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NETWORK ANALYSIS OF INTERBANK CROSS-BORDER FLOWS AT COUNTRY LEVEL (2006 - 2015)

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ABSTRACT

In today's globalized world, economic activities are performed beyond the physical boundaries of countries. It can be seen as increasing activities such as trade of goods, financial flows and trade of intermediate goods. Network analysis, that has been used to analyze formations of complex systems recently, is frequently used to investigate these global economic relations. In this context, international trade networks, financial networks and global production networks (input-output networks) are some of the fields that are analyzed in an interdisciplinary way. In this study, it is aimed to analyze interbank cross-border flows at country-level by applying network analysis. Thus, we expect to investigate the systemic importance and vulnerabilities of countries in international banking sector by applying HITs algorithm from 2006 to 2015. HITs algorithm has an advantage since it takes second order adjacencies of countries into consideration. As a consequence of the analysis, it will be possible to see the effects of global and Eurozone crises on systemic importance and vulnerabilities of countries.

Keywords: Financial crises, international financial network, network analysis, international financial markets, interbank flows
JEL Codes: G00, G01, G15

1. INTRODUCTION

Network analysis has become a very popular and efficient tool to analyze complex systems in various disciplines ranging from natural science to social sciences. Economics has also become one of these disciplines that uses network tools as a result of interaction with other disciplines such as computer sciences, physics, biology, psychology etc. Fields of economics in which network tools are used mostly are international trade and finance. As a new field, global value chain also uses network analysis to analyze global production network.

There exist various definitions of complex system. According to Simon's definition, a complex system is composed of a great number of parts that have interactions with one another in a non-simple way. Properties of these parts and interactions among them cause the system be more than its parts. This feature of complex systems reveals a phenomenon which is known as the 'fallacy of composition'. An example of this phenomenon has been observed during the global crisis. Systemic risk assessment based on micro-prudential approach which depends on whether financial institutions have sufficient capital and risk assessment was criticized due to ignoring interconnectedness of these financial agents. In this case, individual success of financial institutions in risk assessment could not prevent the failure of the system as a whole. It means that individual success of financial institutions in providing an effective risk management does not guarantee the success of financial system as a whole.

After the crisis, another criticism was directed to the current market price-based volatility assessment. As is known, it is expected for stock returns to be high due to increasing risk in economic downturn whereas it is expected to be low due to decreasing risk in economic recovery term. However, Markose (2013) states that market price-based volatility was at its lowest level just before the outbreak of the crisis in 2008. This is called paradox of volatility. The author draws attention to the popularity of market price-based volatility assessment due to data availability, but also to the shortcomings of this method to study balance sheet interconnections for systemic risk.

Network approach, as one of the best ways to analyze these interconnections, has many application in the field of finance. Studies which use network analysis to analyze financial systems follow two distinct empirical methodologies. One of them is simulations and the other is topological research of financial networks. It has also been stated in a study by Bandt et al. (2013) that network analysis is a tool to measure systemic risk in terms of interconnectedness and that it depends on two methods such as a descriptive approach to network topology and an analysis of contagion mechanism. This descriptive approach presents some network metrics that help to understand network structure without modelling economic behaviour whereas contagion analysis helps to understand how failure of a financial agent spreads through the system via simulations.

Even though these methodologies are completely different aspects of network analysis, they work for an objective in common: to determine and analyze the systemicity in the network. Alves et al. (2013) explains sistematicity as a two-dimensional concept. On the one hand, a financial agent can be systemically important in the meaning of causing substantial system-wide losses. On the other hand, a financial agent can be systemically fragile to the defaults of other agents. Network analysis enables us to analyze these two different aspects of systemicity.

2. LITERATURE REVIEW

There are a large number of studies on financial networks includes either topological anaysis or contagion analysis in the literature. In one of the most pioneer studies on financial networks, Allen and Gale (2000) analyzed contagion in an interbank network. They reveals that if the interbank market has a complete network structure, then the initial impact of a financial crisis in one bank may be weakened. However, if the network is incomplete and each bank is connected with a small number of other banks, then neighboring banks feel the initial impact of a crisis much more than the previous case.

Krause and Giansante (2012) modelled an interbank network which consists of banks of different sizes and with heterogeneous balance sheets and analyzed how exogeneous failure of a single bank spreads through the system. They found that spread of a failure of a bank depends on the interconnectedness of the nodes and the tiering in the network.

Battiston and Caldarelli analyzed the role of linkages between nodes in terms of contagion and liquidity in financial network. They revealed that it was necessary to look at the interplay of network topology, liqiudity and capital buffers in order to get idea about default cascades. They also analyzed DebtRank developed by the author as a measure of systemic impact of a financial institution. Depending on DebtRank, they found that there was more to systemic risk than size and position of financial institution in the network. Balance sheets of counterparties of an institution were also important to determine the impact of failure of that institution.

Acemoglu et al. (2015) established a theoritical framework for the economic forces that shape the relationship between the financial network structure and systemic risk. They revealed that as long as the magnitude or the number of negative shocks is below a threshold, more diversified structure of interbank liabilities leads to less fragility. It means that the sparsely connected network is the most fragile whereas the complete network is less fragile. In this context, these findings confirm the analysis by Allen and Gale (2000). However, if negative shocks are larger than a threshold, then completeness does not guarantee stability in terms of efficient use of the excess liquidity.

Markose et al. (2010) analyzed US banks involved in the CDS market for 2007-Q4 and 2008-Q4. This CDS network was composed of obligations between US banks and aggregated non-US sectors. According to eigenvector centrality results, JP Morgan was found to be the most dominant bank in the network. It was folowed closely by the European Banks and then by other US banks such as Goldman Sachs and Citibank. At the end of the eigen-pair analysis, the authors recommended that banks be taxed by a progressive tax rate depending on eigenvector centralities and escrow these funds.

Hub and authority centrality measures have become popular in financial network analysis recently. There are a number of analysis which use these metrics as centrality measures. In one of them, Leon and Perez (2013) analyzed Colombian financial market infrastructure of which functions are composed of trading and registration, clearing and settlement, large-value payment systems and retail payment systems. They build a weighted matrix of which components correspond to daily average gross value of transactions for 2011 within financial market structure mentioned above. The authors conclude that their findings on centralities are intuitive and that these measures also match functioning of local markets's conveniently.

In another study follows hub and authority centrality measures, Leon et al. (2015) analyzed allocation of central bank liquidity within interbank market for Colombia with network tools. Their network consists of two types of transactions that are interbank funds and central bank repos as monetary value and the data base on 2013. They detected the most central nodes (super-spreaders) that might be an important conduit for the transmission mechanism of the monetary policy of central bank in Colombia.

In another study, Leon and Berndsen (2014) used hub and authority centralities in the analysis of Colombian financial system by selecting three financial market structures such as the large payment system, the sovereign securities settlement system and the foreign exchange settlement system for 2012.

Chinazzi et al. (2012) also used hub and authority centralities in their analysis on international financial market as a wighted-directed network on country basis. They analyzed international financial network as five layers (total portfolio investments, equity securities, debt securities, long-term debt securities and short-term debt securities) for 70 countries from 2001 to 2010. The components of these adjacency matrices represented value of security from borrower (debtor) to lender (creditor). They computed hub and authority scores for both binary and weighted cases.

3. DATA AND METHODOLOGY

We aim to analyze international financial network on country basis in a similar way with Chinazzi et al. to see how topological statistics (e.g. clustering coefficient, power-law index, centralities…) capture outbreak of crisis and whether they display distinction between pre-crisis and post-crisis periods. As is seen in the literature review, centrality of financial institutions (countries herein) is also a significant point regarding to propagation of a default.

Markose based her financial network analysis on eigen-pair analysis (Markose, 2012). In both of these analysis, right and left eigenvector centralities which correspond to maximum eigenvalue of the network are identified as systemicity measure. In this context, the author defines right eigenvector centrality as systemic risk index and left eigenvector centrality as systemic fragility index.

The data used in this analysis have been obtained from Bank of International Statement (BIS) database. These data include consolidated foreign claims vis a vis individual countries by nationality of reporting basis. The values are in millions of US dollars and include the period from 2006:q1 to 2015:q1 for 18 countries (Australia, Austria, Belgium, France, Germany, Greece, India, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States). Size of the network is limited due to data availability.

Each component of weighted adjacency matrix X that is built depending on BIS database corresponds to liability from borrower to lender which means that x_{ij} represents gross financial obligation flow from country i to country j. Following Markose et al. (2012), we applied the methodology to M matrix of which elements $(x_{ij} - x_{ji})$ give the netted position between country i and country j. Skew symetrical matrix which is defined as a square matrix that fulfils $m_{ji} = -m_{ij}$ for all possible i and j is presented below for $M = X - X'$ as a 4x4 dimensional matrix.

$$M = \begin{bmatrix} 0 & x_{12}-x_{21} & x_{13}-x_{31} & x_{14}-x_{41} \\ x_{21}-x_{12} & 0 & x_{23}-x_{32} & x_{24}-x_{42} \\ x_{31}-x_{13} & x_{32}-x_{23} & 0 & x_{34}-x_{43} \\ x_{41}-x_{14} & x_{42}-x_{24} & x_{43}-x_{34} & 0 \end{bmatrix}$$

Sum of positive row values of country i represents its net liabilities to counterparties. Following Markose et al. (2012), we obtained M matrix that contains only positive elements and zero for negative values and used this matrix in our calculations.

Before presenting results, it is good to clarify that hub and authority centralities correspond to right and left centralities of eigen-pair analysis of Markose (IMF), respectively. Based on M matrix of which elements represent netted liabilities from one country to another, hub centrality score implies how central a borrower country is since a hub is a node with a large number of outgoing links. If hub centrality score of a country is high, then this country is systemically important which means that failure spreads to the network in case of the country not meeting the liabilities. In a similar way, it can be said that an authority centrality implies how central a lender is since an authority is a node with a large number of incoming links. Thus, if authority centrality score of a country is high, this country is said to be systemically fragile/vulnerable meaning that the country is exposed to default risk of its debtors.

Before discussing results, it will be useful to give some technical information about networks and the methodology used in the analysis.

As stated by Reichardt, the first step to understand complex systems is decomposition of these systems into their parts (Reichardt, 2009). Network analysis allows us to represent complex systems in terms of their parts and interactions/linkages among them. In this context, policymakers have become interested in network analysis to determine the weaknesses of their concerns since these tools are applied to most real-world networks (OECD, 2009).

A network is defined as G=(V, E, f), where V is a finite set of nodes and E is a set of links among these nodes and, f is a mapping which links elements of E to a pair of elements of V. In a weighted network, each link is given a distinct weight and the definition of network becomes G=(V, W, f), where W represents the set of weights W={w_1, w_2, …, w_m}. If two nodes (node i and j) are linked to each other with the link e={i,j} in a network, then these nodes are said to be adjacent. Networks are represented with adjacency matrices which are built as follows (Estrada, 2015):

$$A_{ij} = \begin{cases} 1 & if\ i,j\ \in E \\ 0 & otherwise \end{cases}$$

One of the extents which are analyzed to get information about the topological properties of a network is connectivity. Connectivity is measured by node degree/node strength on the node-level. Higher node degree/strength means stronger impact over the network (Howell, 2012). On the network level, connectivity is measured by density which is a ratio of actual count of links to possible maximum count of links. In a directed network without self-loop and multilink, density coefficient can be formulized as follows (Newman, 2010):

$$\rho = \frac{m}{n(n-1)}$$

in where m is the count of actual links. Density coefficient lies in the range of $0 \leq \rho \leq 1$.

Another extent to be analyzed is clustering refers to the relation between two nodes which have links with a node in common. Clustering is also an indicator of transitivity in a network. Clustering coefficient can also be measured both in the node-level and in the network-level. Clustering coefficient was first introduced for node i in a simple network as follows (Serrano and Boguna, 2006):

$$c_i = \frac{2T_i}{k_i\ (k_i - 1)}$$

where T_i represents the count of triangles passing through the node i. Clustering coefficient in the network-level which is denoted as C is obtained by averaging c_i values. Clustering coefficients both in the node-level and in the network-level lie in the interval [0,1].

Degree disribution is another informative property about network topology. It has been indicated in the literature that most real-world networks such as movie network, www, electrical powergrid network and citation network follow power-law distribution (Barabasi and Albert). These networks which follow power-law distribution are called as scale-free networks in network literature. Scale free networks have some characteristics which distinguish them from random and small-world networks (Mitchell, 2009). First of all, they include small number of hubs which are nodes with high-degree. They also include heterogeneity of connectivity since node degrees/strengths lie on a wide scale. Another property of scale-free networks is self-similarity which means that the shape obtained will look like the previous even though we rescale and reshape the distribution by focusing on a smaller part. Finally, scale-free networks have small-world property which requires small average path length and high degree of clustering.

It is known that power-law distributions belong to the class of fat-tailed distributions which have higher peaks and fat tails compared to Poisson distribution. Power-law distribution can be shown as follows (Hein et al., 2006):

$$P(k) \approx k^{-\gamma}$$

In the statement above, P(k) shows the probability of the occurence of nodes with degree k in the network. γ has a characteristic importance for this distribution. It means that a lower value of γ leads to a higher probability of nodes with many links. In another words, a network with a lower value of γ has a higher quantity of super-nodes which have many links compared to a network with a higher value of γ. It can also be interpreted as such that higher exponent level implies less heterogeneity of connectedness (Leon and Berndsen, 2014).

One way to determine fat-tailed distributions is to look at the kurtosis. If the kurtosis has positive value, then the distribution follows fat-tail distribution (Decarlo, 1997). It is also stated that most reald world networks display right-skewed distributions and these distributions approximate power-law distribution (Leon Rincon et al., 2015). Skewness measure gives information about distributional asymmetry and is used to determine which side of a distribution has a fat-tail. If the skewness measure has positive value, then the fat-tail is on the right and the distribution is right-skewed and vice versa (Lovric, 2010).

In financial networks, power-law distribution refers to such an interpretation that most of the agents have low financial linkages while a few agents high financial linkages. It is an evidence for heterogeneity of connectedness of agents.

Centrality is another important topological property of a network. However, it is more convinient to examine assortativity/disassortativity in order to perceive the importance of centrality. Assortativity means that the nodes with high degree/strength tend to have links with the nodes which have high degree/strength. However, the nodes with high degree/strength tend to have relations with the nodes with low degree/strength in disassortative case (Reichardt, 2009). There are two ways to determine assortative/disassortative structure in a network. One of them is to plot degree and ANND statistics on the same graph and to see the relationship between them. ANND is a statistic shows how connected neighbors of node i are with one another (Fagiolo et al.,2010). It is measured as the average degree of neighbors of i. It can be formulized as follows (Barrat et al., 2004):

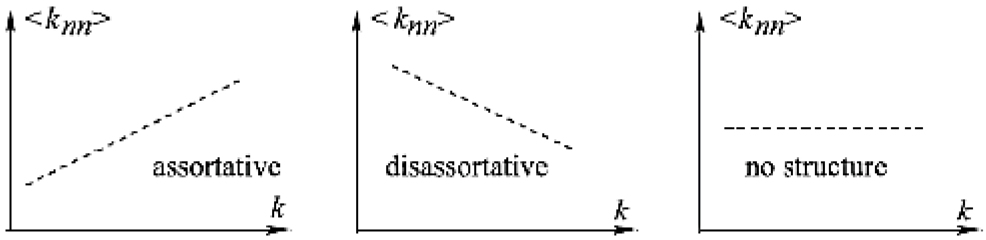
$$< k_{nn,i} >= \frac{1}{k_i} \sum_j k_j$$

ANND for the nodes which have degree k is calculated with the formula below:

$$< k_{nn}(k) >= \frac{1}{N_k} \sum_{\frac{i}{k_i}=k} k_{nn,i}$$

It is possible to decide whether there is a disassortative structure in a network. If the relation between the degree and the ANND is positive, then it is thought there is an assortative structure in the network. On the contrary, if the relation between the degree and the ANND is negative, then there is a disassortative structure in the network.

Figure 1: Assortative / Disassortative Structure



Source: Caldarelli.

The other way of determination of assortative/disassortative structure is to calculate assortativity correlation coefficient. Newman defines assortativity coefficient by adjusting standart Pearson correlation coefficient as follows (Newman; Csardi):

$$r = \frac{\sum_{ij} ij(e_{ij} - a_i b_j)}{\sigma_a \sigma_b}$$

where $a_i = \sum_j e_{ij}$ and $b_j = \sum_i e_{ij}$ are fraction of edges start and end at node i and node j, respectively. And σ_a and σ_b are the standart deviations of the distributions of a_i and b_j. This assortativity measure lies in the interal [-1,1]. If r = 1, then there is perfect assortativity between i and j. If r = -1, then there is perfect disassortativity between the nodes.

Disassortativity is one of the reasons of core-periphery structure in a network (Fuge et al.). Centrality measure enables one to determine the nodes in the core and the periphery. Besides, it can be said that centrality measures enable one to determine sistemicity of an agent in financial networks since dimensions of systemic importance are defined as size, interconnectedness and substitutability each of which are related to centrality concept (Alves et al., 2013). There are a lot of centrality measures such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality etc. to measure the importance of the nodes in a network.

Eigenvector centrality is the one which is most commonly used to determine significance of the nodes in a network. The logic behind the eigenvector centrality is to decompose the adjacency matrix and to find the most explanatory vector to represent it. Let A be an adjacency matrix, Λ be a diagonal matrix consist of eigenvalues of A and Γ an orthogonal matrix whose columns correspond to eigenvectors of A. Then, the equity below holds:

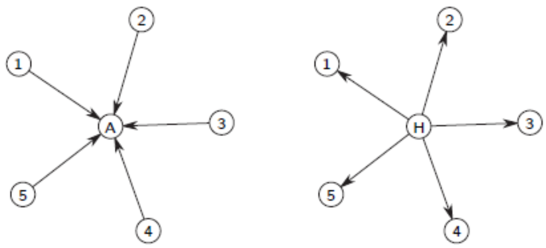
$$A = \Gamma \Lambda \Gamma'$$

If the eigenvalues are ordered from bigger to smaller such as $\lambda_1 \geq \lambda_2 \dots \lambda_n$, then the first column of Γ is the principal eigenvector of the adjacency matrix A. This eigenvector whose elements can be considered as weights of each node is accepted as the leading vector of the system. In network analysis, elements of the principal eigenvector correspond to eigenvector centrality of the nodes in the graph (Leon Rincon et al., 2015).

Eigenvector centrality is one of the centrality measures commonly used. However, it has some drawbacks. First of all, it is more convinient to use eigenvector centrality for undirected networks of which adjacency matrices are symetrical despite it is used for directed networks in the literature. In a directed network case, network has two sets of eigenvectors which are right eigenvector and left eigenvector. Thus it may cause an issue to decide on which eigenvector centrality to use. Even this problem is overcome, there is another issue for eigenvector centrality of directed networks. If there is a node with only outgoing links and no incoming links, then this node will have zero centrality. It will cause also other nodes with only one incoming link which originates at that node to have zero centrality. In this meaning, it will cause some information loss (Newman, 2010). In this context, hub and authority centralities that are derived from HITS algorithm can be thought as an alternative to eigenvector centrality.

HITS algorithm was developed by Kleinberg to calculate hub and authority centralities of web pages which are results of a specific query on the Internet. Kleinberg based his analysis on a directed network in his original study. As is known, there are two types of link in directed networks: in-links and out-links. In this context, hubs are nodes with myriad out-links and authorities are nodes with myriad in-links.

Figure 2: Hub and Authority



(a) Authority (b) Hub

Source: Knorn, 2005.

Kleinberg aimed to calculate two different centrality measure for these distinct type of nodes. Kleinberg remarked that these authoritative pages which are related to initial query should not only have large in-links. It is also necessary to be an overlap in the sets of pages which point to these authoritative pages. Similarly, hub pages should have links to multiple relevant authoritative pages. These two different classes of nodes exhibit *mutually reinforcing relationship* means that a good hub is a node that points to many good authorities and a good authority is a node that is pointed to by many good hubs. Kleinberg used an algorithm, HITS algorithm, uses an iterative process that maintains and updates two weghts for each page. In this context, each web page has two non-negative weights: an authority weight $x^{<p>}$ and a hub weight $y^{<p>}$. And there are two operations ($\mathcal{I}$ *and* $\mathcal{O}$) that update these weights. $\mathcal{I}$ updates the x weights and $\mathcal{O}$ updates the y weights during the iterations. Kleinberg also expressed this mutually reinforcing relationship between hubs and authorities with equations as follows (Kleinberg, 1999):

$$x^{<p>} \leftarrow \sum_{q:(q,p)\in E} y^{<p>}$$

$$y^{<p>} \leftarrow \sum_{q:(p,q)\in E} x^{<q>}$$

As it is understood from the equations above, authority weight of a node is proportional to the hub weights of the nodes point to it. Similarly, hub weight of a node is proportional to the authority weights of the nodes it points to.

First of all, Kleinberg defined a vector y which elements consist of $y^{<p>}$ values and a vector x which elements consist of $x^{<p>}$. Assuming that G=(V,E) with V={p_1, p_2, …, p_n} and A is adjacency matrix of graph G, he proved that y and x converge to their equilibrium values y* and x* (which are hub centrality and authority centrality, respectively) at the end of this iteration process. He concluded that x* (authority centrality vector) is the principal eigenvector of $A^T A$ and y* (hub centrality vector) is the principal eigenvector of AA^T (Kleinberg, 1999).

Kleinberg's algorithm uses the way which is used to calculate eigenvector centrality. However it eliminates zero-centrality problem of eigen-pair analysis by calculating hub and authority centralities of nodes simultaneously and iteratively depending on that mutually reinforcing relationship. Leon and Perez summarized this iterative process as the estimation of eigenvector centrality of two modified versions of adjacency matrix (Leon and Perez, 2013). On this basis, $M_{hub} = AA^T$ and $M_{auth} = A^T A$ can be called as hub matrix and authority matrix of which eigenvector centralities refer to hub centrality and authority centrality, respectively (Kolaczyk, 2009).

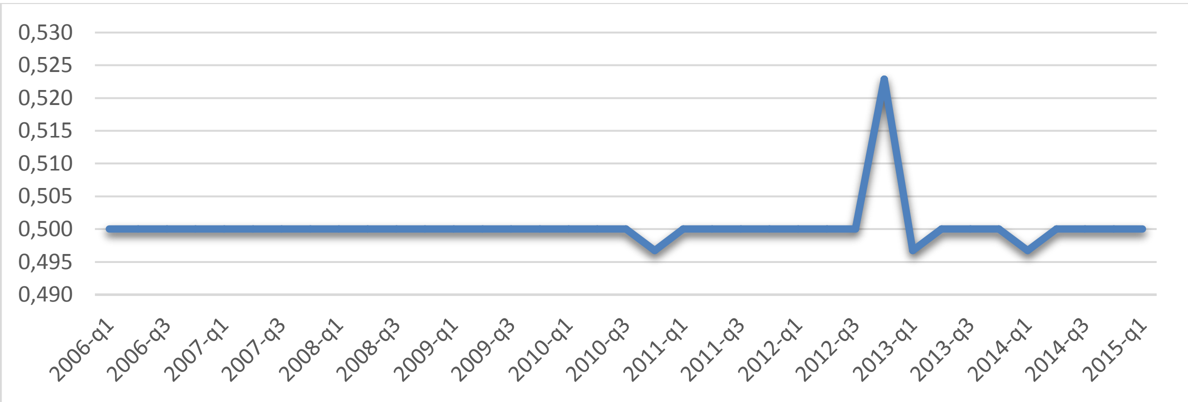
Leon and Perez explains the logic behin these hub and authority matrices like that (Leon and Perez, 2013). Multiplication of a directed (non-symetrical) adjacency matrix with transpose of itself enables one to identify second-order adjacencies. Clearly, in the case of M_{auth}, multiplication of A^T with A sends weights backwards towards the pointing node. However, multiplication of A with A^T sends weights forwards towards to the pointed node. Since M_{hub} and M_{auth} are symetrical matrices with non-negative elements, hub and authority centrality vectors will also contain positive and non-zero scores.

Although eigenvector centrality and hub-authority centrality measures have the same content that importance of a node in the network depends on how important its neighbors are, hub and authority centralities have some advantages compared to eigenvector centrality (Leon Rincon et al., 2015). First of all, it avoids the problems arise from directed (non-symetrical) networks as mentioned above. It also gives two distinct centrality scores for each node as hub score and authority score which correspond to eigenvector centrality as recipient and as originator of links. This eliminates the confusion arises from the selection of right and left eigenvector centralities. Since hub and authority centralities are calculated as proportional to each other, it is possible to capture the in-between role of the nodes to their scores.

4. FINDINGS AND DISCUSSIONS

As explained in methodological part, density is a network statistic between 0 and 1 that indicates tha ratio of number of actual links over number of all possible links. Figure 3 shows density coefficient over the period.

Figure 3: Density Coefficient



The coefficients does not capture the fluctuations in cross-border flows in banking sector much since the formula of coefficient only depends on the number (not weight) of the links. It is almost around 50% since the matrices used in the analysis contain only positive elements of netted skew-symetric matrices. According to the results, there is a small decline in the beginning of the Eurozone crisis and in the first quarter of 2014, and also a small increase in the fourth quarter of 2012. However, if this coefficient were based on weights, it would be more informative about cross-border financial relationships.

Figure 4: Clustering Coefficient

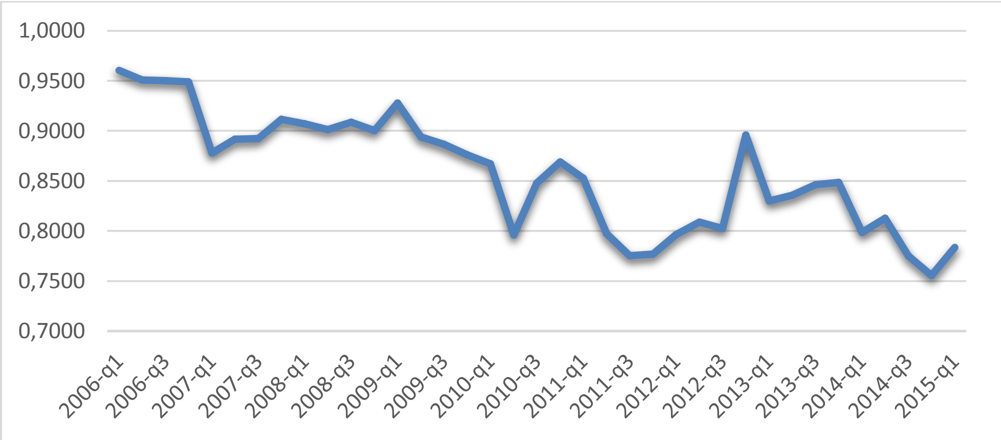
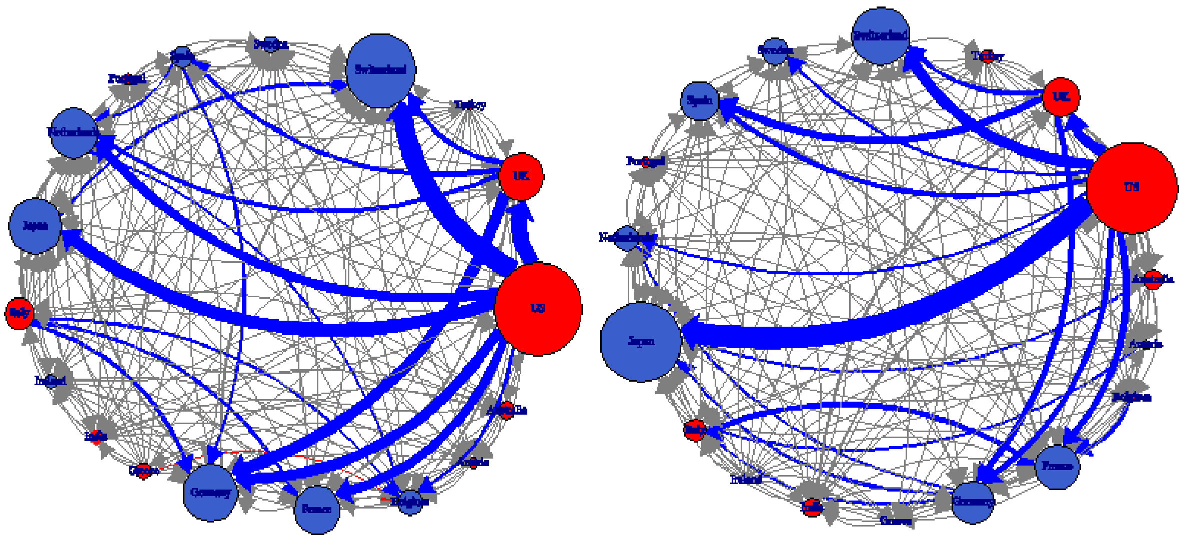


Figure 4 presents the trend of clustering coefficient within the period of analysis. General view indicates a decreasing trend within the period however there are rises and falls for some quarters. Clustering, as an indicator of transitivity, also gives an idea about the connectivity since a decrease of transitivity also implies a decrease of connections between node pairs. The first decline in clustering is in 2007 when negative effects of US mortgage crisis started. Second severe decline of clustering is at the second quarter of 2010 which corresponds to the beginning of Eurozone crisis. This decline indicates how countries' loss of credibility affects financial linkages among them. After an increase, clustering coefficient has another decline at the end of the 2011 that corresponds to the term when crisis spreads other Eurozone countries and four banks in Greece have negative equity. After another recovery period from forth quarter of 2011 to forth quarter of 2012, there is a gradually decline and another bottom at the end of the 2014 which corresponds to the outbreak of Greek crisis again. Clustering coefficient declines from almost 0.95 to 0.75 within the period.

Figure 5: Network Visualization



2006:q1 2015:q1

It can also be observed in the networks visualizations in Figure 5 that cross-border banking linkages among countries weaken from 2006:q1 to 2015:q2. In this graphs, red-colored countries are net borrower countries and blue-colored countries are net Lenders in the international banking system. The size of net borrowers and net lenders depends on hub and authority centralities that is mentioned above, respectively.

As explained above, degree distribution is one of the important characteristics of networks. Table 1 shows kurtosis and skewness values that give an idea about the distribution for out-strength. Positive and high values of kurtosis and skewness implies that the out-strength distribution has fat-tailed and right-skewed charasteristic.

Table 1: Kurtosis and Skewness Values

Year	Skewness	Kurtosis	Year	Skewness	Kurtosis	Year	Skewness	Kurtosis
2006-q1	3.28	12.75	2009-q2	3.1	11.95	2012-q3	3.39	13.55
2006-q2	3.2	12.31	2009-q3	2.87	10.82	2012-q4	3.14	12.29
2006-q3	3.34	13.13	2009-q4	2.86	10.77	2013-q1	3.33	13.23
2006-q4	3.36	13.24	2010-q1	3.04	11.77	2013-q2	3.4	13.61
2007-q1	3.33	13.03	2010-q2	3.2	12.48	2013-q3	3.41	13.61
2007-q2	3.29	12.8	2010-q3	3.29	13.03	2013-q4	3.34	13.23
2007-q3	3.34	13.1	2010-q4	3.37	13.42	2014-q1	2.3	7.83
2007-q4	3.25	12.61	2011-q1	3.35	13.29	2014-q2	3.28	12.89
2008-q1	3.28	12.84	2011-q2	3.37	13.39	2014-q3	3.35	13.21
2008-q2	3.25	12.63	2011-q3	3.4	13.52	2014-q4	3.39	13.42
2008-q3	3.37	13.34	2011-q4	3.46	13.85	2015-q1	3.3	12.9
2008-q4	3.43	13.7	2012-q1	3.46	13.91			
2009-q1	3.23	12.64	2012-q2	3.46	13.92			

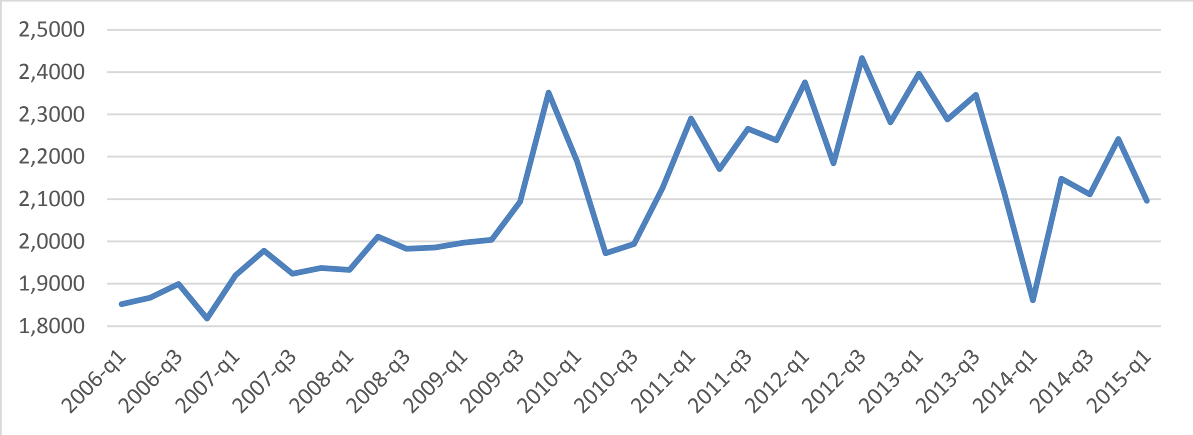
However, it is necessary to make sure statistically about that whether the data fit power-law distribution. In this frame, the results of Kolmogorov-Smirnov test for fitness to power-law is given below:

Table 2: Kolmogorov-Smirnov Test Results

Year	γ	KS statistics	p-value	Year	γ	KS statistics	p-value
2006-q1	1.85217	0.09197	0.99996	2010-q4	2.12657	0.10302	0.99999
2006-q2	1.8671	0.09127	0.99997	2011-q1	2.29044	0.11553	0.99998
2006-q3	1.89957	0.10452	0.99943	2011-q2	2.17095	0.09399	0.99999
2006-q4	1.81773	0.08467	0.99999	2011-q3	2.26632	0.1321	0.99903
2007-q1	1.91999	0.08003	0.99999	2011-q4	2.23879	0.15652	0.99545
2007-q2	1.97806	0.09537	0.99956	2012-q1	2.37575	0.10827	0.99998
2007-q3	1.92373	0.07186	0.99999	2012-q2	2.18474	0.11345	0.99999
2007-q4	1.93725	0.07657	0.99999	2012-q3	2.43322	0.07916	0.99999
2008-q1	1.93245	0.08325	0.99999	2012-q4	2.28102	0.11542	0.99856
2008-q2	2.01169	0.10381	0.999	2013-q1	2.39642	0.08336	0.99999
2008-q3	1.98276	0.07024	0.99999	2013-q2	2.28799	0.08951	0.99999
2008-q4	1.98543	0.08205	0.99999	2013-q3	2.3464	0.08247	0.99999
2009-q1	1.99693	0.11348	0.99782	2013-q4	2.11331	0.10778	0.99982
2009-q2	2.00365	0.09561	0.9999	2014-q1	1.86104	0.13503	0.98093
2009-q3	2.09345	0.11799	0.99988	2014-q2	2.14833	0.10103	0.99996
2009-q4	2.35143	0.12862	0.99997	2014-q3	2.11088	0.09984	0.99976
2010-q1	2.18917	0.09578	0.99999	2014-q4	2.24196	0.10725	0.99984
2010-q2	1.97217	0.10466	0.99795	2015-q1	2.09619	0.12133	0.99938
2010-q3	1.99369	0.13342	0.95223				

p-probability values that are higher than 0.05 indicate that we cannot reject the null hypothesis states that the distribution follows a power-law. Power-law distribution means that there are some countries with high outgoing financial links (liabilities) while there are a lot of countries with low outgoing financial links (liabilities). In this context, power-law distribution implies a heterogeneous structure in terms of connectivity which means that some countries are more/less connected than other countries.

Figure 6: Power-law exponent - γ



Exponent γ can be also an informative indicator about the change of connectedness property of the network. As explained above, higher γ values imply less heterogeneity of connectedness while lower γ values imply more heterogeneity of connectedness in the network. Since KS test results depends on out-strength, change of exponent γ represents the change of heterogeneity of countries' indebtedness in the international banking system. In Figure 6, there are two severe declines within the period. The first term corresponds to the outbreak of Eurozone crisis. It can be seen how credibility of countries in crisis is damaged. After that there is an out-flow from the banking system of these countries to other countries since their systemic risk increases. Finally, this situation causes them to have diffuculty in borrowing. Decrease of borrowing of these systemically important countries due to outflow of money from their banking system and increase of indebtedness of other less systemically important countries due to movement of this outflow cause connectedness to become more inhomogeneous over/throughout the network.

The second decline of power-law exponent is from 2013:q3 to 2014:q1. This term includes the effects of explanations of FED about indicators of economic recovery and possibility of ending expansionary policies and asset purchases. These explanations cause a panic and upset the global financial balances especially for developing economies.

Assortative/disassortative structure is another important characteristics of complex networks. The results for assortativity correlation coefficient based on out-strength are given in Table 3.

Table 3: Assortativity Correlation Coefficient

Year	Assortativity Correlation Coefficient	Year	Assortativity Correlation Coefficient	Year	Assortativity Correlation Coefficient
2006-q1	-0.03611	2009-q2	-0.03147	2012-q3	-0.04711
2006-q2	-0.04155	2009-q3	-0.02522	2012-q4	-0.04677
2006-q3	-0.04132	2009-q4	-0.03179	2013-q1	-0.05748
2006-q4	-0.03578	2010-q1	-0.03656	2013-q2	-0.05335
2007-q1	-0.03972	2010-q2	-0.04155	2013-q3	-0.05541
2007-q2	-0.03618	2010-q3	-0.04055	2013-q4	-0.0491
2007-q3	-0.03772	2010-q4	-0.03896	2014-q1	-0.05498
2007-q4	-0.03343	2011-q1	-0.04958	2014-q2	-0.05793
2008-q1	-0.03545	2011-q2	-0.05486	2014-q3	-0.05842
2008-q2	-0.03515	2011-q3	-0.05075	2014-q4	-0.05449
2008-q3	-0.03552	2011-q4	-0.05311	2015-q1	-0.05137
2008-q4	-0.03262	2012-q1	-0.05109		
2009-q1	-0.0253	2012-q2	-0.05347		

In spite of not being high enough to imply 'perfect disassortativity', the negative assortativity correlation coefficients imply that there is a disassortative structure in the network. In other words, the countries with low financial linkages tend to be in relation with the countries that have high financial linkages.

As mentioned in methodological part, lack of assortativity is one of the indicators of core-periphery structure which involves some central nodes (hubs) and a periphery around these hubs. The way of determination of these hubs is to investigate centrality scores of the nodes.

As mentioned before, hub and authority centralities capture more information about systemic risk and vulnerability of countries in international financial network since they take second-order adjacencies into consideration. In this frame, it may be enlightening to compare first –degree and second-degree indicators of this global financial markets. Comparison of share of liabilities in total as a first-degree indicator and hub centralities as a second-degree indicator of systemic importance can be seen in the Table 4.

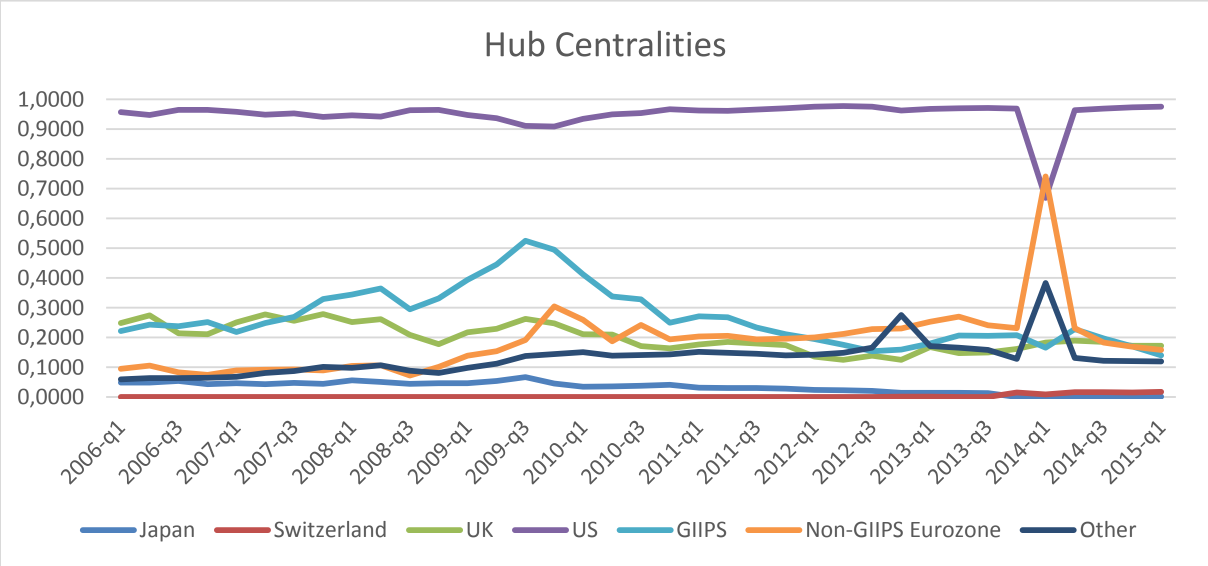
Table 4: Comparison of hub and authority scores with first-degree indicators (2008:q2)

Ranking	Countries	Hub centrality	Countries	Share of liabilities in total (%)	Countries	Authority centrality	Countries	Share of receivables in total (%)
1	US	0.942	US	0.461	Switzerland	0.496	Germany	0.181
2	UK	0.262	UK	0.159	UK	0.457	France	0.179
3	Italy	0.128	Italy	0.069	Germany	0.420	Switzerland	0.158
4	Spain	0.095	Spain	0.051	France	0.407	Japan	0.107
5	Ireland	0.066	Germany	0.044	Japan	0.361	UK	0.106
6	Australia	0.063	Ireland	0.036	Netherlands	0.227	Netherlands	0.087
7	Germany	0.055	Australia	0.035	Belgium	0.114	Belgium	0.074
8	Greece	0.051	Greece	0.027	Spain	0.067	Spain	0.034
9	Japan	0.051	Japan	0.021	Ireland	0.050	Italy	0.028
10	India	0.025	Austria	0.020	Sweden	0.022	Ireland	0.020
11	Portugal	0.023	Netherlands	0.018	Italy	0.015	Sweden	0.011
12	Netherlands	0.020	Portugal	0.016	Austria	0.012	US	0.006
13	Austria	0.020	India	0.016	Portugal	0.004	Austria	0.006
14	Turkey	0.014	Turkey	0.012	US	0.001	Greece	0.002
15	France	0.008	France	0.009	Greece	0.000	Portugal	0.002
16	Sweden	0.005	Sweden	0.002	Australia	0.000	Australia	0.000
17	Belgium	0.004	Belgium	0.002	Turkey	0.000	Turkey	0.000
18	Switzerland	0.000	Switzerland	0.000	India	0.000	India	0.000

Values in Table 4 belong to the term 2008:q2 that is just before the outbreak of the crisis. It can be observed that the top four countries are the same in terms of both hub score and share of liabilities. However, Ireland is fifth systemically important country in terms of high degree indicator while it has a lower level in the ranking in terms of share. Portugal is also in the same situation. Conversely, countries such as Germany, Austria, the Netherlands have a higher level in the ranking in terms of share when compared to high degree indicator. This difference stems from the importance of interconnectedness of the network.

When it comes to authority centrality, ranking is largely different from the first-degree indicator. Share of receivables tell us that Germany is the most vulnerable country since it has the largest receivables in the system. However, authority centrality also captures the second-order adjacencies. Thus, Germany has lower level in the ranking. Switzerland and the UK have higher vulnerability than Germany in terms of high-degree indicator. This result means that these countries are linked to borrower countries which have higher importance in the network than the borrower countries to which Germany is linked.

Figure 7: Hub and Authority Centralities of Some Countries and Country Groups



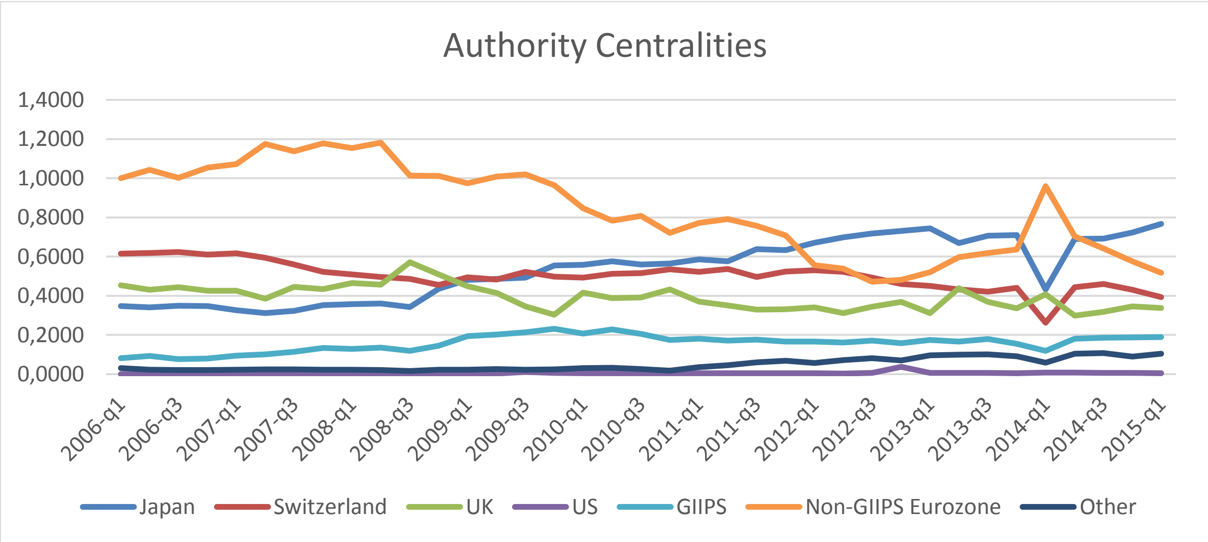
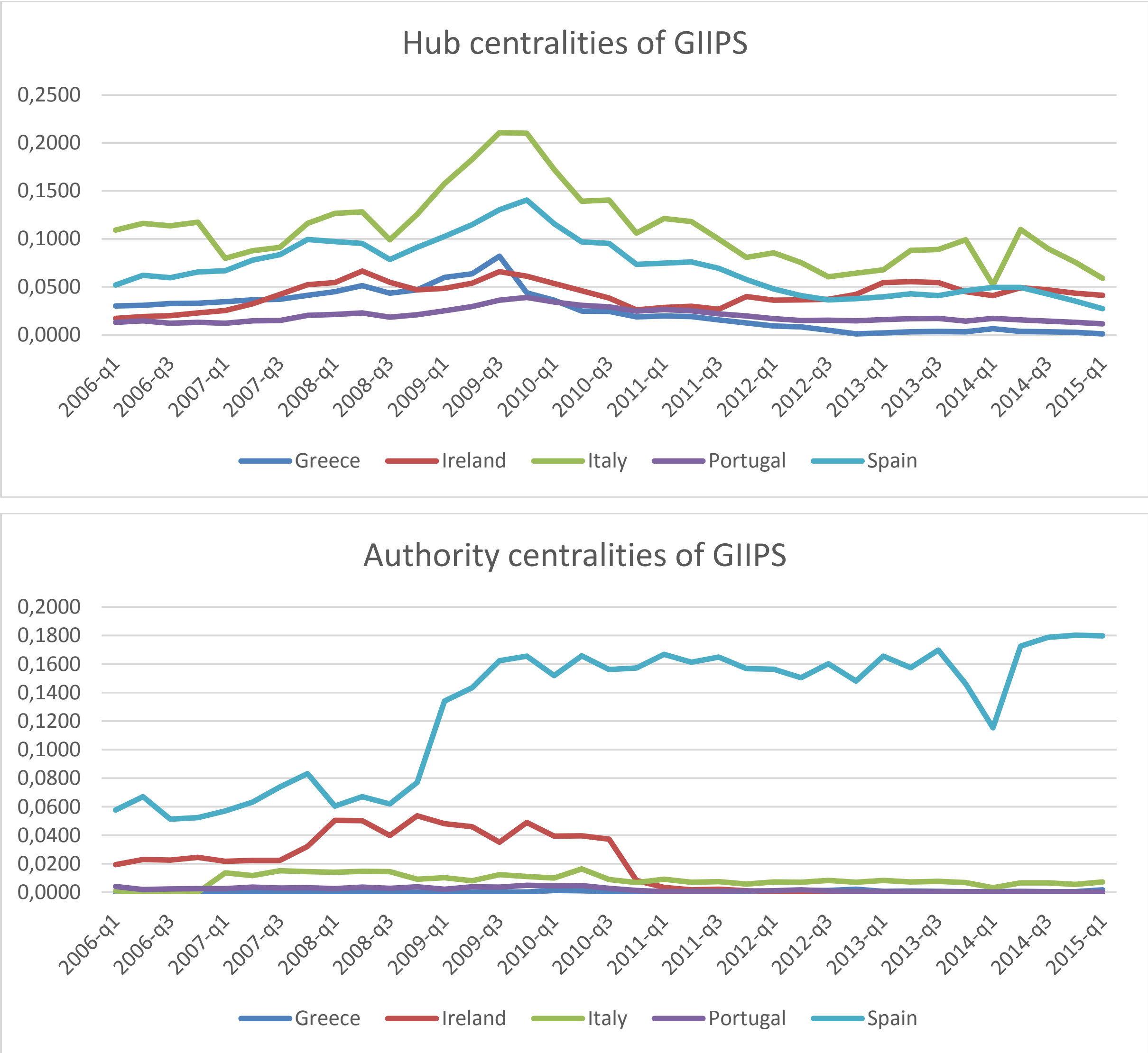


Figure 7 presents a general view for the hub centralities (systemic importance as mentioned) and authority centralities (systemic vulnerability) of some countries and country groups. First of all, US is the most systemically important country within the period except 2014:q1. Systemic importance of US is always high before the outbreak of the crisis and there is an increase after 2008:q2. However, systemic importance of US declines when Eurozone crisis starts at the end of 2009. Aggregated systemic importance of GIIPS countries (Greece, Ireland, Italy, Portugal, Spain) has its peak at the end of 2009. Systemic importance of the UK decreases after the outbreak of global crisis, however it increases with the outbreak of Eurozone crisis. It means that most of the liabilities of the UK is towards the GIIPS countries. This trend is also same for non-GIIPS (Austria, France, Belgium, Germany, Netherlands) Eurozone countries. Their systemic importance has a peak with the outbreak of Eurozone crisis while they are not affected much by 2008 crisis. However, non-GIIPS countries become the most systemically important group in 2014:q1 accompanied by a decrease of systemic importance of the US. This term corresponds to the implementation of reduction in asset purchases by US. Given this, decrease in systemic importance of US becomes reasonable. Other countries (Australia, India, Sweden, Turkey) also becomes more systemically important at this term. However, the expectations about continuation of US expansionary policies rise after estimation on growth of US economy for 2014:q1 implies economic shrinkage. Change of systemic importance after 2014:q2 in terms of US and other groups and countries can be interpreted depending on this explanation. Japan and Switzerland are systemically vulnerable countries since these countries are important lender for this international banking network.

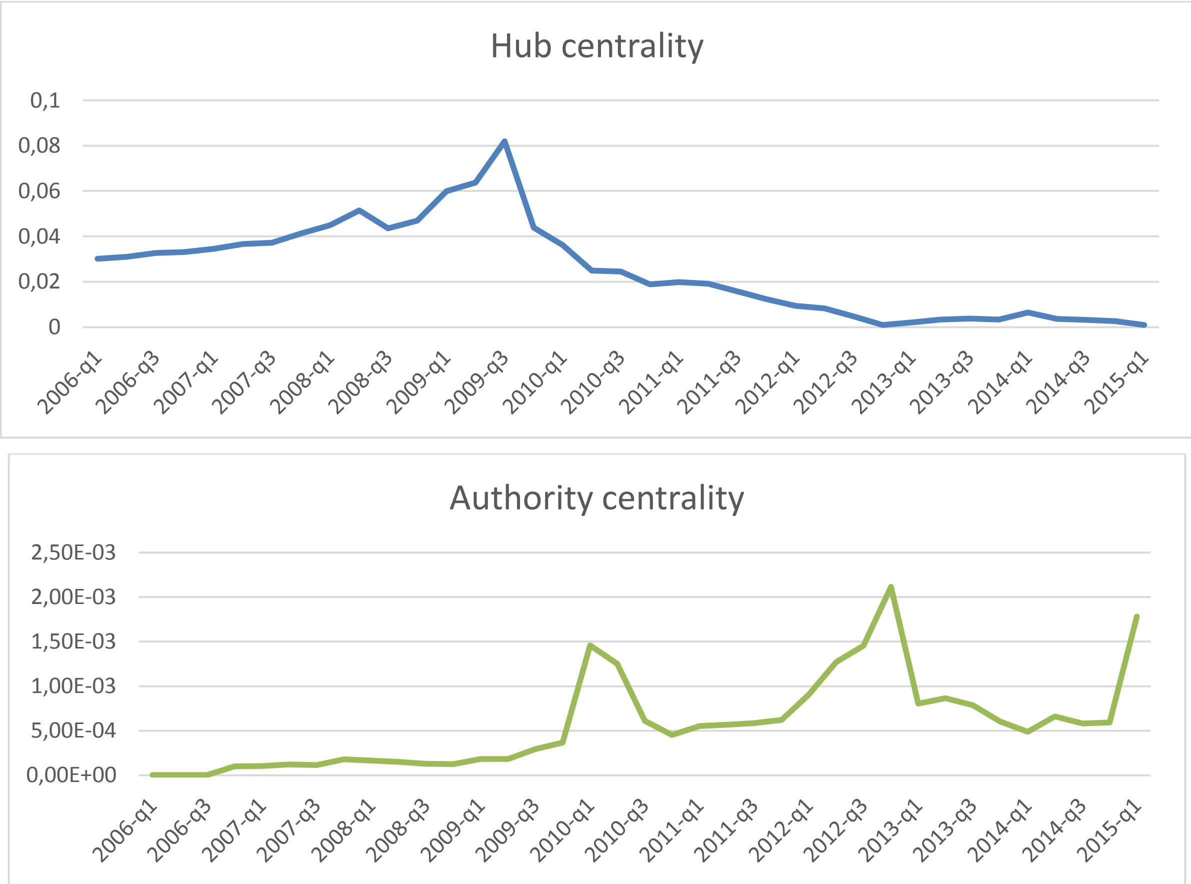
Figure 8: Hub and Authority Centralities of GIIPS



According to the results in Figure 8, Italy is the most systemically important country among GIIPS within the period. Hub centrality of Italy increases rapidly after the outbreak of the global crisis and has a peak with the Eurozone crisis. This trend is same also with the trend of hub centralities of Spain, Portugal and Greece. However, systemic importance of Ireland follows a different structure. Systemic importance of Ireland has another peak at 2013:q1 as well as global and Eurozone crises. When it comes to systemic vulnerability, it can be said that Spain becomes a systemically vulnerable country rather than being a systemically important country after global crisis. On the contrary, Greece, Portugal and Italy seem like systemically important countries rather than being systemically fragile countries.

Hence the centrality scores of Greece are lower relative to the other countries, it can be better to have a close look at them since Greece has importance in the network in financial meaning within the period. Figure 9 presents the hub and authority scores of Greece.

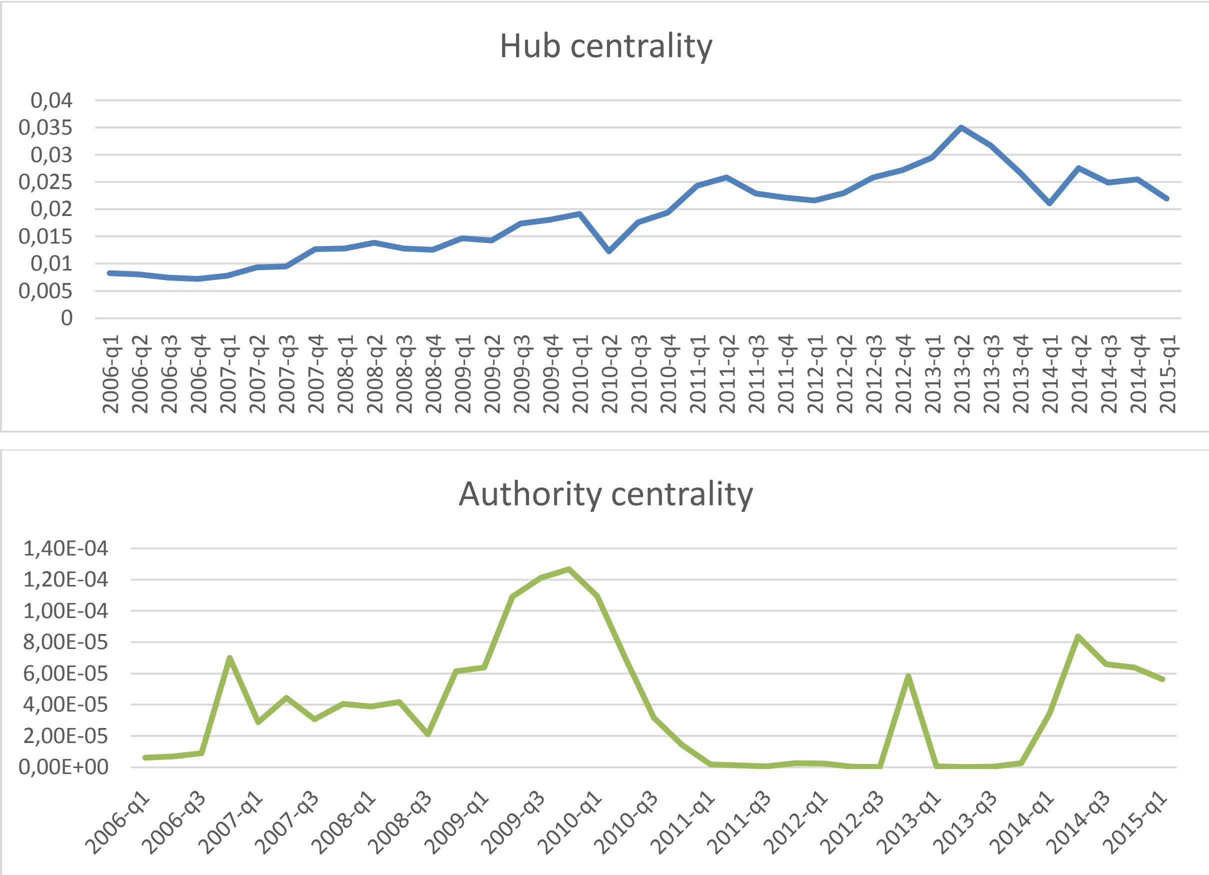
Figure 9: Hub and Authority Centralities of Greece



First of all, depending on values of hub and authority scores, it can be seen that Greece is more systemically important country rather than being systemically vulnerable country. Systemic importance of Greece increases from the beginnig of the period. It reaches its peak at 2008:q2 just before the outbreak of global crisis. However, its systemic vulnerability increases as of 2009:q4 while its systemic importance decreases. Thus, it can be said that Eurozone crisis is more effective than global crisis for Greece in terms of systemic vulnerability. Systemic vulnerability of Greece starts increasing again after 2010: q4 and reaches its peak at 2012:q4 which is the term some European countries (Italy, Spain, Portugal and Ireland) suffer from crisis.

Nevertheless centrality scores of Turkey are very low compared to other countries in the network, it can be said that Turkey is a systemically important country rather than being systemically vulnerable country since its hub scores are higher than its authority scores (Figure 10). However, authority scores of Turkey are more fluctuant.

Figure 10: Hub and Authority Centralities of Turkey



The first rise of authority score of Turkey is at 2006:q4 that corresponds to term of explanation of FED to raise interest rates. Vulnerability of Turkey's banking system starts increasing sharply after the outbreak of global crisis and has its peak at 2009:q4. It can be said that Eurozone crisis does not affect the vulnerability of Turkey much. Another increase is between 2013:q3 and 2014:q2 which is the term involves declaration of US about possibility of cutting down on expansionary policies due to recovery of economic indicators.

5. CONCLUSION

We have analyzed the cross-border banking activities of 18 countries within the period 2006:q1-2015:q1 via network analysis. It can be seen in the findings that the network disassortative -core-periphery- structure. Power-law structure is another important property of the network. It has been revealed by many studies that financial networks have power-law distribution. However, power-law distribution in even such a small network implies scale-free property over again.

Our results show that network statistics capture the effects of both global and Eurozone crises. Clustering coefficient, exponent of power-law, centralities of countries are affected by the crises. However, core-periphery and scale-free structures of the network has remained same. It is also observed in the analysis that hub and authority scores are more informative indicators when compared to first degree indicators such as share of liability in total liabilities since they take interconnectedness into consideration.

This study has been done with a limited data of international banking system since all countries in the international banking system do not present their data. Undoubtedly that the results will be more reliable with more comprehensive data. Further step of this analysis might be extension of the analysis including other countries.

REFERENCES

Acemoğlu, D., Ozdaglar, A., Salehi, A. 2015, "Systemic Risk and Stability in Financial Networks", American Economic Review, vol. 105, no. 2, pp. 564-608.

Allen, F., Gale, D. 2000, "Financial Contagion", The Journal of Political Economy, vol. 108, no. 1, pp. 1-33.

Alves, I. et al. 2013, "The Structure and Resilience of the European Interbank Market", ESRB Occasional Paper Series, No:3, pp. 1-43.

Bandt, O., Heam, J.C., Labonne, C., Tavolaro, S. 2013, "Measuring Systemic Risk in a Post-crisis World", ACP Banque de France, Débats économiques et financiers, no. 6,

Barabasi, A., Albert, R. "Emergence of Scaling in Random Networks", http://snap.stanford.edu/class/cs224w-readings/barabasi99scaling.pdf, (13.03.2016).

Barrat, A., Barthelemy, M., Vespignani, A. 2004, "Traffic-Driven Model of the World Wide Web Graph", Algorithms and Models for the Web-Graph, Third International Workshop, ed. Stefano Leonardi (Springer).

Battiston, S., Caldarelli, G., "Systemic Risk in Financial Networks", Journal of Financial Management Markets and Institutions, vol. 1, no. 2, pp. 129-154.

Caldarelli, G. "Lectures in complex networks", http://www.ifr.ac.uk/netsci08/Download/Invited/ws1_Caldarelli.pdf .

Chinazzi, M., Fagiolo, G., Reyes, J., Schiavo, S. 2012, "Post-Mortem Examination of the International Financial Network", University of Trento Department of Economics, no. 02/2012.

Csardi, G., Package 'igraph', https://cran.r-project.org/web/packages/igraph/igraph.pdf .

Decarlo, L. 1997, "On the Meaning and the Use of Kurtosis", Psychological Methods, vol. 2, no.3, 1997, pp. 292-307.

Estrada, E. 2015, "Introduction to Complex Networks: Structure and Dynamics", Evolutionary Equations with Applications in Natural Sciences, Lecture Notes in Mathematics 2126, J. Banasiak, M. Mokhtar-Kharroubi (eds.), Springer International Publishing Switzerland.

Fagiolo, G., Reyes, J., Schiavo, S. 2010, "The Evolution of the World Trade Web: A Weighted-Network Analysis". **Journal of Evolutionary Economics**. c.20, s. 4, pp. 479-514.

Fuge, M., Tee, K., Agogino, A. "Network Analysis of Collaborative Design Networks: A Case Study of OpenIDEO", http://www.markfuge.com/papers/fuge_tee_openideo_jcise_final_2013.pdf, 14.03.2016.

Hein, O., Schwind, M., König, W.2006, "Scale-Free Networks – The Impact of Fat Tailed Degree Distribution on Diffusion and Communication Processes", Wirtschaftsinformatik, vol.48, 267–275.

Howell, A. 2012, "Network statistics and modeling the global trade economy: exponential random graph models and latent space models: is geography dead?", University of California, unpublished thesis.

Kleinberg, J. M. 1999, "Authoritative Sources in a Hyperlinked Environment", Journal of the ACM, c. 46, pp. 604-632.

Knorn, F. 2005, "Ranking and importance in complex networks", http://www.hamilton.ie/publications/Studienarbeit_Florian_Knorn__screen.pdf .

Kolaczyk, E.D. 2009, Statistical Analysis of Network Data Methods and Models, Springer.

Krause, A., Giansante, s. 2012, "Interbank lending and the spread of bank failures: A network model of systemic risk", Journal of Economic Behavior & Organization, vol. 83, pp. 583-608.

Leon, C. Perez, J. 2013, "Authority Centrality and Hub Centrality as Metrics of Systemic Importance of Financial Market Infrastructure", Borradores de Economia, No: 754.

Leon, C., Berndsen, R.J. 2014, "Rethinking financial stability: Challenges arising from financial networks' modular scale-free architecture", Journal of Financial Stability, vol. 15, pp. 241-256.

Leon Rincon, C.E., Machado, C., Sarmiento Paipilla M. 2015, "Identifying Central Bank Liquidity Super-Spreaders in Interbank Funds Networks", EBC Discussion Paper, vol. 2015-010.

Lovric, M.2010, "Skewness", International Encyclopedia of Statistical Science, Springer: New York.

Markose, S., Giansante, S., Gatkowski, M., Shaghaghi, A. 2010, "Too Interconnected To Fail: Financial Contagion and Systemic Risk in Network Model of CDS and Other Credit Enhancement Obligations of US Banks", University of Essex Discussion Paper Series, no. 683, pp.1-59.

Markose, S. 2012, "Systemic Risk from Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation with Super-Spreader Tax", IMF Working Paper, no. 12/282.

Markose, S. 2013, "Systemic Risk Analytics: A Data Driven Multi-Agent Financial Network (MAFN) Approach, pp.1-29.

Mitchell, M. 2009, Complexity A Guided Tour, Oxford University Press.

Newman, M.E.J., "Mixing Patterns in Network", http://arxiv.org/pdf/cond-mat/0209450v2.pdf .

Newman, M.E.J. 2010, Networks An Introduction. 1st pr. Oxford University Press.

OECD. 2009, "Applications of Complexity Science for Public Policy- New Tools for Finding Unanticipated Consequences and Unrealized Opportunities".

Reichardt, J. 2009, "Introduction to Complex Networks", Structure in Complex Networks Lecture Notes in Physics, s. 766,(Springer-Verlag Berlin Heidelberg).

Serrano, M.A., Boguna, M. 2006,"Clustering in Complex Networks: General Formalism", Physical Reiew E, 74, 056114.