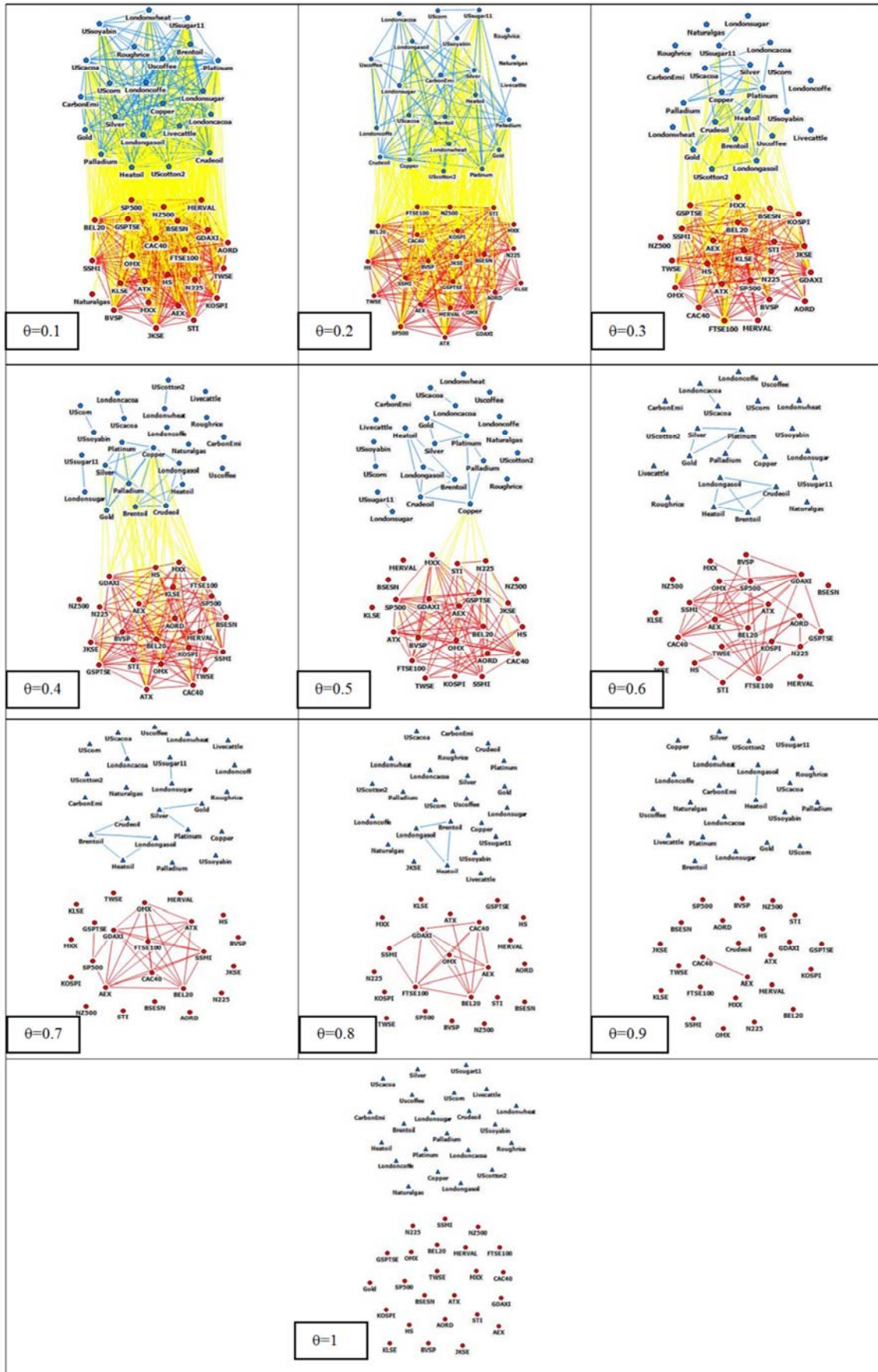


Figure 3. Threshold networks for the first half of 2012 (after crisis) are drawn from the threshold 0.1 to 1 respectively.

Figure 3 shows after crisis situations. In this situation, all nodes are connected with the largest cluster at threshold $\theta = 0.1$. And the nodes are severed with the increase of threshold. However, the disconnection rate of nodes between commodity and stock indices after crisis is higher than before crisis. At threshold $\theta = 0.4$, a giant cluster is found where all metal and energy commodities interact with stock indices. At threshold $\theta = 0.5$, Copper is the only one commodity that maintains the interaction with financial market. Copper make interaction with the indices of ATX, FTSE-100, GDAXI, OMX, Bel20, and CAC-40. Two layers are separated at threshold $\theta = 0.6$ after crisis compared to at threshold 0.7 during crisis. At high threshold like 0.6, 0.7 or 0.8, the intra-link of financial indices show more sturdy association than commodity futures in both periods. Commodity groups form sectorial cluster at these high threshold. At high threshold the energy and metal sector shows high intra-link compared with agriculture futures.

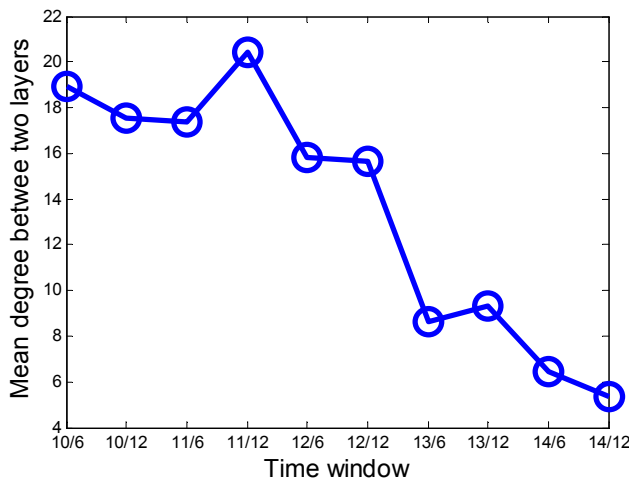


Figure 4. Mean degrees vs time: between two groups. Each value in horizontal axis (year/month) corresponds to each 6-month period.

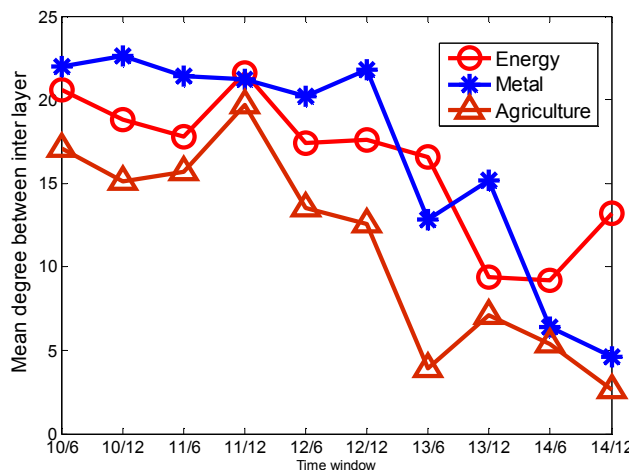


Figure 5. Mean degrees vs time: between stock indices with individual group of commodities. Each value in horizontal axis (year/month) corresponds to each 6-month period.

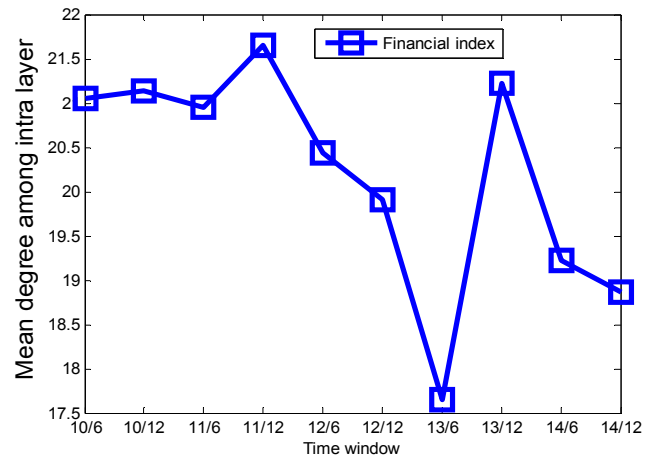
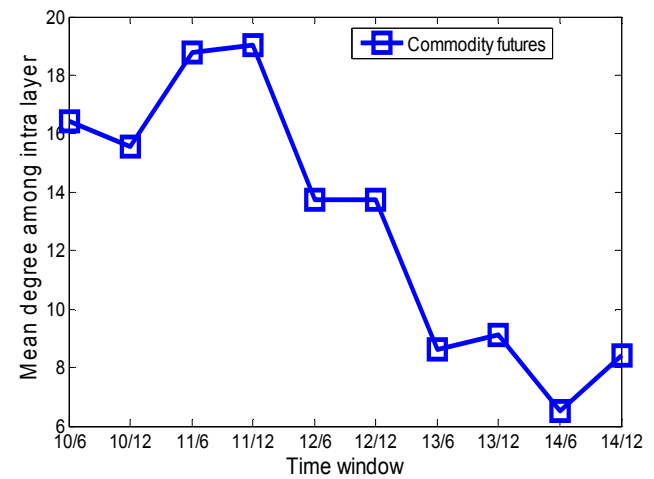


Figure 6. Mean degrees vs time: financial indices only. Each value in horizontal axis (year/month) corresponds to each 6-month period.



(d)

Figure 7. Mean degrees vs time: commodity futures only. Each value in horizontal axis (year/month) corresponds to each 6-month period.

Figure 4 shows the mean degrees between two groups of threshold networks with threshold $\theta = 0.1$. Transitions of the degrees are observed during crisis and calm state. The graph runs decreasing manner while crisis, drastic change occurs within investigation period. The mean degree is higher at the first half of 2010 and the peak value is observed in the last half of 2011 when sovereign debt crisis spread all over the world. It implies, two groups interact stalwartly due to the crisis. They turn into feeble after 2011. The sharp transition is found in the first half of 2012 and 2013 respectively which implies that both indices are going to calm state. In the last half of 2013, interactions upturn slightly due to Cypriot crisis. The rest of the period, the degrees between two groups decline.

Figure 5 shows the interaction of individual group of commodities (energy, metal and agriculture) with stock index. The mean degree between the sectorial cluster of energy commodities and stock index is similar with the mean degree between two layers till the last half of 2012. The transition of

mean degrees between two layers is found in the first half of 2013 while for energy commodities occur in next half period. The interactions of energy commodities with stock indices sharply increase due to Russian crisis during the last half of 2014. We found strong interactions of metal commodities with stock indices in comparison with other indices. The inter-links of metal commodities are almost similar from beginning of 2010 to the first half of 2012. It may imply the long term effect of sovereign crisis on these commodities. After a small peak in last half of 2012 due to Russian crisis, a sharp transition of inter-links is found during the first half of 2013. Again, the effect of Cypriot crisis causes to increase the degree between the commodities of metal and stock indices. After that, the inter-links decrease. The inter-degrees of agricultural commodities are lower than other commodities. The change of inter-degrees is similar with the change of mean degrees between two layers (figure 4).

The topology dynamics of links among similar indices is

given in figures 6 and 7. After the beginning of sovereign debt crisis in 2010, the degrees of financial indices did not change significantly till the first half of 2011 and sharply increase in the last period of 2011. While the degrees of commodity futures show sharp increase one period earlier than the financial indices. It implies that the severe effect of ESD crises on commodity futures spread quickly than those of financial indices. Then, the degrees of financial indices decrease sharply till the first half of 2013. However, the links of commodity futures first sharply shrinkage and then it becomes steady. Again, the transition is observed in the early period of 2013. A harsh increase of links among financial indices is found in the last of 2013 due to Cypriot crisis. On the other hand, the variation of degrees of commodity futures is not momentous due to crisis. After Cypriot crisis, the degrees of financial indices decrease in the rest of periods while the degree of commodity futures upsurges due to Russian crisis in the last period of 2014.

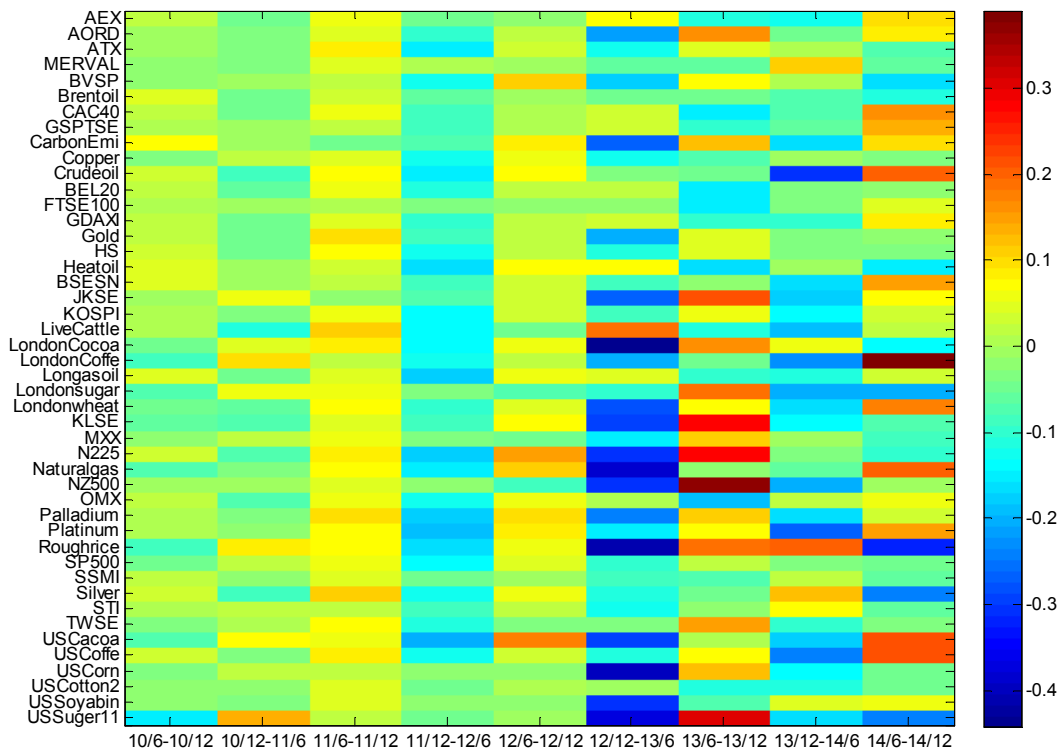


Figure 8. Change of clustering coefficient in threshold network.

In figure 8, color plot the state of clustering coefficient in threshold networks has been indicated by the color bar. The network has been drawn at a threshold $\theta = 0.1$ between two subsequent periods. Vertical line represents an index of a market while horizontal line represents the change of state between two periods. Different colors are used to denote the different states of the market. To demonstrate the significant increase of clustering coefficient of threshold network in the crisis period, completely red-colored bars are used. Yellow color implies that the network or market state changes mildly in comparison to previous period while dark blue colors point out the sharp fall of clustering coefficient representing that the markets are going to calm state from crisis. Other light

colors indicate that the market is in the similar state as it was before.

The study has been found that the clustering coefficient fluctuates over the period. The clustering coefficient indicator identifies that market states have changed mildly in the last half of 2011 due to sovereign debt crisis but are not changed severely up to the last half of 2012. The remarkable change of clustering coefficient is found in first half of 2013 due to Cypriot crisis. The indices such as AORD, EU Carbon Emission, JKSE, London Cocoa, KLSE, London wheat, MXX, N225, Natural Gas, NZ500, Rough Rice, US Cocoa, US Corn, US Soya bin, US Sugar11 etc. come in calm state. In the last half of 2013, the significant increase of clustering

coefficient are observed for AORD, JKSE, London Cocoa, London Sugar, KLSE, N225, NZ500, Rough Rice, TWSE, US Corn, US sugar11. It implies that these indices are more responsive to crisis in this period. Some indices enter into calm state in the first half of 2014. Again, the significant increase of clustering coefficient are found for the indices of CAC40, Crude oil, London coffee, London wheat, Natural gas, US cocoa, US coffee due to Russian crisis in last half of 2014.

It has been also found that Asian financial indices and agricultural sector under commodity market are more responsive during as well as after crisis. So, the change of clustering coefficient over the period can identify the financial state of each index which can be useful for portfolio investment.

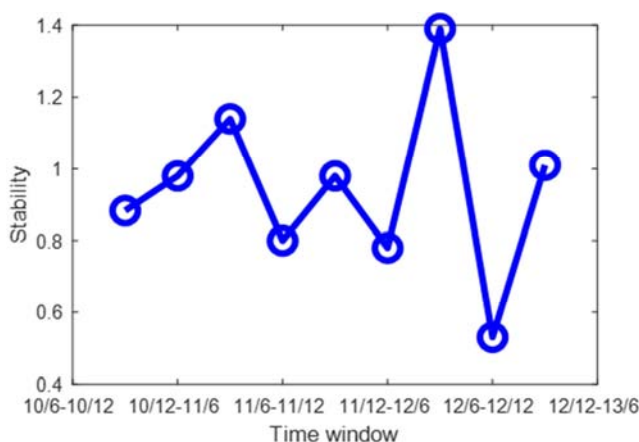


Figure 9. Dynamic change of network structure with evolution of time.

The dynamic similarity between TNs with the nearest year is shown in figure 9. The similarity value switches back and forth within the range between -0.2 to 0.1 with the evolution of time. The threshold network of the first half of 2010 is almost similar with the network of the last half of 2010 and the value of similarity is near to 0 which implies that market is similar state as it was before. The similarity index is going to positive direction after the last half of 2010. The higher positive value of similarity index between two TNs of 2011 implies that market is under crisis in the last half of 2011. After that, market temporarily stabilizes in the beginning half of 2012. The network structure between two periods of 2012 is almost similar. The similarity index between two threshold network of the first half of 2012 and the first half of 2013 carry highest negative value which implies that network is dissimilar but stable. Being temporarily stable in the first half of 2013, the significant change of the network structure is observed in the last half of 2013 due to Cypriot crisis. Again, the network structure is changed remarkably in the beginning half of 2014 where the similarity value is much less than 1. It infers that world financial and commodity market is under calm state in the last half of 2014. In the last half of 2014, although market is entered turbulent state due to Russian crisis but network structure is almost similar.

The significant change of network structure is found

during last half of 2011 and first half of 2012 and last half of 2012 and first half of 2013. Before the crisis, rapid variation has been observed in network.

This similarity index can be used as an “early warning system” for financial markets. By providing a simple instrument to identify similarities to previous states during an upcoming crisis, one can judge the current situation properly and be prepared to react if the crisis materializes. Certainly, an indication for a crisis is also given when the network structure undergoes rapid changes.

5. Conclusion

The structure of world commodity and financial networks are investigated around sovereign debt crisis using threshold technique. The dynamic change of topological properties in threshold networks are observed at threshold 0.1 over time. The trend of inter-links between two groups with evolution of time is unlike with the trend of inter-degrees between subgroups of commodities with stock indices. During Cypriot crisis, financial indices are more strongly connected than commodity futures. After sovereign debt crisis, the big transition of the market graph is found at the beginning half of 2013. We assign this period as a stable state of the world market. The clusters of similar group are identified with the increase of threshold. Two groups are separated from network at threshold 0.7 and 0.6 during and after crisis respectively. The dynamic of clustering coefficient identify the indices which are more reactive to crises. The dynamic change of the network structure is measured by our proposed method. The change of the network structure can be used as an early warning of upcoming crisis.

Acknowledgements

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Appendix

World Stock Indices and Commodity Futures:

23 world stock indices name:

France (CAC40), Germany (GDAXI), the United Kingdom (FTSE100), Switzerland (SSMI), Netherland (AEX), Belgium (BEL20), Austria (ATX), Sweden (OMX), and Newzland (NZ500). In the Asian and Australian economic zone we include 13 countries: Japan (N225), South Korea (KOSPI), Singapore (STI), Hong Kong (HS), Indonesia (JKSE), Taiwan (TWSE), Malaysia (KLSE), India (BSESN), and Australia (AORD). The number of countries in American economic zone is five, including the United States (SP500), Canada (GSPTSE), Mexico (MXX), Argentina (MERVAL), and Brazil (BVSP).

23 commodity futures (sector wise):

Agriculture:

Live cattle future, London cocoa future, London coffee future, London sugar future, London wheat future, Rough

Rice future, US Cocoa future, US Coffee future, US Corn future, US Cotton2 future, US Soybean future, US Sugar11 future

Metal:

Copper future, Gold future, Silver future, Palladium future, Platinum future,

Energy:

Brent Oil futures, Crude oil future, Heating oil future, London gas oil future, Natural gas future, EU CO₂ emission,

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