Network Structure and Systemic Risk in European Banks- Insights from Network Science

Farhad Reyazat- PhD in Risk Management[1]

October 2015

Abstract

The financial crisis 2007-8 has underscored the need to go beyond the analysis of individual institutions' soundness and assess whether the linkages across institutions may have systemic implications. The undeniable need to prevent such a crises in the future as well as to assess previous errors by way of comprehensive compliance has made such an assessment absolutely imperative.

This paper explains the suitable analytical tool for assessing and monitoring systemic risk in EU banks which in turn enables us to visualise the relationship between the financial network topology and systemic risk. This paper aims to examine the structure of financial network at an individual country's level using network formation theory and then illustrate the structure of this network. The concept of core-periphery network is empirically tested in the paper by using the probit regressions testing whether network position can be predicted by individual network variables. The same methodology as Craig & Von Peter used for perfect core periphery structure. (Craig & Von Peter, 2010). The results confirmed the previous finding in this fields (for example see (Farboodi., 2014)). It shows that interbank relations coming to a core-periphery structure where the fit with Betweeness is much better than the fit with cross border exposures. The model indicates that there is a small number of very interconnected banks that trade with many other banks and a large number of banks that trade with a small number of counterparties.

When we study the banking network, with a consideration of all the complexities of the financial structure, one key question is 'how can we improve our understanding?' One of the key goal of this paper is to map out the effect of cross-border bilateral exposures and their macroeconomics consequences, as well as evaluate the topology of network and its effect on shocks transmission.

The paper points out that (i) banking network coming into scale free structure ;(ii) interbank structure follow the core-periphery structure (iii) the composition of banks group within the core sector remains remarkably stable over time. (iv) among centrality measures the fit of Core with Betweeness is much better than others; (v) countries with shallow domestic financial markets and concentrated exposures to a few lenders are more prone to synchronized shifts in cross-border flows; (vi) the importance of heterogeneity in network structure and the role of concentration of counterparty exposures in explaining its systemic importance of a banking sector in the economy; (vii) American banks positions in the network changed from fragile section to important and fragile; and(viii)common factors (such as global risk aversion) increasingly drive global financial markets and tend to intensify abruptly during periods of stress, amplifying shock transmission.

This paper contributes to the existent literature by examining the structure of banking network and developing a framework that explains how interdependencies between banks at country level emerge endogenously by mapping out the banking network.

[1] The author would like to thank Professor Richard Werner from Southampton University, Professor Philip Arestis Director of Cambridge Centre for Economics and Public Policy University of Cambridge, as well as Daren Acemoglu, professor of Massachusetts Institute of Technology (MIT)

Keywords: Contagion, systemic risk, counterparty risk, financial stability, interconnectedness, financial network. European banks.

Section 1: Introduction

The financial crisis 2007/8 has vividly illustrated the costs and benefits of increased interconnectedness. Suffice to say, linkages, and interconnectedness will be used interchangeably in this paper exposing lacunae in the global financial architecture. As a result, effective financial system surveillance requires the monitoring of direct and indirect financial linkages, whose disruption could have important implications for the stability of the entire financial system. Proactively tracking potential systemic linkages is very crucial for regulators and policy makers worldwide. Tracking potential systemic linkages and interconnectedness highlighted the role of network analysis. There are some studies that aid this challenge (See (Allen and Babus, 2007)). Allen and Babus' (2007) study allows regulators and policy makers to assess externalities to the rest of the financial system, by tracking the rounds of spillovers likely to arise from direct financial linkages. With interconnected financial markets around the world, the analysis of 'networks' in the financial system would help deepen understanding of systemic risk and is key to preventing future financial crises.

Section 2: Why Cross-Country Exposures is the Focus of this paper

The financial crisis 2007/8 has demonstrated that significant risks to national banking sectors can stem not only from domestic asset and credit markets but also from cross-border exposures due to interconnectedness. Among our pool, German banks are a good case in this regard. Prior to the financial crisis 2007/8, country risk indicators in Germany at the national level typically issued no alerts. However, a significant portion of German banks' claim was on American borrowers (on the balance sheet or the main part off balance sheet), which exposed the German Banks, making them highly vulnerable to the international credit shocks. Likewise, Belgium, the Netherlands and Switzerland were adversely affected through their banks' US exposures. This is why our main focus of attention is on cross country exposure in this study.

Section 3: Network Measurements

This study intends to measure systemic risk using interlinkages between banks, -we implement Gerlach's approach (Gerlach, 2009) using the network approach model of IMF's (Chan-Lau, et al., 2009) as our method for assessing interlinkage. Then applying the concept of 'Too-big-to-fail" (PCT test) we add a factor of the institutions' sizes (total assets of banks) and the total exposures relative to the national marketplace.

Using the combined index of institutions' sizes, Gross Domestic Product and Herfindahl index, we introduce four ratios to capture the importance of bilateral lending activities for the banking sector and the economy overall. Network variables are defined as follows:

Equation 1:

$$\text{Bilateral Exposures to GDP} = \frac{Exposure\ of\ banking\ sector\ of\ country\ i\ vs\ \ country\ j}{GDP\ of\ country\ i}$$

To calculate the bilateral exposures to GDP we divide the total exposures of the banking sector of a country *i* by the GDP of the country *i* in that year.

Equation 2:

$$\text{Bilateral Exposures to total banks assets} = \frac{Exposure\ of\ banking\ sector\ of\ country\ i\ vs\ \ country\ j}{total\ banks\ assets\ of\ country\ i}$$

To calculate the bilateral exposures to total assets, we divide the total exposures of the banking sector of a country *i* by the total assets of the banking network of the country *i* in that year.

Equation 3:

$$\text{Bilateral Exposures to total Exposures} = \frac{Exposure\ of\ banking\ sector\ of\ country\ i\ vs\ \ country\ j}{Total\ exposure\ of\ network}$$

To calculate the bilateral exposures relative to total exposure of the network we divide the total exposures of the banking sector of a country *i* by the total exposures of the whole banking network in that year.

Equation 4:

$$\text{Bilateral Exposures to Concentration Index} = \frac{Exposure\ of\ banking\ sector\ of\ country\ i\ vs\ \ country\ j}{Concentration\ Index\ of\ country\ i}$$

To calculate the bilateral exposures relative to concentration index we divide the total exposures of the banking sector of a country *i* by the total assets of the banks in country *i* plus the given Herfindhal index of the country *i* times by the GDP of the country *i* in that year.

Centrality Measures

To analyse the banking network in selected countries, centrality measures have been used in the second part of the study. The most commonly used centrality measures are Degree, Closeness and Betweenness proposed by Freeman(1978) and different variations of Eigenvector centrality which was pioneered by Katz (1953) and Bonacich (1972), Bonacich (1987). Degree centrality (or simply Degree) counts the number of neighbours of each node. It is a local measure that only takes the immediate neighbourhood of the node into account. It can count neighbours with incoming links, outgoing links or either, and can be weighted by link properties; for example, the weighted out-degree is referred to as out-strength. While the insight underlying Closeness centrality is that nodes that have shorter geodesic paths to other nodes are more central. This closeness is important, as it will play a role on the eventual spread of shocks across the network. The ability to calculate this ratio of centrality is explored: it is generally calculated as the average length of geodesic paths from a node to each other node in the network. Betweenness centrality defines nodes through which a high share of geodesic paths pass as central. What is known today as Eigenvector centrality encapsulates the idea that the centrality of a node depends directly on the centrality of the nodes that link to it (or that it links to). Eigenvector centrality measures assume parallel duplication along walks. A famous commercialization of Eigenvector centrality is Google's PageRank algorithm (Page, et al. 1999), which adds a random jump probability for ’dangling’ nodes and thus allows the measure to be calculated for all types of networks. PageRank and Eigenvector centrality can be thought of as the proportion of time spent visiting each node in an infinite random walk through the network. For calculating Eigenvector centrality, the network must be strongly connected (i.e. the underlying transition matrix must be non-singular).

To sum up all different centrality measures, degree is the number of links in the network, distance to other nodes via shortest paths is closeness, betweenness is defined as number of shortest paths going through the node, eigenvector says nodes that are linked by/to other important nodes are more central (parallel duplication via walks). Why are centrality measures important in a network? The centrality of nodes, or the identification of which nodes are more "central" than others, has been a key issue in network analysis ((Freeman L. , 1978), Bonacich (1987), Borgatti (2005). According to Freeman (1978), central nodes were identified as those in the focal point or "in the thick of things" (p.215-239). To describe the issue, he used a network consisting of 5 nodes. The middle node has three advantages over the other nodes: it has more ties, it can reach all the others more quickly, and it controls the flow between the others. This level of influence on other nodes and as a result the entire network will prove to be important. Based on these three features, Freeman (1978) introduced three different measures of node centrality previously seen: degree, closeness, and betweenness. Degree can also be identified as the number of nodes that a focal node is connected to, and measures the involvement of the node in the network. The failure in considering the global structure of the network is the main limitation of this measurement. For example, a node might be well connected using other factors, but not be in a position to reach others quickly to access information or resources Borgatti (2005), Brass (1984).

For this purpose, closeness centrality was defined as shortest distance to all other nodes from a focal node. Although this measure couldn't be easily applied to a network with disconnected components, it has the benefit of capturing the most information in a connected network. Betweenness evaluates the degree to which a node lies on the shortest path between two other nodes, and is able to funnel the flow in the network. In this way the node can assert control over the flow. The limitation of this measure is the fact that a large proportion of nodes in a network do not lie on a shortest path between any two other nodes, and thus receive the same score of 'zero'. In the case of weighted networks Barrat, et al., 2004) generalised degree by taking the sum of weights instead of the number of ties, however to generalise closeness to weighted network Newman (2001) apply Dijkstra (1959) algorithm; and to generalise betweenness Brandes (2001) apply Dijkstra (1959) algorithm to weighted network. The focal point of this generalisations lies with tie weights, and the original feature of the measures (number of ties) was ignored so the second set of generalisation incorporates both the number of ties and the weights by using a tuning parameter, (Opsahl, et al., 2010).

The followings are illustrations of a few centrality measures. In each of the following networks, X has higher centrality than Y according to a particular measure.

Figure 1 example of

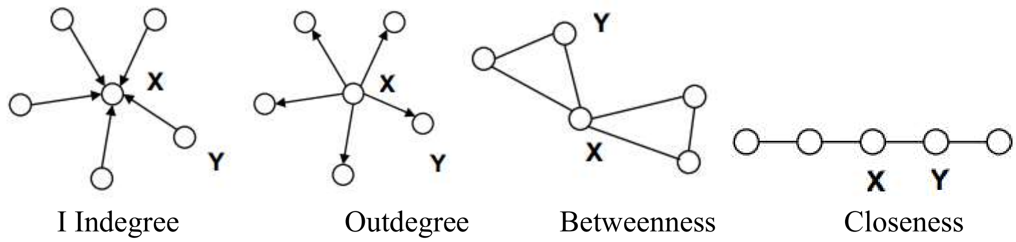
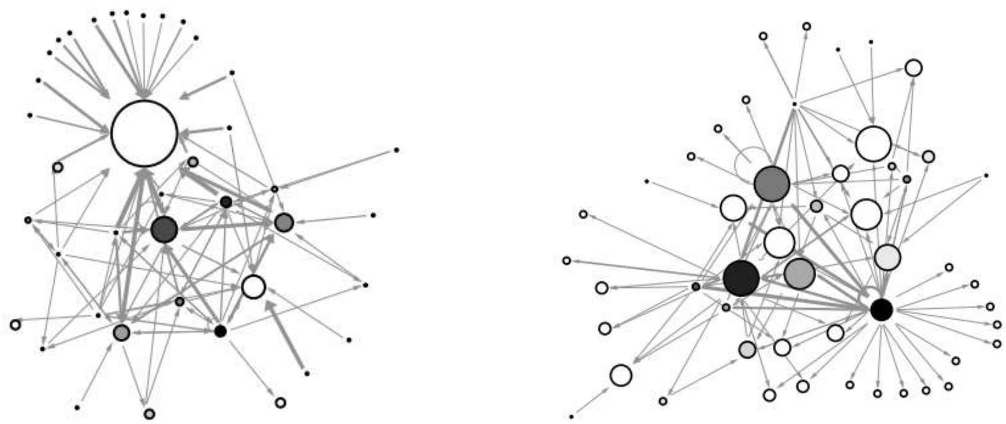


Figure 2 Degree Centralization Examples:



High centralised: one node trading with many others **Low centralised: more evenly distributed**

Source: Network centrality Slides are modified from Lada Adamic (Adamic, 2015)

Node level centrality measure: a node's average shortest path is the average length of the shortest path from that node to each other node reachable from it. Finding out the central node in the network could help to protect the network from breaking.

Betweenness Centrality: A node's betweenness centrality is the number of directed shortest paths between all other pairs of nodes that pass through the given node. In other words, it is the number of shortest paths going through the nodes. With the exception of betweenness centrality, all of the node-level centrality measures have an optional weight property; any numeric arc property can be used as a weight. In a link, a link's betweenness centrality is the number of directed shortest paths (besides the link itself) that pass through the given link.

Equation 5: Betweenness Centrality

$$C_b(i) = \sum_{j \neq k} g_{jk}(i)/g_{jk}$$ (Freeman, Borgatti, & White, 1991)

If g_{jk} is the number of geodesics linking points j to k in a graph, and $g_{jk}(i)$ is the number of such paths that contain point i. Usually normalised by:

$$\acute{C}_B(i) = (C_B(i)/[(n-1)(n-2)/2]$$

Where bracket is the number of pairs of vertices excluding the vertex itself, and in equation, 5 where g_{jk} = the number of geodesics connecting *jk*, and $g_{jk}(i)$ = the number of geodesics that actor *i* is on.

Closeness Centrality: What if it is not important to have many direct links or be "between" others? If we still want to have a node in the "middle" of things not too far from the centre, the closeness is important. The closeness measure is based on the length of the average shortest path between a vertex and all vertices in the graph. Such that closeness is the distance from/to other nodes via the shortest paths which could be calculated as:

$$C_c(\mathrm{i}) = \left[\sum_{j=1}^{N} d(i,j)\right]^{-1}.$$

Normalised closeness centrality is calculated as, $\acute{C}_c(i) = (C_c(i))/(N-1)$. So closeness is the length of shortest path to all others.

CheiRank vs PageRank: A node's PageRank is the expected amount of time spent visiting that node in a random walk over the network. The parameter *alpha (α)* adds a small probability of moving between any two pairs of nodes, which allows the metric to be calculated even for networks that are not strongly connected. When alpha is equal to zero, PageRank is equal to the standard eigenvector centrality. A node's CheiRank is calculated by first transposing the network (that is, reversing the direction of all directed links) and then calculating its PageRank. While the PageRank ranks the network nodes in average proportionally to a number of ingoing links, the CheiRank ranks nodes in average proportionally to a number of outgoing links. The physical meaning of PageRank vector components is tied to the original purpose for which the Google search engine builders implemented it. That is they give the probability of finding a random website surfer on a given node (or website) when the surfer follows the given directions of network links. In a similar way the CheiRank vector components give the probability to find a random website surfer on a given node (or website) when a surfer follows the inverted directions of network links. Since each node belongs both to CheiRank and PageRank vectors the ranking of information flow on a directed network becomes two-dimensional. For more detail see (Ermann, Chepelianskii and Shepelyansky, 2012).

Eigenvector centrality: Degree centrality depends on having many connections, but what if these connections are isolated? A central node should be one connected to more influential nodes. Connection to a more important node is more important. A node's eccentricity is the longest *path* from that node to any other node in the network. A path is any route between two nodes where no node is visited more than once.

Maximum Clique: As previously mentioned, a network can interchangeably be referred to as a graph. A graph may contain many complete subgraphs ('cliques'), i.e. sets of nodes where each pair of nodes is connected. So a clique of graph G is a complete subgraph of G, the largest possible size is referred to as 'Maximum Clique', the maximum clique is one way of finding the 'core'. The maximum clique cannot be extended by including one more adjacent vertex, so it is not a subset of a larger clique. For more details see (Wasserman & Faust, 1994).

Newman Modularity: Modularity is a measure of the structure of a network. The networks with high modularity have dense connections between nodes within modules but sparse connections between nodes in different modules. In methods for detecting modules (also called groups, clusters or communities), networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules (see Newmann (2006)).

Section 4: Core-Periphery network structure

Recent empirical evidence suggests that financial networks exhibit a core periphery network structure. This paper aims to examine the structure of financial networks at national level in selected countries using network formation theory for illustrating the structure of this network. Then we explained the role of core periphery network structure in the stability or fragility of the system. We will focus on the core periphery network as it is not only relatively simple and intuitively appealing but also it is a fair representation of the complex empirical structures.

Perhaps one of the most important questions to ask is if there exist any relationships between fragility or robustness of the system and its structure? In biology, Smilkov, Hidalgo and Kocarev (2014) in their article "Beyond network structure: How heterogeneous susceptibility modulates the spread of epidemics" argue that for the SIS model (corresponding to the Susceptible-Infected-Susceptible 'damage' status of the network) differential susceptibility can make networks more vulnerable to the spread of diseases when the correlation between a node's degree and susceptibility are positive, and less vulnerable when this correlation is negative.

Section 5: Outcome of the Network Analysis

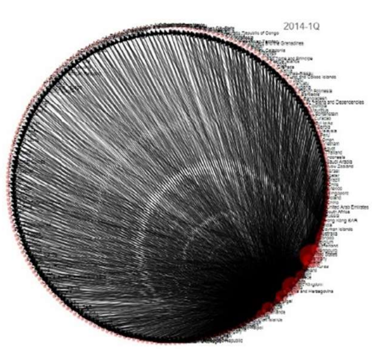
Putting the data into perspective

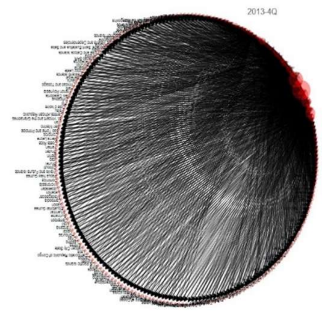
The network perspective is readily introduced by looking at bilateral lending relationships between the countries in selected samples. In this part we look at three data samples:

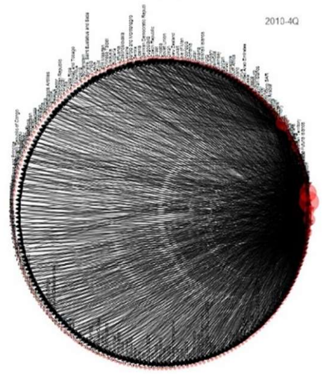
A. Main sample including EU banks, American banks, Canadian, Australian, Chilean, Indian, Japanese, South Korean and Turkish banks
B. EU banks and American banks
C. EU banks

The above banks exposures to 219 countries with total, 145,990 exposures were considered. (Appendix 1) There are a number of possible ways to explore the data, of which we will highlight the most relevant for monitoring banking sector risk. One of the most basic approaches is to look at absolute numbers of exposures. The following figures mapped out and compared the bilateral exposure of the banking system in the selected countries on a quarterly basis since 2005. Let's start by mapping out the sample A countries. The illustration clearly indicates that the banking network follows a core-periphery structure. They consist of a dense cohesive core and a sparse, loosely connected periphery. This meso-scale feature network known as core-periphery structure, which entails identifying densely-connected core nodes and sparsely-connected periphery nodes. A scale-free structure of the network could be seen not only in 2014 but also before, starting in 2005 we examined all quarters and all quarters having the same structure. (Figures 3,4)

A:







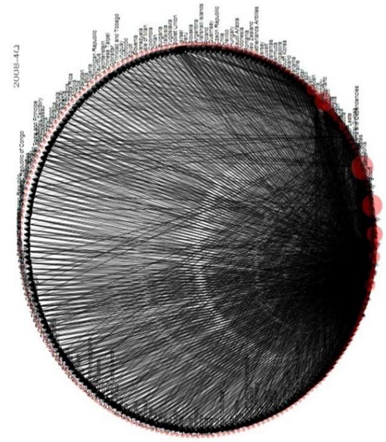
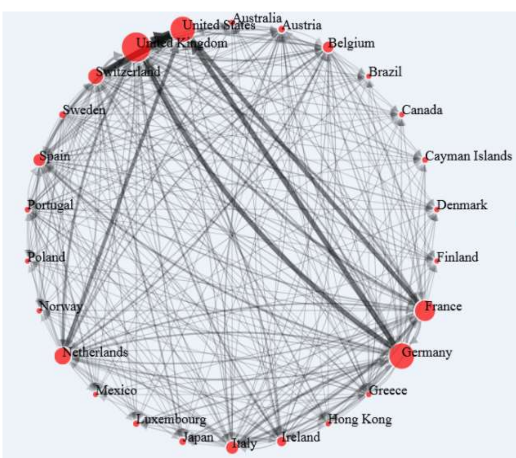


Figure 3 Network Structure 2014-Q1 2010-Q4 Figure 4 2013-Q4 2008-Q4

Source: Author's own figure

A: Selected EU countries



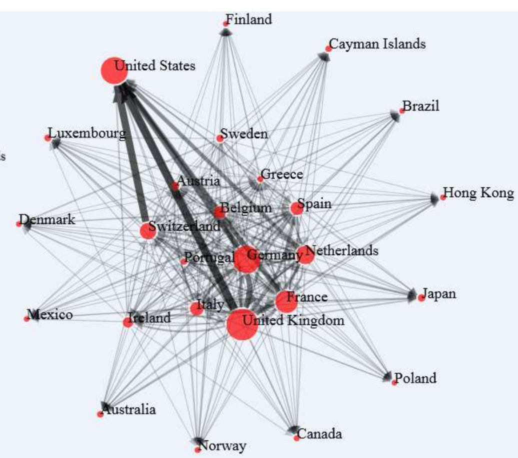


Figure 5: Bilateral Exposure 2007-Q3 **Figure 6: Bilateral Exposure 2007-Q3**

Source*: *Author's own figure

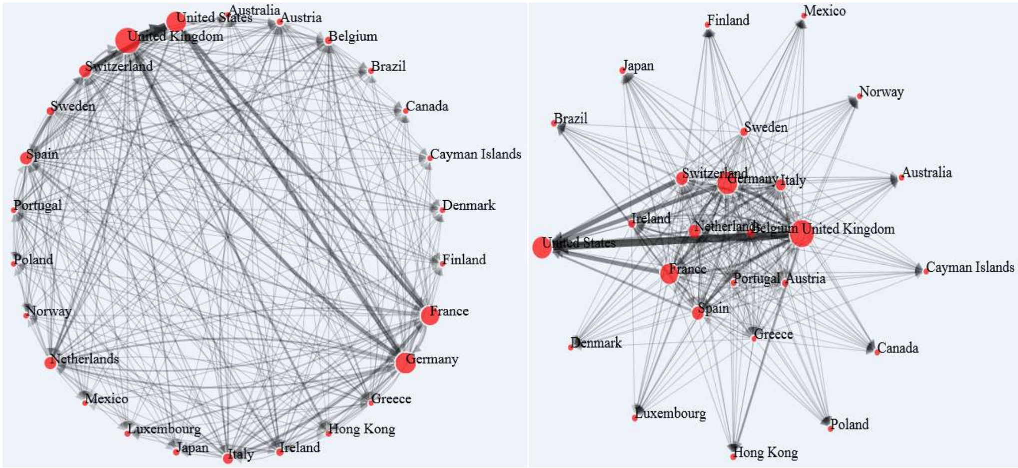


Figure 7: Bilateral Exposure 2011-Q3
Source: Author's own figure

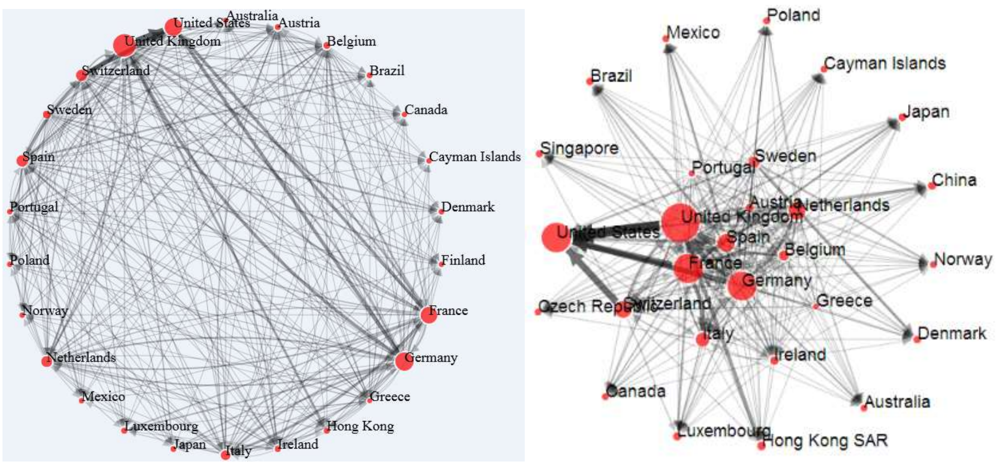


Figure 8: Bilateral Exposure 2014-Q1

Source: Author's own figure

B: Selected EU Countries & United States

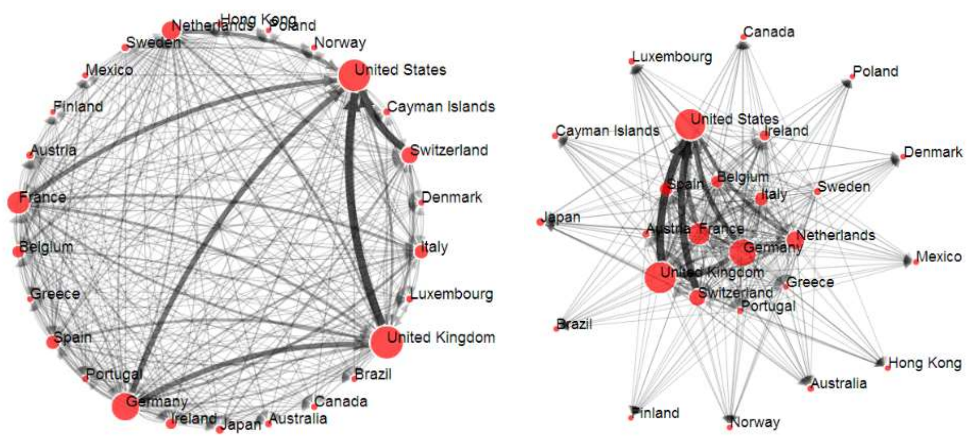


Figure 9: Bilateral Exposures 2007-3Q
Source: Author's own figure

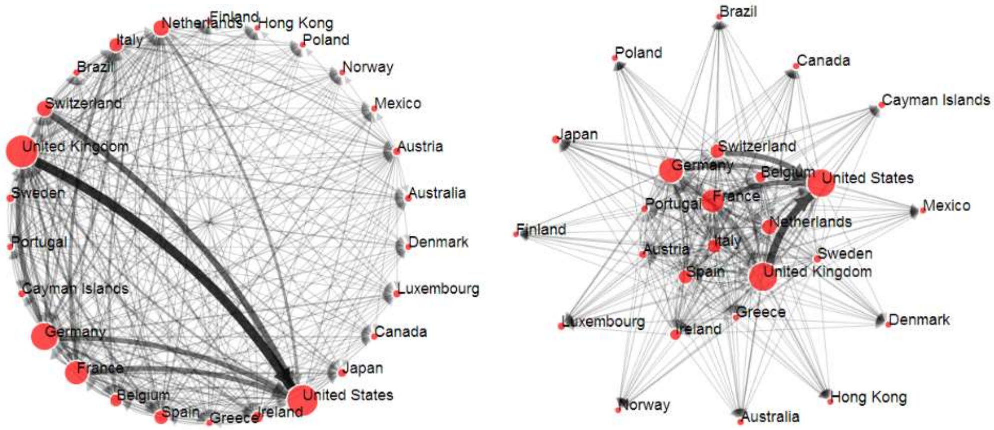


Figure 10: Bilateral Exposure 2008-Q3 Source: Author's own figure

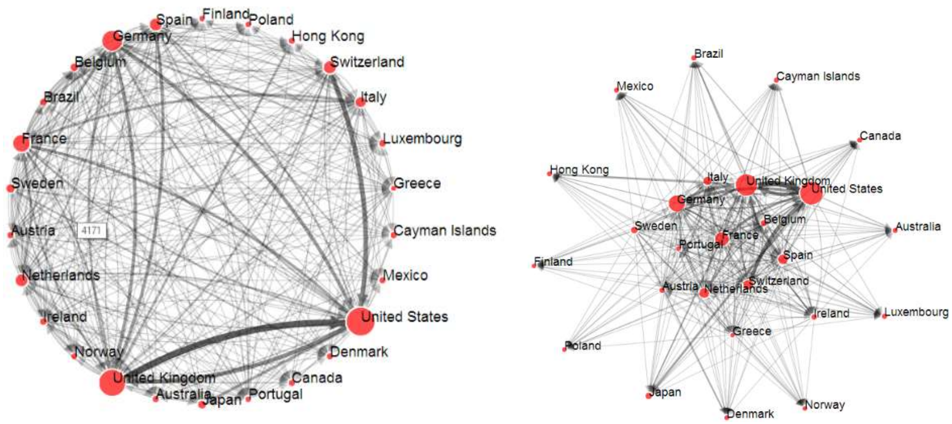


Figure 11: Bilateral Exposure 2012-Q3

Source: Author's own figure

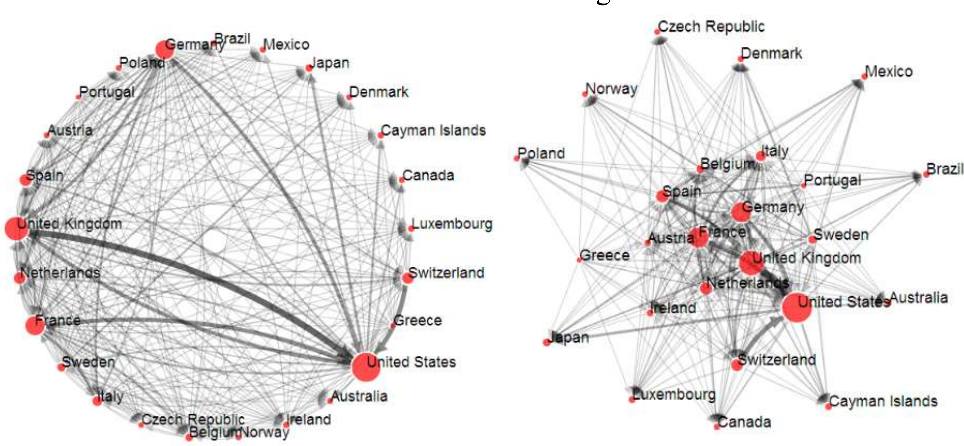
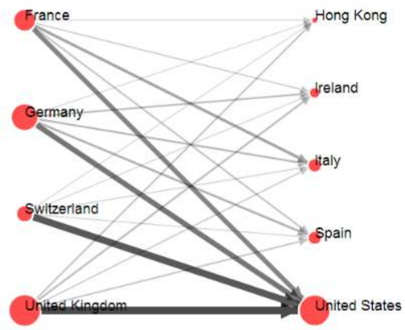


Figure 12: Bilateral Exposure 2014-Q1

Source: Author's own figure



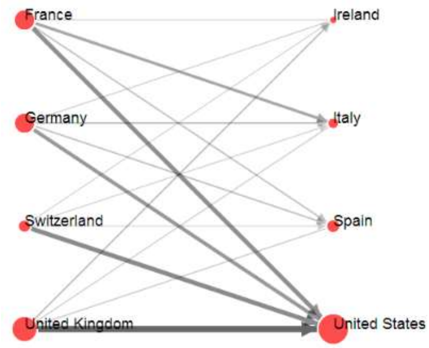


Figure 13: 2007-Q3 **Figure 14: 2014-Q1**

Source: Author's own figure

The structure of networks in EU countries sample B and C showing the same result as well. (Figures 5-12). Based on the EU banks illustration two group of Core banks including American, British, German and French Banks are peripheries, the rest of the banks, are separated. The structure of networks in EU countries and US clearly state that British, French, German and American banks play as the core of network in all periods since 2007. Figures 13 and 14 indicate the bilateral connection of the network in terms of giving and receiving of the exposures from 2007 till 2014 are almost the same. Such simple charts can already give valuable hints as to which other countries one should look for in order to assess banking sector risk at country level. At the same time, one can easily assume the reverse perspective and ask which countries will mainly be affected by problems – say – of the euro-area peripheral countries. Regional or local hotspots can thus easily be traced to the international banking system. A further possibility in monitoring bilateral exposures is to take into account the time dimension of the data. For instance, comparison of the data over time reveals to which countries domestic exposure has become significantly larger or smaller in recent times In doing so, one can also trace the build-up and decline of bank exposures to current hotspots, such as the euro area periphery (see figures 13, 14) – with the stronger movements warranting further investigation into the causes of the changes and their possible implications for banking sector risk.

How to develop the perspective

In order to assess structural vulnerabilities of banks in an international comparison it makes sense to look at the data not only in absolute, but also in relative terms. At the first step we looked at the perspective of selected countries banks' exposure at absolute figures of exposures.

In the next step, the potential impact of banking sector problems on economic activity is measured by the relative size of the country (potential bail out in case of failing). The smaller the size of GDP to total exposure of banks, the more severely banking sector problems would affect economic activity or – in case banks need to be supported by the government – could increase public debt. By these metrics, Swiss banks were vulnerable before and after the recent financial crisis. However, the degree of vulnerability diminished during the last three years. For detailed outcome see Figures 15-22.

Bilateral exposure relative to GDP highlights the contribution of Swiss banks to the aggregate systemic risk of the network in particular during the 2007 financial crisis (Figure 15, 16). Although the illustration of 2014-Q1 shows the systemic risk of Swiss banks decreased but their exposure to American banks increased. (Figure 18)

A: Selected EU countries

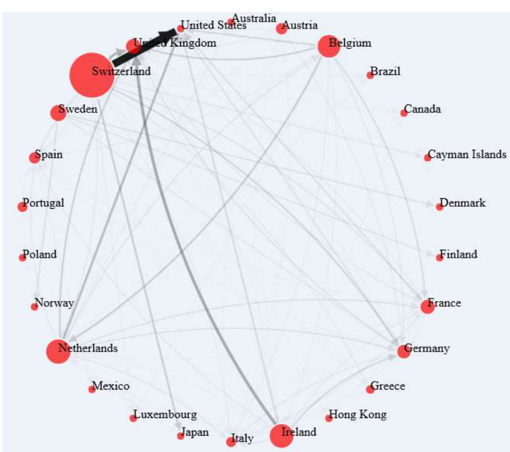


Figure 15: Bilateral Exposure relative to GDP 2007-Q3

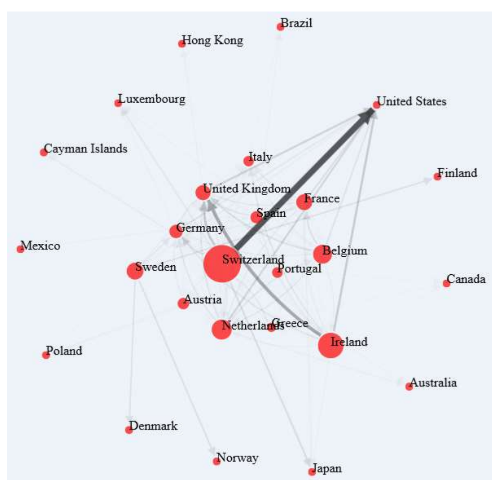
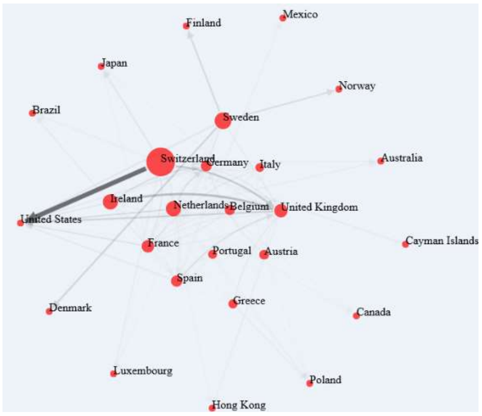


Figure 16: Bilateral Exposure relative to GDP 2008-Q4

Source: Author's own figure



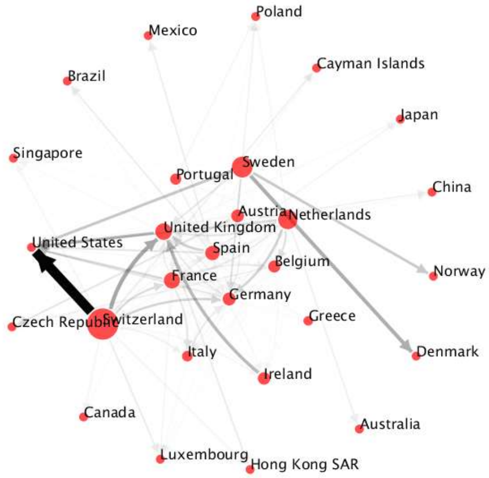
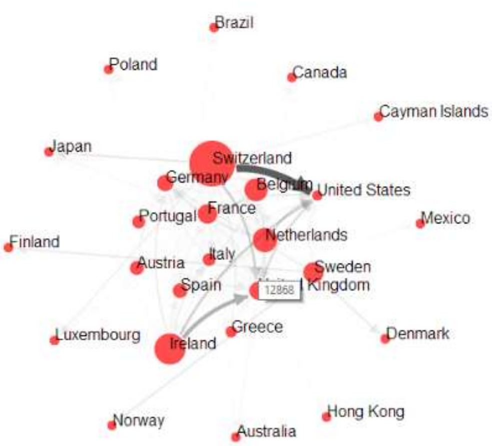


Figure 17: Bilateral Exposure relative to GDP 2011- Q3

Figure 18: Bilateral Exposure relative to GDP 2014- Q1

Source: Author's own figure

B: Selected EU countries & United States



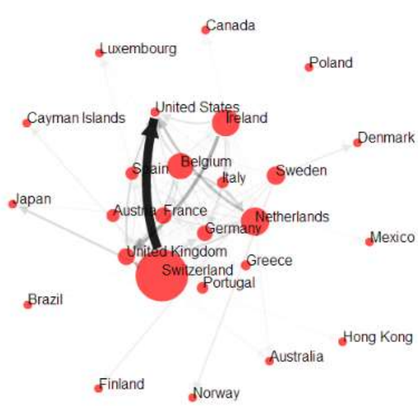


Figure 19: Bilateral Exposure relative to GDP 2007-Q3

Figure 20: Bilateral Exposure relative to GDP 2008-4Q

Source: Author's own figure

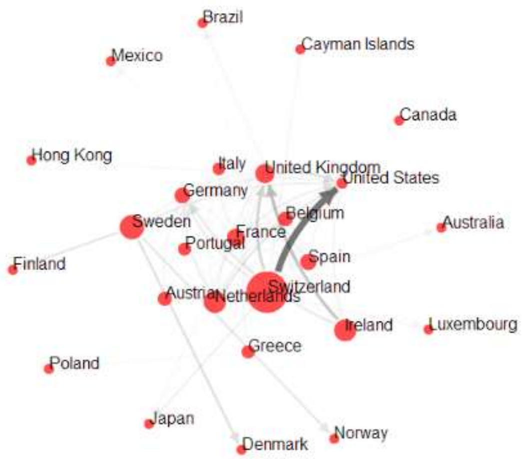


Figure 21: Bilateral Exposure relative to GDP 2011- Q3

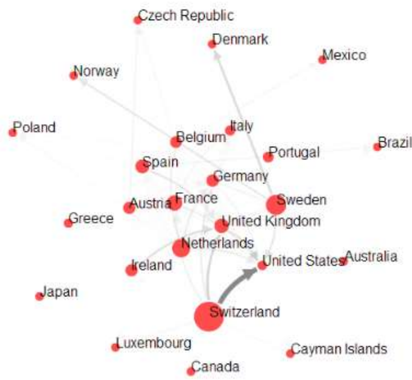
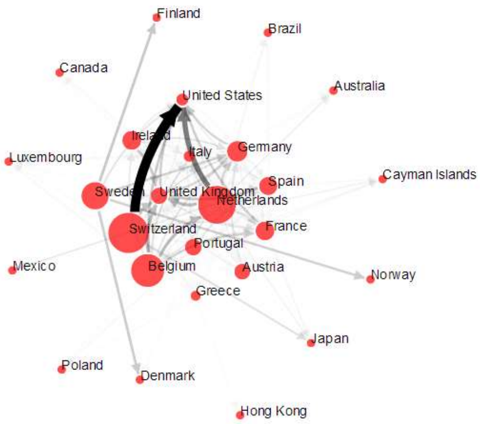


Figure 22: Bilateral Exposure relative to GDP 2014- Q1

Source: Author's own figure

In the third step, to capture the vulnerability of the national banking sector to cross-country spill-over effects, we look at the overall exposure of banks to total exposures. In the fourth step the impact of banking sector systemic risk will be assessed by "relative size of the banking sector", i.e. the size of the banking industry could be measured by the total assets of the banks. Figures 25 and 26. The greater the size of the banking sector relative to national GDP, the more severely that country's banking sector problems would affect economic activity or – in case banks need to be supported by the government – could increase public debt. In the fifth step, we consider the "concentration index", i.e. the diversification of banks' foreign exposure across other countries. To this end, we apply the Herfindahl Index to the GDP of the country and the total assets of banks to measure concentration of a country's top borrowers. This ratio is relevant for the analysis of banks' vulnerability to first-round contagion effects. For a banking sector that is highly exposed to a single or very few other countries, contagion risk may be stronger than for a country that is well diversified in its foreign lending exposure. Bilateral exposure relative to index in 2007-Q4 shows the vulnerability of Swedish, Belgium and Netherland Banks. This vulnerability slightly diminished over the period and in 2014 is much smaller.



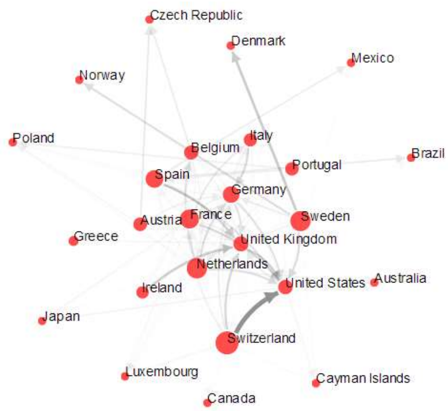
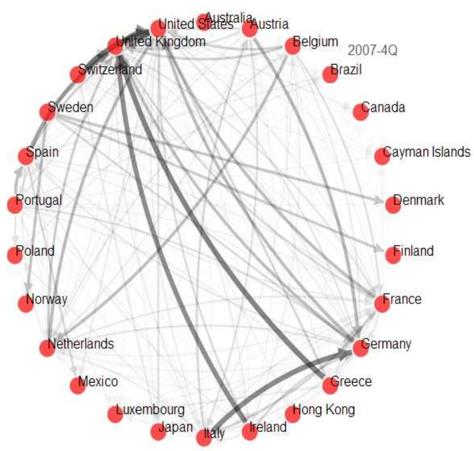


Figure 23: Bilateral Exposure relative to total assets 2006- Q4

Figure 24: Bilateral Exposure relative to total assets 2014- Q1

Source: Author's own figure



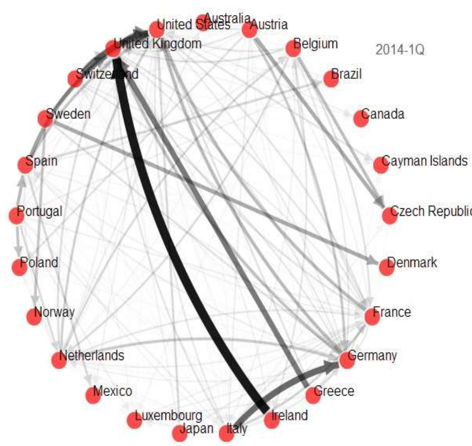


Figure 25: Bilateral Exposure relative to total Exposure 2007- Q4

Figure 26: Bilateral Exposure relative to total Exposure 2014-Q1

Source: Author's own figure

Section 6: Centrality Measures

A clique is a subset of a network (that is, a subset of the nodes and all associated links in a network) that forms a complete graph. The maximum clique is the largest possible clique in a network. Maximum clique measure shows the core of the system. (Figures 27 - 29). Maximum clique index is showing the same countries as core of the system. Basically maximum clique index confirmed the previous result in terms of core countries.

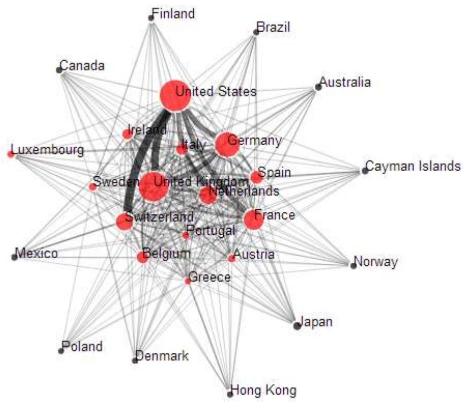


Figure 27: Maximum Clique 2006- Q4
Source: Author's own figure

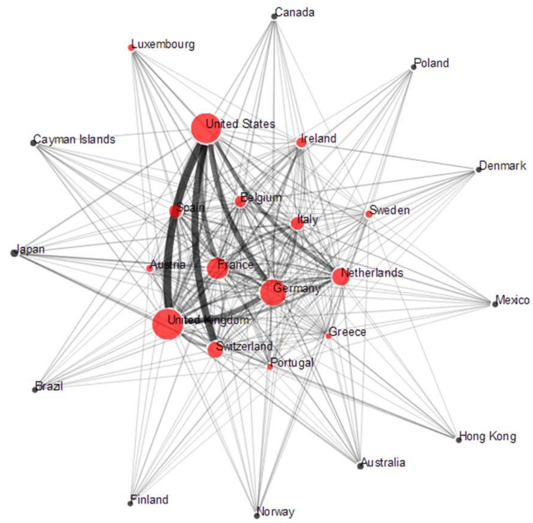


Figure 28: Maximum Clique 2007- Q3

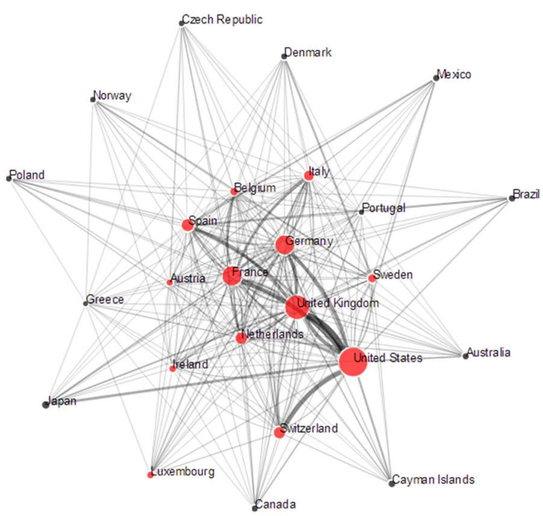


Figure 29: Maximum Clique 2014- Q1
Source: Author's own figure

Newman metrics and Max clique measure of sample A also verify the core-periphery structure of banking network. (Please see Figures (30,31)). These measures were used for all data from 2005 till 2014 with the same result of verifying the core-periphery structure of the banking network.

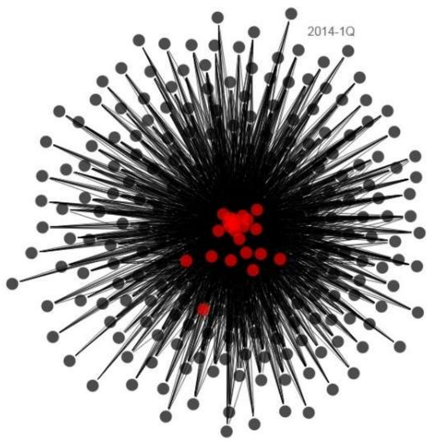


Figure 30: Maximum Clique 2014-Q1

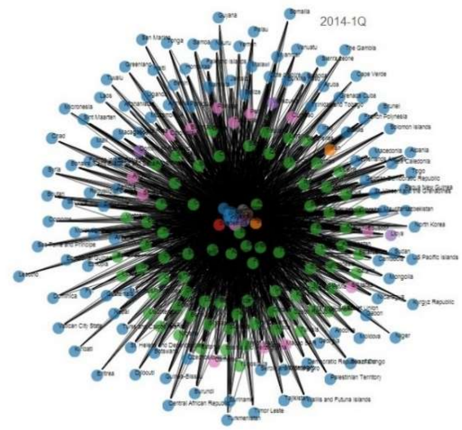


Figure 31: Newman Measure 2014- Q1

Source: Author's own figure

(For more details of network centrality measure and connectedness including Newman, Max clique, cheiRank and closeness for all countries in 2014-1Q see table at appendix 2.)

Betweenness is one of the most important centrality indices, which basically counts the number of shortest paths going through a node. (Geisberger, Sanders and Schultes, 2008). We examine the betweenness measure starting from 2005 with the index of 100, we could see this index increased the most for American banks with 4.5 times comparing to 2005. Although in 2007-Q4 (financial crisis time) the French banks' betweeness was the most remarkable (Figure 32) but in 2014-Q1 American banks led with the highest result. (Figure 32)

Table 1 Betweenness, Source: Author's own computation

	United States	United Kingdom	Switzerland	Germany	France
2005-2Q	100	100	100	100	100
2005-3Q	96.9	92.3	134.2	96.6	112.8
2005-4Q	107.1	97.6	106.5	89.5	100.6
2006-1Q	106.8	119.4	119	79.6	90.1
2006-2Q	119.4	100.9	120.1	85.6	98.6
2006-3Q	119	106.9	115.7	89.8	95.5
2006-4Q	124.5	107.1	138.6	87	93.9
2007-1Q	128.5	60.4	134.7	82.1	109.3
2007-2Q	138.9	55.5	150.2	80.7	114.2
2007-3Q	129.4	53	121.5	89.9	105.4
2007-4Q	119.5	56.2	143.5	86	112.1
2008-1Q	158	57.4	142.8	83.9	103.9
2008-2Q	125.4	61	136.9	81.6	113
2008-3Q	115.5	65.1	129.8	99.8	104.3
2008-4Q	110.4	61.3	115.2	89	112.6
2009-1Q	121	71.3	124.8	90.3	102.8
2009-2Q	132.1	57.6	130.9	82.2	113.8
2009-3Q	123.4	57.8	122.6	75.3	118.2

	United States	United Kingdom	Switzerland	Germany	France
2009-4Q	148.7	59.1	130.7	83.1	117.7
2010-1Q	167.6	67.9	158.5	107.3	47
2010-2Q	159.9	73.4	204.3	100.1	36.9
2010-3Q	182.7	60.6	210.1	99.1	42.6
2010-4Q	212.5	60.1	181.1	98.6	48.5
2011-1Q	187.3	52.3	232.1	102.8	55.1
2011-2Q	204	54.7	204.3	102.3	50.8
2011-3Q	195.6	62.1	174.5	108.3	63.9
2011-4Q	221	100.4	179.9	104.4	56.8
2012-1Q	235.5	77	234	121.6	0.5
2012-2Q	232.8	80.3	209.7	128.4	0.5
2012-3Q	230.3	73.5	211.2	126.6	0.5
2012-4Q	251	69.6	171.7	116.3	0.5
2013-1Q	247.8	82.9	160.1	131.5	0.5
2013-2Q	257.8	64.2	180.6	118.5	0.5
2013-3Q	259.7	84.5	173.5	121.7	0.5
2013-4Q	428.9	69.9	0.3	121.9	0.6
2014-1Q	445.8	78.8	0.3	129.3	0.6

Centrality Measures

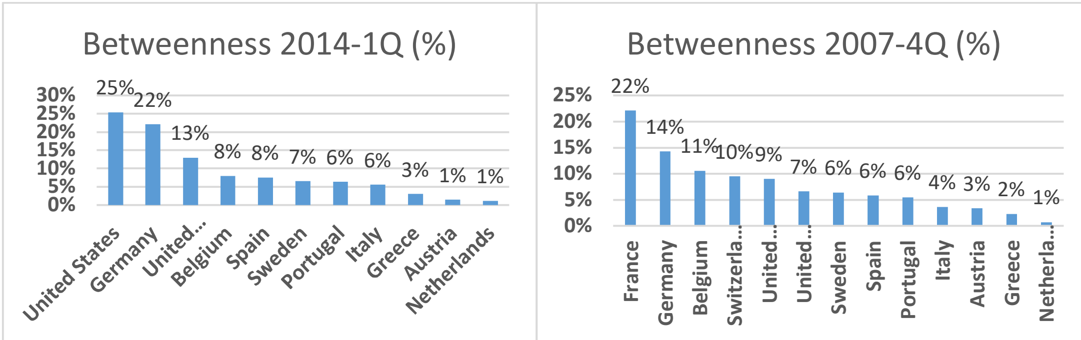


Figure 32: Betweenness 2007-Q4 & 2014-Q1
Source: Author's own figure

Figure 33: CheiRank vs PageRank

The cheiRank PageRank two dimension shows the systemic important and fragile role of American and British Banks in 2014-Q1 with different roles for American banks in 2007, which American banks were only fragile in 2007. (Figures 34,35)

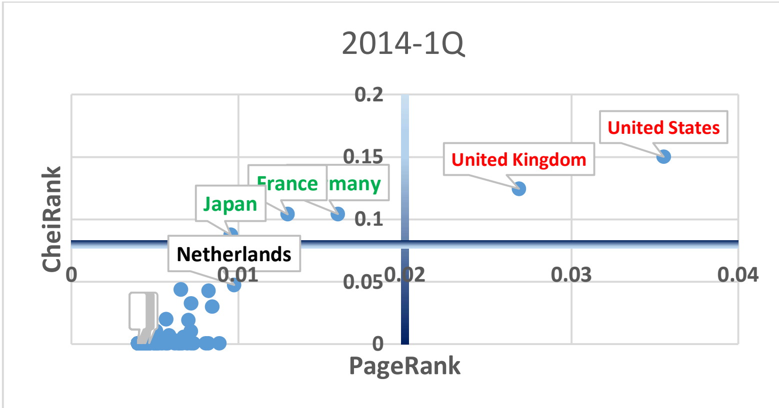


Figure 34: CheiRank vs PageRank 2014- Q1

Source: Author’s own figure

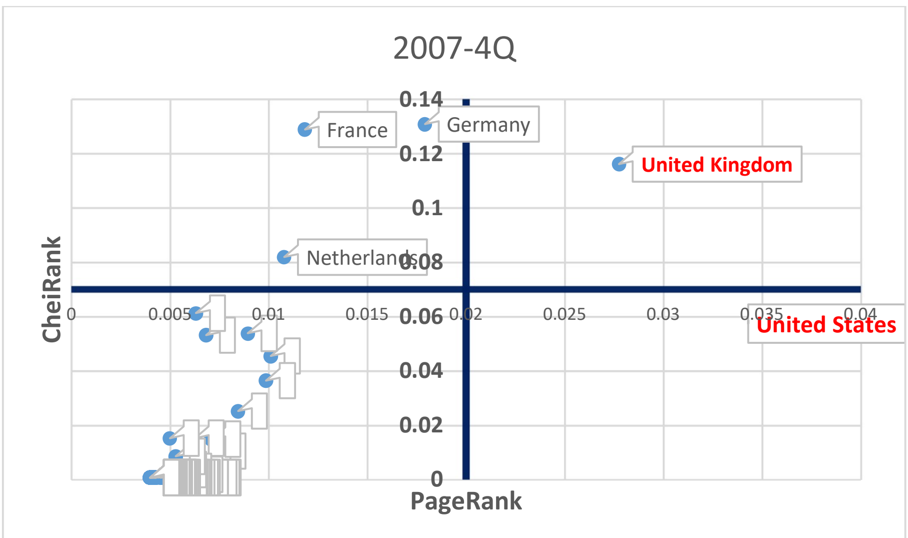


Figure 35: CheiRank vs PageRank 2007-Q4
Source: Author’s own figure

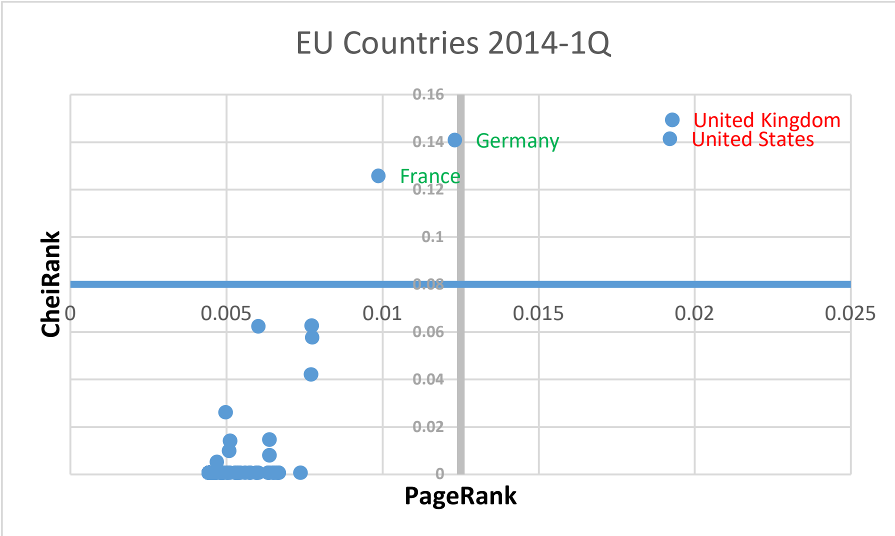


Figure 36: CheiRank vs PageRank EU countries 2014-1Q
Source: Author's own figure

Section 7: Core Periphery Model

This section provides evidence that banking network at country level is tiered rather than flat, in the sense that banking network follow the core periphery structure. We capture the concept of tiering by developing a core periphery model, and devise a procedure to test the model to real-world networks. Using International Bank of Settlement data on bilateral exposures (ultimate risk) among EU banks, we find strong evidence of tiering in the banking network at country level.

Getting a better picture of the network structure will be a crucial step in developing systemic risk assessments of the interbank market. The idea of the Core Periphery model a small set of Core banks is highly connected, while Periphery banks are not connected with each other but only to the Core. Recently, attention has been shifting towards models of the network structure that might be particular to socio-economic relationships and less so to phenomena in the natural world. Its implications are mainly to account for the complexity noted by researchers Markose (2012) in terms of banks' obligations and connectivity. A number of authors have argued that interbank relations might be coming to a core-periphery structure, a setting first proposed in sociology for networks of acquaintanceships Borgatti and Everett, (2000). Craig and Von Peter (2010) apply this model to interbank data. (Fricke & Lux, 2014) have applied the core-periphery framework to data of the electronic platform e-MID that basically is used for shortterm (overnight) liquidity provision. More specifically, this analysis is applied in a core-periphery (CP) analysis of the UK interbank market is provided by Langfield, Liu and Ota (2012) who use a comprehensive data set on connections between UK banks with a detailed breakdown into a large number of financial instruments across these banks.

The testable hypothesis here will be, whether banking network at county level follows the core periphery structure or not. This means that there is a small number of very interconnected banks that trade with many other banks and a large number of banks that trade with a small number of counterparties.

Similarly, to test the concept of an interbank core-periphery network in a quantitative way, Craig and von Peter (2010) introduce system that implements a strict definition. In a perfect Core Periphery structure, the following two conditions are satisfied:

Condition 1: core banks are all bilaterally linked with each other and both lend to and borrow from at least one periphery bank;

Condition 2: periphery banks are linked to core banks only and do not lend to each other.

To test the hypothesis we track the evolution of the network on a quarterly basis from 2005 Q1 through 2015 Q3.

For our procedure we first estimate the Core Periphery model, finding the number of core countries for every period. In our dataset, the core varies between 13 and 21 countries. Figure 56 plots the core size per period. Although over a long period of time the core size stays relatively stable around 15.

The structure we identified is highly persistent. First, the size of the core and the associated error score are stable over time (see Figure 37). Importantly, the composition of banks group within the core also remains remarkably stable over time. This can be shown by means of the estimated transition matrix:

$$P(s/\acute{s}) = \begin{array}{lcc} & Core & Periphery \\ Core & \%94.77 & \%5.23 \\ Periphery & \%1.04 & 0.98.96 \end{array}$$

The element $P_{\text{Core}-\text{Peripher}}$ P represents the frequency with which core banks move to the periphery over time. The fact that the values on the diagonal are close to unity confirm that banks tend to remain in the same tier (core or periphery). Estimating a separate transition matrix for each quarter demonstrates its stability over time (Figure 37).

We also calculate the transition matrix between the states of being in the core and in the periphery. Most importantly, the transition from core to core indicates that on average 98% of the core banks stay in the core the next period. As we found that the number of core banks is quite stable, the flow from and to the core is in absolute terms almost equal. The higher persistence in the periphery merely reflects that it consists of much more countries.

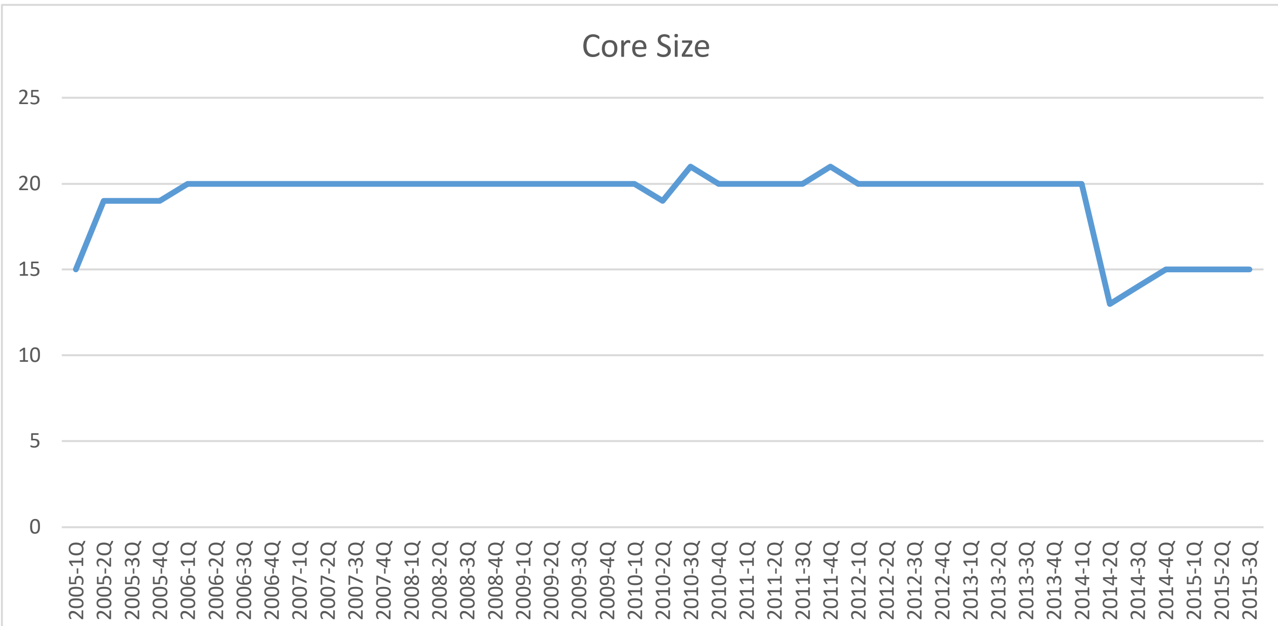


Figure 37: Structural Stability over time, size of the core (number of core banks group)
Source: Author's own figure

Core Membership and Bank-Specific Variables

Table 2 reports the results of probit regressions testing whether network position can be predicted by individual network variables. This will help provide insight into how core nodes and peripheral nodes are formed within the network.

Using the binary variables by Craig Von Peter Core Index, core membership takes the value 1 for banks that were determined to be in the core, and 0 for the remaining banks. (It is regressed on a constant and the regressors shown in the rows, which rely only on consolidated bank data (except for some variables, which require the network data). The columns show the different regressions, each comprising 8872 observations.

The cells show the maximum likelihood estimates of the coefficients. T statistics are shown in parentheses, Significance is denoted by *(5%) and **(1%) ***(10%).

Total banks exposures are the natural logarithm of total exposures (in 1000s USD plus 1); Betweenness is the logarithm of normalised betweenness Centrality indicator which could be used as connectedness index Freeman (1978). The fit with Betweeness is much better than that with cross border exposures.

Table 2 Core membership and bank-specific variable, probit regressions test

Dependent Variable: CORE
2005-Q1 – 2015Q3

Regresssors	1	2	3	4	5	6	7	8	9	10	11	12	13
Exposures	0.04		-0.00	0.01	0.03				0.01	-0.00	0.01		0.01
	(60.20)		(-1.17)	(24.64)	(37.58)				(28.51)	(-1.56)	(22.87)		(28.10)
Closeness			3.46			0.11	3.25		-0.64	3.29		-0.03	-0.75
			(96.41)			(2.79)	(91.93)		(-14.16)	(77.95)		(-0.84)	(-15.89)
Betweenness		0.12		0.12		0.12		0.12	0.13		0.12	0.12	0.13
		(211.29)		(178.10)		(98.49)		(165.78)	(106.75)		(156.01)	(98.72)	(106.76)
Pagerank					38.59		6.17	4.82		6.23	1.81	4.99	4.15
					(44.57)		(7.86)	(9.60)		(7.93)	(3.58)	(9.22)	(7.98)
C	-0.26	0.02	-1.70	-0.05	-0.32	-0.03	-1.62	-0.00	0.24	-1.63	-0.06	0.01	0.28
	(-40.50)	(14.79)	(-108.96)	(-16.64)	(-53.93)	(-1.79)	(-100.40)	(-0.70)	(11.45)	(-93.53)	(-16.67)	(0.75)	(12.95)
R-squared	0.29	0.83	0.65	0.84	0.42	0.83	0.66	0.84	0.85	0.66	0.85	0.84	0.85
No. of observations	8872	8872	8872	8872	8872	8872	8872	8872	8872	8872	8872	8872	8872

Dependent Variable: CVPCORE
Method: Least Squares

Sample: 1 8872
Included observations: 8872

By using Least Square technique between core variable as independent and all other variables separately or jointly, (above figures) we show here a core-periphery network- few highly interconnected and many sparsely connected banks- endogenously emerges in our model. In other words, we show here that there is a small number of very interconnected banks that trade with many other banks and a large number of banks that trade with a small number of counterparties. This structure is consistent with that in the calibrated model of Farboodi (2014) and Gofman (2012) as well as empirical evidence on intermediation in several markets, including the federal funds market (Bech & Atalay, 2008), (Allen & Saunders., 1986), (Afonso and Lagos., 2012) and (Afonso, Kovner and Schoar., 2011), international interbank markets (Boss, et al., 2004) for Austria; (Chang, Lima, Guerra, & Tabak., 2008) for Brazil; (Craig and Von 2010) for Germany and (Lelyveld and Veld. 2012) for Netherlands), and the OTC derivatives market (Atkeson and Eisfeldt 2013).

The single most effective regressor in predicting whether or not a country will be a "core-bank country" (CBC) is the one that takes network data into account. A country's betweenness predicts quite reliably whether or not it is in the core, as in seen by its lack of variability in the regression table. Betweenness is the probability with which a node lies on the shortest path between any two unconnected nodes. The probit regression makes clear that connectedness predicts core membership better than does exposure values. This is not surprising: the core comprises the banks that jointly intermediate between the periphery, so a bank that helps to link pairs of unconnected banks also contributes to the core performing this role for the market as a whole. Comparing table 2 to table in appendix 3 the decrease in the relationship pre and post-2014 between the total exposures a country faces and its status as a 'core-bank country (CBC) shows that the importance of lending/borrowing to become a CBC has increased; to be counted as a CBC purely from lending/borrowing transactions, a country must be willing to allocate more of its resources to these activities.

The same can be said regarding the relationship between a country's status as a CBC and its betweenness in the banking sector; for a country post-2014 to be considered a CBC it must be much more connected to the banking activities around it. This leads to those left classified as CBCs in the core-periphery model with an average of more connections of lending/borrowing to other countries. It also points to a model of fewer even more highly connected CBCs, which can be seen as the average number of CBCs fell from 20 to 15 in the years before and after 2014. (See Figure 37)

The increase in the t-statistics of exposure and PageRank post-2014 show that there is a reduced standard error in calculating their relationship to a country's status as a CBC (as the t-statistic is the ratio of estimated correlation coefficient over standard error). Coupled with the respective correlation coefficients, this backs up the data found suggesting that countries really must lend/borrow more to be a CBC, as well as indicating that CBCs have a much higher visibility on the Web and noticeable impact on the online banking industry than pre-2014.

The general slight decrease in R-squared values in the regressions undertaken for years before and after 2014 indicates there is a little more spread of countries above and below the line of best fit for each regression. However, since the change is so small, it can be said to have little to no effect on the validity of the regression analysis.

Is the importance of bank total exposures for network position an expression of economies of scale and scope? This question should be addressed with a definition of total exposures that is unrelated to a bank's interbank activity. The intermediary function that core banks perform, by inflow exposures and outflow exposures in the interbank market, of course contributes to their reported balance sheet size. We thus compute the intrinsic exposures of a bank as (the logarithm of) total bilateral exposures (ultimate risk). Intrinsic exposures, when used alone, delivers a poor fit and the coefficient is too small to identify core banks at the default threshold (column 1). The variable remains significant but adds little explanatory power when used jointly with other centrality measures. The single most effective regressor will be one that takes network data into account. Column 2 shows that a banks' connectedness predicts quite reliably whether or not it is in the core, where we measure connectedness by betweenness centrality. Betweenness is the probability with which a node lies on the shortest path between any two unconnected nodes. The probit regression makes clear that connectedness predicts core membership better than does bank exposure. This is not surprising when one recognizes tiering as a 'group version' of betweenness: the core comprises the banks that jointly intermediate between the periphery, so a bank that helps to link pairs of unconnected banks also contributes to the core performing this role for the market as a whole.

More intriguing is the presence of outliers: for reasons of specialization, some very large banks in terms of exposures, were found to be far less connected than their total exposures and presence in the core would suggest. This touches on the open question of whether 'too-big-to-fail' or 'too-connected-to-fail' is the relevant criterion for financial stability. However, the prediction can be further improved by focusing on the size and centrality measures of interbank intermediation activity. Exposures, betweenness and PageRanks jointly predict the core membership slightly better (Column 11). Column 8 shows that connectedness variables in their own predict core membership nearly as reliably as size and betweenness (Column 4) , and better than closeness variable, without requiring the bilateral data necessary for these two regressors. Finally, we include the aforementioned variables jointly to examine their respective explanatory power. In regression 13, it is clear that each regressor remains significant in concert with the others: total bilateral exposures, betweenness, PageRank and Closeness all contribute to explaining which banks form the core.

All in all, the results of Table 2 show that network position is predictable by banks specific features. Banks are in the core because they are well-connected, both when measured by connectedness (betweenness centrality mainly); they are also in the core due to their ability to carry out large transactions, as measured by their total bilateral exposures or by the volume of interbank intermediation they perform.

Section 8: Conclusion

As was seen from the models a stable financial system ought not propagate or magnify shocks to the other parts of the network. The model employed shows that the nature of systemic risk depends on the interplay of the network topology. Systemic risk as we defined is a network architecture that subjects the entire network to failure or reduced efficiency from the effect of a singular local incident or simultaneous shocks. How the banks relate with one another, the means of communication and other transfer between banks is key and the model indicated that the actual nature of financial transactions over the network, individual banks' assets and also the buffer stemming from banks' size are determinants of correlation between network topology and systemic risk. Other factors evidenced were the nature of the shocks to the network, the source of the shock, where it falls within the network topology and sub-connections within the network will show how much a network will propagate a shock.

Being too big to fail, as well as being too interconnected, too central, and too correlated to fail was also examined and were shown to be reasons why the network can arrive to unstable configurations detrimental for the entire system. The differentiation ration between global and local components of financial institutions have played a key role. In the desire to expand coverage and maximise individual profits and interests without the due care taken for the external impact such measures impose on the stability of the system as whole, banks and other key financial institutions have a role in increasing systemic risk over the financial network. In this paper we empirically test that the interbank network structure follows the core-periphery model, a setting first proposed in sociology for networks of acquaintanceships, (Borgatti and Everett, 2000), which covers the network complexity.

The framework for studying and visualising the relationship between the financial network topology and systemic risk due to contagion of bilateral exposures is presented such that if banks were willing to minimize systemic risk when they take decisions, they would need to have sufficient information regarding the financial situations of the other banks, such as the exposures each bank has on each other. We saw that the centrality measures the fit of Core with Betweeness is a best fit for capturing centrality in this network. How much does a particular node exert influence on others? Take a scenario where one bank wants to evaluate the riskiness associated with a loan to another bank, it should be able to know the exposures of its counterparty, what other firms are affected by its counterparty? The probability of defaults depending on its own counterparties, and so on. Centrality measures will be best evaluated with crucial access to information and banks can better analyse the probability of defaults due to contagion effects.

A global view (rather than local only) is required for a more thorough assessment of the network topology. The systemic risk in a network of interlinked financial institutions in selected countries, was then analysed using a metric for the systemic importance of players in the global picture. To identify and monitor possible sources and channels of contagion in a system a robust framework is required. This allows for intervention just in time to prevent networks from descending into full blown critical situations.

The systemic risk in a network of interlinked financial institutions in selected countries, was analysed using a metric for the systemic importance of players. The methodology involved applying calculations to a dataset of consolidated cross-border mutual exposures on several bases: ultimate risk of bank default, relative bank size to size of the economy, size of the banks and concentration index, the role of balance sheet size, and the domestic network property for each country's banks. Then each regions contribution to systemic risk was analysed. The results we came to outlined the contribution of banks' size, size of economy and concentration of counterparty exposures to a given country's banks and therefore its systemic importance.

It is concluded that proactively tracking potential systemic linkage should be in the agenda of regulators globally. Unprecedented levels of financial interconnections during stress events means that although counter intuitive, actions geared at enhancing soundness of a particular bank or institution may undermine the stability of other banks or of the whole network. Interconnectedness in the financial system was part of the problem in the financial crisis, Stiglitz (2014). This paper carefully uses the network approach to analyse interconnectedness, and therefore provides some insights to monitor systemic risk. As a result, there are suggestions of a potentially fruitful road of forming policies to mitigate against systemic risk. It is highlighted that a better regulation is at the focus of financial reform needs. This reform should encapsulate much more than the singular dimensional need for higher capital ratios or better liquidity ratios for instance. The new connected world needs a new financial architecture with a new approach to regulation that takes as a major variable the multi-tiered complexity interconnectedness involves. Similarly, supervising cross border resolutions of banks and financial institutions should get more attention in the risk management approach of financial systems, and a more assertive global supervisory for financial systems is needed, to capture and monitor proactively the interconnectedness between countries' financial systems. The findings of the network approach attempts to answer the question of the ideal structure of a more stable banking system and highlights that we don't know enough yet. However, these findings could provide part of a puzzle even if not the whole picture. The study succeeds in making firm contributions to the existent literature by developing a framework that explains how interdependencies between banks at country level emerge endogenously.

Bibliography

A. H., Cont, R., & Minca, A. (2012). Stress testing the resilience of financial networks. *International Journal of Theoretical and Applied Finance, 15(1)*, 1-20.

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2013). Systemic Risk and Stability in Financial Networks. *Working Paper No. 18727, National Bureau of Economic Research, Cambridge, MA, USA*.

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2013, January). Systemic Risk and Stability in Financial Networks. *The National Bureau of Economic Research*.

Acharya, V., Pedersen, L., Philippon, T., & Richardson, M. (2010). Measuring systemic risk. *Working Paper*.

Adamic, L. (2015). *Introductory social network analysis.* University of Michigan.

Adrian, T., & Brunnermeier, M. K. (2008). *CoVaR.* Staff Report, Federal Reserve Bank of New York.

Afonso, G., & Lagos., R. (2012). *Trade dynamics in the market for federal funds. .* New York: FRB of New York Staff Report.

Afonso, G., Kovner, A., & Schoar., A. (2011). *The importance of trading relationships in he fed funds market. he fed funds market.* working paper Fed New-York.

Albert, R., & Baraba´si, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics, 74*, 47-97.

Albert-László, B., & Réka, A. (October 1999). Emergence of scaling in random networks. *Science, 286*, 509-512.

Alessandri, P., Gai, P., Kapadia, S., Mora, N., & Puhr, C. (2009). Towards a Framework for Quantifying Systemic Stability. *International Journal of Central Banking, Vol. 5(3)*, 47-81.

Allen, F., & Babus, A. (2007). *Networks in Finance: Network-based Strategies and Competencies.* Chapter 21, Working Paper 08–07 (Wharton School publishing).

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy, 108*, 1-33.

Allen, F., & Gale, D. (2000). Financial Contagion. *Journal of Political Economy, Vol. 108*, pp. 1–33.

Allen, L., & Saunders., A. (1986). The large-small bank dichotomy in the federal funds market. *Journal of Banking & Finance ,10 (2)*, 219-230.

Alvarez, F., & Barlevy, G. (May 2014). Mandatory Disclosure and Financial Contagion. *Interconnectedness: Building Bridges between Research and Policy Conference.* Washington D.C.

Amini, H., Cont, R., & Minca, A. (2010). Resilience to contagion in financial networks. *http://ssrn.com/abstract=1865997*.

Atkeson, A. G., & A. L. Eisfeldt, P.-O. W. (2013). *The market for otc derivatives.* National Bureau of Economic Research.

Bak, P., Chen, K., Scheinkman, J., & Woodford., M. (1993). Aggregate fluctuations from independent sectoral shocks: self-organized criticality in a model of production and inventory dynamics. *Ricerche Economiche,47*, 3-30.

Barabási, A.-L. (April 2002). *Linked: The New Science of Networks.* Perseus Publishing.

Barrat, A., Barthelemy, M., R., P.-S., & Vespignani, A. (2004). The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences 101 (11)*, 3747-3752.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B. C., & Stiglitz, J. E. (2009). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *National Bureau of Economic Research, Working Paper 15611.*

Bech, M., & Atalay, E. (2008). The topology of the Federal Funds Market. *ECB Working Paper No. 986.*

Beyeler, W., Bech, M., Glass, R., & Soramäki, K. (2007). Congestion and cascade in payment systems. *Physica A 382(2)*, 693-718.

Bigio, S., & LaO, J. (2013). *Financial Frictions in Production Networks.* working paper.

Blume, Lawrence, Easley, D., Kleinberg, J., Kleinberg, R., & Tardos, ´. (2011). Which netnetworks are least susceptible to cascading failures? *52nd IEEE Annual Symposium on Foundations of Computer Science (FOCS)*, (pp. 393-402).

Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology,2(1)*, 113-120.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology, 92*, 1170–1182.

Borgatti, S. P. (2005). Centrality and network flow. *Social Networks, 27*, 55-71.

Borgatti, S. P., & Everett, M. G. (2000). Models of core/periphery structures. *Social Networks, 21(4),* , 375-395.

Boss, M., Breuer, T., Elsinger, H., Jandacka, M., Krenn, G., Puhr, C., & Summer., M. (2006). *Systemic Risk Monitor: Risk Assessment and Stress Testing for the Austrian Banking system.* OeNB Financial Stability Report 11. 83–95.

Boss, M., Elsinger, H., Lehar, A., & Summer, M. (2004). The network topology of the interbank market. *Quantitative Finance,4*, 677-684.

Boss, M., Elsinger, H., Summer, M., & Thurner, S. (2004). Network Topology of the Interbank Market. *Quantitative Finance, Vol. 4*, pp. 677–684 .

Brandes, U. (2001). A Faster Algorithm for Betweenness Centrality. . *Journal of Mathematical Sociology 25,*, 163-177.

Brass, D. (1984). Being in the right place: A structural analysis of individual influence in an organization. . *Administrative Science Quarterly, 29:* , 518-539.

C.-L. J., Espinosa, M., Giesecke, K., & Sole, J. A. (2009). *Assessing the Systemic Implications of Financial Linkages.* IMF Global Financial Stability Report, Vol. 2, April 2009.

Caballero, R. J., & Simsek, A. (2013). Fire sales in a model of complexity. *Journal of Finance, 68*, 2549–2587.

Castrén, O., & Kavonius, I. K. (2009). Balance sheet interlinkages and macro-financial risk in the euro area. . *ECB Working Paper Series No. 1124*.

Chang, E. J., Lima, E. J., Guerra, S. M., & Tabak., B. M. (2008). Measures of interbank market structure: An application to brazil. *Brazilian Review of Econometrics, 28(2)*, 163-190.

Chan-Lau, J., Espinosa, M., Giesecke, K., & Solé., J. (April 2009). *Assessing the Systemic Implications of Financial Linkages.* Chapter 2, Global Financial Stability Report,.

Cont, R. (2009). *Measuring systemic risk. .* Working paper.

Cont, R., & Moussa, A. (2010). *Too interconnected to fail: contagion and systemic risk in financial network.* Columbia University: Financial Engineering Report 2010-03.

Cont, R., Moussa, A., & Santos, E. (2012). *Network Structure and Systemic Risk in Banking Systems .* In Handbook of Systemic Risk, edited by J.P. Fouque and J. Langsam: Cambridge University Press.

Craig, B., & Von Peter, G. (2010). *Interbank tiering and money Centre Banks.* BIS Working Papers No 322.

Degryse, H., & Nguyen, G. (2007). Interbank exposures: An empirical examination of contagion risk in the Belgian banking system. *International Journal of Central Banking*, 123-171.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik 1,* , 269-271.

Durlauf, S. N. (1993). Nonergodic Economic Growth. *Review of Economic Studies, 60*, 349-366.

E. H., Lehar, A., & Summer, M. (2006). Risk assessment for banking systems. *Managment Science, 52(9)*, pp 1301-1314.

Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial Networks and Contagion . *American Economic Review*.

Elsinger, H., Lehar, A., & Summer, M. (2006). Risk assessment for banking systems. *Management Science 52(9)*, 1301-1314.

Elsinger, H., Lehar, A., & Summer, M. (2006). Risk Assessment for Banking Systems. *Management Science, Vol. 52, No. 9*, pp. 1301–14.

Elsinger, H., Lehar, A., & Summer, M. (2006). Systemically important banks: an analysis for the European banking system. *International Economics and Economic Policy, 3(1)*, pp 73-89.

Ermann, L., Chepelianskii, A. D., & Shepelyansky, D. L. (2012). Toward two-dimensional search engines. *Journal of Physics A: Mathematical and Theoretical, Vol 45 No 27*.

Espinosa-Vega, M., & Solé, J. (April 2010). *Cross-Border Financial Surveillance: A Network Perspective.* IMF Working Paper, No WP/10/105.

Farboodi, M. (2014). *Intermediation and voluntary exposure to counterparty risk.* working paper.

Farboodi., M. (2014). *Intermediation and voluntary exposure to counterparty risk.* Chicago: Working Paper, University of Chicago available at: http://home.uchicago.edu/~farboodi/MaryamFarboodiJMP.pdf.

Freeman, L. (1978). Centrality in social networks: I. Conceptual clarification. *Social Networks,1*, 215-239.

Freeman, L. C., Borgatti, S. P., & White, D. R. (1991). Centrality in valued graphs: A measure of betweenness based on network flow. *Social Networks 13 (2),*, 141-154.

Freixas, X., Parigi, B., & Rochet, J. C. (2000). Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. *Journal of Money, Credit, and Banking, vol 32*, pp 611-638.

Fricke, D., & Lux, T. (2014). Core-periphery structure in the overnight money market: Evidence from the e-mid trading platform. *Computational Economics.*

Furfine, C. H. (2003). Interbank Exposures: Quantifying the Risk of Contagion. *Journal of Money, Credit and Banking, Vol. 35, No. 1.* .

G, I., Masi, G. d., Precup, O., Gabbi, G., & Caldarelli, G. (2008). A network analysis of the Italian overnight money marke. *Journal of Economic Dynamics and Control, vol. 32(1),* , 259-278.

G10. (January 2001). *Report on consolidation in the financial sector.* IMF.

Gai, P., & Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A 466(2120)*, 2401-2423.

Gai, P., Haldane, A., & Kapadia, S. (2011, 5). Complexity, concentration and contagion. *Journal of Monetary Economics.Vol: 58*, pp. 453-470.

Galbiati, M., & Soramäki, K. (2011). Agent-based model of payment systems. *Journal of Economic Dynamics and Control 35(6)*, 859-875.

Geisberger, R., Sanders, P., & Schultes:, D. (2008). Better Approximation of Betweenness Centrality. *ALENEX*, 90-100.

Gerlach, S. (2009). *Defining and Measuring Systemic Risk.* European Parliament's Committee on Economic and Monetary Affairs. Retrieved April 24, 2013.

Gofman, M. (2012). *Efficiency and stability of a ancial architecture with too interconnected to fail institutions. .* Available at SSRN 2194357.

Goldin, I., & Mariathasan, M. (2014). The Butterfly Defect: How globalization creates systemic risk, and what to do about it. *Princeton University Press, July*.

Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology, 83*, 1420-1443.

Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory 1*, 201–233.

Haldane, A. (2009). Rethinking the Financial Network. *Bank of England.* London.

Haldane., A. G. (2014). *Managing global finance as a system.* Speech given by Andrew Haldane at the Maxwell Fry Annual Global Finance Lecture, Birmingham University. avialable at: http://www.bankofengland.co.uk/publications/Documents/speeches/2014/speech772.pdf.

Hattori, M., & Suda, Y. (2007). Developments in a cross-border bank exposure network. *Research on global financial stability: the use of BIS international financial statistics, CGFS Publications*, No. 29, pp. 16–31.

Hellwig, M. (1995). Systemic aspects of risk management in banking and finance. *Swiss Journal of Economics & Statistics*, 131(IV):723{737.

Jovanovic, B. (1987). Micro Shocks and Aggregate Risk. *Quarterly Journal of Economics, 102,*, 395-409.

Katz, L. (1953). A new index derived from sociometric data analysis. *Psychometrika, 18*, 39-43.

Kaufman, G. G. (1996). Bank Failures, Systemic Risk, and Bank Regulation. *16 CATO J. 17, 21 n.5, (quoting Alan Greenspan, Remarks at a Conference on Risk Measurement and Systemic Risk, Nov, 16, 1995*.

Kaufman, G. G. (1999). *Banking And Currency Crises And Systemic Risk: A Taxonomy And Review .* Loyola University Chicago and Federal Reserve Bank of Chicago.

Langfield, S., Liu, Z., & Ota, T. (2012). *Mapping the UK Interbank System.* London: UK Financial Sevices Authority.

Lelyveld, v., & Liedorp, F. (2006). Interbank contagion in the dutch banking sector: A sensitivity analysis. *International Journal of Central Banking*.

Long, J. B., & Plosser, C. I. (1983). Real Business Cycles. *Journal of Political Economy, 91*, 39-69.

Marsh, B. (2010, May 1). Europe's Web of Debt. *The New York Times*.

Martínez-Jaramillo, S., Castañón, C. L., Fernando, O. P., Embriz, A., & Dey, F. L. (2010). Systemic risk, stress testing and financial contagion: Their interaction and measurement. *A paper prepared for the BIS CCA Conference on Systemic risk, bank behaviour and regulation over the business cycle.* Buenos Aires: BIS CCA-006-2010.

McGuire, P., & Tarashev, I. N. (2008). *Global monitoring with the BIS international banking statistics.* Bank for International Settlements, BIS Working Papers 244.

McGuire, P., & Tarashev, N. (December 2006). Tracking international bank flows. *BIS Quarterly Review*, 27-40.

Memmel, C., & Stein, I. (2008). *Contagion in the German Interbank Market.* Frankfurt: Deutsche Bundesbank.

Milgram, S. (1967). Psychology Today. *The Small World Problem. Psychology Today, 2*, 60–67.

Mistrulli, P. E. (2007). *Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns.* Rome, Italy: Temi di Discussione 641, Bank of Italy, Economic Research Department.

Morris, S. (2000). Contagion. *Review of Economic Studies*, 57-78.

Müller, J. (2006). Interbank Credit Lines as a Channel of Contagion. *Journal of Financial Services Research (Swiss National Bank).* , pp 37-60.

Murray, A., & Rawcliffe, G. (2010). *International Financial Contagion – Easy to Define, Difficult to Measure.* Fitch Ratings Global Special Report. October 6, 2010. .

Newman, M. (2001). Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality. *Physical Review E 64, 016132.*

Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences USA - 103 (23): 8577–8696. doi:10.1073/pnas.0601602103.*, 8577-8696.

Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control, 31*, 2033{2060.

Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network Models and Financial Stability. *Journal of Economics Dynamics & Control, 31*, pp. 2033-60.

Okuma, R. (August 2012). Sectoral interlinkages in balance sheet approach. *Sixth IFC Conference on Statistical Issues and Activities in a Changing Environment.* Basel: Bank of International Settlement.

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks 32,*, 245-251.

Page, L., Brin, S., Motwani, R., & T Winograd, T. (1999). *The pagerank citation ranking: Bringing order to the web.* Technical Report 1999-66, Stanford InfoLab.

Peter, G. v. (2010). *International banking centres: a network perspective.* In Research on global financial stability: the use of BIS international financial statistics. CGFS Papers No. 40. pp. .

Rönnqvist, S., & Sarlin, P. (06/2014). Bank Networks from Text: Interrelations, Centrality and Determinants. *eprint arXiv:1406.7752*.

Rosenberg, J., & Schuermann, T. (2006). A general approach to integrated risk management with skewed, fat-tailed risks. *Journal of Financial Economics 79*, 3569-614.

Schweitzer, F., Fagiolo, G., Sornette, D., & Vega-Redondo, F. (2009). Economic Networks:The New Challenges. *Science , 325*, 422.

Sheldon, G., & Maurer, M. (1998). Interbank lending and systemic risk: An empirical analysis for switzerland. *Swiss Journal of Economics and Statistics, 134(IV)*, 685-704.

Sheldon, G., & Maurer, M. (1998). Interbank Lending and Systemic Risk: An Empirical Analysis for Switzerland. *Swiss Journal of Economics and Statistics, 134(4.2)*, pp 685–704.

Smilkov, D., Hidalgo, C. A., & Kocarev, L. (2014). Beyond network structure: How heterogeneous susceptibility modulates the spread of epidemics. *Scientific Reports 4, Article number: 4795*.

Soramäki, K., Bech, M. L., Arnold, J., Glass, R. J., & Beyeler, W. E. (March 2006). *The Topology of Interbank Payment Flows.* Federal Reserve Bank of New York, Staff Report no. 243.

Soramaki, K., Bech, M., Arnold, J., Glass, R., & Beyeler, W. (2007). The topology of interbank payment flows. *Physica A, Vol. 379*, 317-333.

Sorkin, A. R. (2009). *Too Big to Fail: The Inside Story of How Wall Street and Washington Fought to Save the Financial System.* Viking.

Stiglitz, J. E. (May 2014). Interconnectedness and Financial Stability. *Interconnectedness: Building Bridges between research and policy.* Washington D.C.

U. C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability, 7(3)*, 111-125.

U. C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability, 7(3)*, pp 111–125.

Upper, & Worms. (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review, 48(4)*, 827-849.

Upper, C., & Worms, A. (2004). Estimating Bilateral Exposures in the German Interbank Market: Is There a Danger of Contagion? *European Economic Review, Vol 48*, pp. 827–849.

Van Lelyveld, I., & Veld., D. i. (2012). *Finding the core: Network structure in interbank markets.* DNB Working Paper No. 348 / July.

Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications.* Cambridge: Cambridge University Press.

Watts, D. (2003). *Six Degrees: The Science of a Connected Age.* W. W. Norton & Company. ISBN 0-393-04142-5.

Watts, D. J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences of the United States of America, 99*, 5766–5771.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature 393 (6684)*, pp. 440-442.

Weistroffer, C., & Möbert, J. (2010). *Monitoring cross-border Exposure, A primer on how to exploit the BIS banking statistics .* Frankfurt: Deutsche Bank Research Dep.

Wells, S. (2004). *Financial Interlinkages in the United Kingdom’s Interbank Market and the Risk of Contagion.* London: Bank of England, Working Paper no 230.

Wells, S. (2004). *Financial interlinkages in the United Kingdom's interbank market and the risk of contagion.* London: Working Paper 230, Bank of England.

Wetherilt, A., Zimmerman, P., & Soramäki, K. (2008). The sterling unsecured loan market during 2006–2008: insights from network topology. *in Leinonen (ed), BoF Scientific monographs, E 42*.

Zhou, H., Huang, X., & Zhu, H. (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking and Finance*, 2036-2049.

Appendix 1

Data:
To monitor cross border exposures of banks' in selected countries use banking data to compare banks' cross-border exposures, both at the individual country level and in a network context. In the first step 177,111 data was gathered. The data were purified for EU and Us banks as followings:

Data table for selected banks

Banks	Period	Starting time	Ending Time	No of collected Data
Australian Banks	Quarterly	2005-1Q	2014-1Q	8103
Austrian Banks	Quarterly	2005-1Q	2014-1Q	8,103
Belgian Banks	Quarterly	2005-1Q	2014-1Q	8,103
Canadian Banks	Quarterly	2005-2Q	2014-1Q	7,884
Chilean Banks	Quarterly	2005-2Q	2014-1Q	7,884
Finnish Banks	Quarterly	2010-2Q	2014-1Q	1,752
French Banks	Quarterly	2005-1Q	2014-1Q	8,103
German Banks	Quarterly	2005-1Q	2014-1Q	8,103
Greek Banks	Quarterly	2005-1Q	2014-1Q	8,103
Irish Banks	Quarterly	2006-1Q	2014-1Q	7,821
Indian Banks	Quarterly	2005-2Q	2014-1Q	7,884
Italian Banks	Quarterly	2005-1Q	2014-1Q	8,103
Japanese Banks	Quarterly	2005-2Q	2014-1Q	7,884
South Korean Banks	Quarterly	2013-4Q	2014-1Q	418
Dutch Banks	Quarterly	2005-1Q	2014-1Q	8,103
Portuguese Banks	Quarterly	2005-1Q	2014-1Q	8,103
Spanish Banks	Quarterly	2005-2Q	2014-1Q	7,884
Swedish Banks	Quarterly	2005-2Q	2014-1Q	7,884
Swiss Banks	Quarterly	2005-2Q	2014-1Q	7,884
British Banks	Quarterly	2005-1Q	2014-1Q	8,103
Turkish Banks	Quarterly	2005-2Q	2014-1Q	7,884
American Banks	Quarterly	2005-1Q	2014-1Q	8,103
Total				145,990

Appendix 2

Network Centrality Measure and connectedness 2014-1Q.

vertex_id	CheiRank	CheiRank-0	PageRank	PageRank-0	closeness	cvpcore	maxclique	newman
Afghanistan	0.0007	0.0000	0.0040	0.0036	0.489	FALSE	0	4

vertex_id	CheiRank	CheiRank-0	PageRank	PageRank-0	closeness	cvpcore	maxclique	newman
Albania	0.0007	0.0000	0.0041	0.0037	0.498	FALSE	0	1
Algeria	0.0007	0.0000	0.0040	0.0037	0.509	FALSE	0	3
Andorra	0.0007	0.0000	0.0040	0.0036	0.507	FALSE	0	1
Angola	0.0007	0.0000	0.0044	0.0041	0.510	FALSE	0	3
Argentina	0.0007	0.0000	0.0042	0.0039	0.516	FALSE	0	2
Armenia	0.0007	0.0000	0.0040	0.0036	0.504	FALSE	0	1
Aruba	0.0007	0.0000	0.0040	0.0036	0.494	FALSE	0	1
Australia	0.0194	0.0181	0.0070	0.0081	0.697	TRUE	1	5
Austria	0.0106	0.0095	0.0051	0.0052	0.617	TRUE	1	2
Azerbaijan	0.0007	0.0000	0.0040	0.0037	0.514	FALSE	0	0
Bahamas	0.0007	0.0000	0.0042	0.0039	0.515	FALSE	0	2
Bahrain	0.0007	0.0000	0.0042	0.0039	0.518	FALSE	0	0
Bangladesh	0.0007	0.0000	0.0041	0.0038	0.511	FALSE	0	3
Barbados	0.0007	0.0000	0.0040	0.0037	0.507	FALSE	0	1
Belarus	0.0007	0.0000	0.0040	0.0036	0.509	FALSE	0	0
Belgium	0.0104	0.0105	0.0072	0.0081	0.722	TRUE	1	0
Belize	0.0007	0.0000	0.0040	0.0036	0.502	FALSE	0	1
Benin	0.0007	0.0000	0.0040	0.0036	0.496	FALSE	0	1
Bermuda	0.0007	0.0000	0.0044	0.0042	0.522	FALSE	0	2
Bhutan	0.0007	0.0000	0.0040	0.0036	0.442	FALSE	0	0
Bolivia	0.0007	0.0000	0.0040	0.0036	0.505	FALSE	0	3
Bonaire, Saint Eustatius and Saba	0.0007	0.0000	0.0040	0.0036	0.465	FALSE	0	4
Bosnia and Herzegovina	0.0007	0.0000	0.0041	0.0038	0.506	FALSE	0	1
Botswana	0.0007	0.0000	0.0040	0.0036	0.498	FALSE	0	1
Brazil	0.0007	0.0000	0.0073	0.0083	0.519	FALSE	0	2
Brunei	0.0007	0.0000	0.0040	0.0037	0.488	FALSE	0	1
Bulgaria	0.0007	0.0000	0.0046	0.0043	0.518	FALSE	0	0
Burkina Faso	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	1
Burundi	0.0007	0.0000	0.0040	0.0036	0.470	FALSE	0	4
Cambodia	0.0007	0.0000	0.0040	0.0036	0.501	FALSE	0	1
Cameroon	0.0007	0.0000	0.0040	0.0036	0.506	FALSE	0	3
Canada	0.0327	0.0383	0.0072	0.0084	0.563	TRUE	1	2
Cape Verde	0.0007	0.0000	0.0040	0.0037	0.481	FALSE	0	4
Cayman Islands	0.0007	0.0000	0.0082	0.0101	0.524	FALSE	0	2
Central African Republic	0.0007	0.0000	0.0040	0.0036	0.420	FALSE	0	0
Chad	0.0007	0.0000	0.0040	0.0036	0.468	FALSE	0	1
Chile	0.0009	0.0002	0.0045	0.0043	0.547	TRUE	0	2
China	0.0007	0.0000	0.0089	0.0107	0.524	FALSE	0	2
Chinese Taipei	0.0007	0.0000	0.0051	0.0053	0.516	FALSE	0	2
Colombia	0.0007	0.0000	0.0047	0.0045	0.515	FALSE	0	0
Comoros	0.0007	0.0000	0.0040	0.0036	0.468	FALSE	0	1
Costa Rica	0.0007	0.0000	0.0040	0.0037	0.505	FALSE	0	3
Cote d'Ivoire	0.0007	0.0000	0.0040	0.0036	0.502	FALSE	0	3
Croatia	0.0007	0.0000	0.0047	0.0046	0.518	FALSE	0	0
Cuba	0.0007	0.0000	0.0040	0.0036	0.483	FALSE	0	4

vertex_id	CheiRank	CheiRank-0	PageRank	PageRank-0	closeness	cvpcore	maxclique	newman
Curacao	0.0007	0.0000	0.0040	0.0036	0.506	FALSE	0	1
Cyprus	0.0007	0.0000	0.0045	0.0042	0.516	FALSE	0	0
Czech Republic	0.0007	0.0000	0.0065	0.0069	0.519	FALSE	0	2
Democratic Republic of Congo	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	1
Denmark	0.0007	0.0000	0.0058	0.0059	0.527	FALSE	0	2
Djibouti	0.0007	0.0000	0.0040	0.0036	0.418	FALSE	0	0
Dominica	0.0007	0.0000	0.0040	0.0036	0.361	FALSE	0	2
Dominican Republic	0.0007	0.0000	0.0040	0.0036	0.509	FALSE	0	3
Ecuador	0.0007	0.0000	0.0040	0.0036	0.514	FALSE	0	3
Egypt	0.0007	0.0000	0.0042	0.0040	0.514	FALSE	0	0
El Salvador	0.0007	0.0000	0.0040	0.0037	0.506	FALSE	0	3
Equatorial Guinea	0.0007	0.0000	0.0040	0.0036	0.470	FALSE	0	4
Estonia	0.0007	0.0000	0.0041	0.0037	0.506	FALSE	0	3
Ethiopia	0.0007	0.0000	0.0040	0.0036	0.502	FALSE	0	1
Faeroe Islands	0.0007	0.0000	0.0040	0.0036	0.490	FALSE	0	1
Falkland Islands	0.0007	0.0000	0.0040	0.0036	0.492	FALSE	0	1
Fiji	0.0007	0.0000	0.0040	0.0036	0.494	FALSE	0	1
Finland	0.0022	0.0019	0.0051	0.0051	0.532	FALSE	1	2
France	0.1041	0.1389	0.0130	0.0167	0.547	TRUE	1	2
French Polynesia	0.0007	0.0000	0.0040	0.0036	0.493	FALSE	0	1
Gabon	0.0007	0.0000	0.0040	0.0036	0.502	FALSE	0	1
Georgia	0.0007	0.0000	0.0040	0.0036	0.510	FALSE	0	3
Germany	0.1043	0.1199	0.0160	0.0206	0.865	TRUE	1	4
Ghana	0.0007	0.0000	0.0040	0.0037	0.507	FALSE	0	3
Gibraltar	0.0007	0.0000	0.0040	0.0037	0.510	FALSE	0	1
Greece	0.0049	0.0014	0.0044	0.0042	0.629	TRUE	1	2
Greenland	0.0007	0.0000	0.0040	0.0036	0.479	FALSE	0	4
Grenada	0.0007	0.0000	0.0040	0.0036	0.445	FALSE	0	2
Guatemala	0.0007	0.0000	0.0040	0.0037	0.500	FALSE	0	3
Guernsey	0.0007	0.0000	0.0041	0.0038	0.513	FALSE	0	0
Guinea	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	1
Guinea-Bissau	0.0007	0.0000	0.0040	0.0036	0.472	FALSE	0	1
Guyana	0.0007	0.0000	0.0040	0.0036	0.482	FALSE	0	1
Haiti	0.0007	0.0000	0.0040	0.0036	0.485	FALSE	0	1
Honduras	0.0007	0.0000	0.0040	0.0036	0.495	FALSE	0	1
Hong Kong SAR	0.0007	0.0000	0.0081	0.0097	0.527	FALSE	0	2
Hungary	0.0007	0.0000	0.0050	0.0050	0.519	FALSE	0	2
Iceland	0.0007	0.0000	0.0040	0.0037	0.515	FALSE	0	0
India	0.0057	0.0015	0.0057	0.0063	0.714	TRUE	1	0
Indonesia	0.0007	0.0000	0.0046	0.0045	0.516	FALSE	0	2
Iran	0.0007	0.0000	0.0040	0.0036	0.513	FALSE	0	0
Iraq	0.0007	0.0000	0.0041	0.0037	0.506	FALSE	0	3
Ireland	0.0059	0.0069	0.0067	0.0077	0.530	TRUE	0	2
Isle of Man	0.0007	0.0000	0.0041	0.0038	0.514	FALSE	0	0
Israel	0.0007	0.0000	0.0041	0.0038	0.522	FALSE	0	2

vertex_id	CheiRank	CheiRank-0	PageRank	PageRank-0	closeness	cvpcore	maxclique	newman
Italy	0.0302	0.0323	0.0084	0.0101	0.712	TRUE	1	0
Jamaica	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	3
Japan	0.0877	0.1122	0.0096	0.0122	0.661	TRUE	1	2
Jersey	0.0007	0.0000	0.0044	0.0043	0.518	FALSE	0	2
Jordan	0.0007	0.0000	0.0040	0.0037	0.516	FALSE	0	0
Kazakhstan	0.0007	0.0000	0.0040	0.0037	0.515	FALSE	0	0
Kenya	0.0007	0.0000	0.0040	0.0037	0.509	FALSE	0	3
Kuwait	0.0007	0.0000	0.0041	0.0037	0.518	FALSE	0	0
Kyrgyz Republic	0.0007	0.0000	0.0040	0.0036	0.455	FALSE	0	2
Laos	0.0007	0.0000	0.0040	0.0036	0.470	FALSE	0	5
Latvia	0.0007	0.0000	0.0041	0.0037	0.514	FALSE	0	0
Lebanon	0.0007	0.0000	0.0040	0.0037	0.511	FALSE	0	0
Liberia	0.0007	0.0000	0.0042	0.0039	0.511	FALSE	0	0
Libya	0.0007	0.0000	0.0040	0.0036	0.509	FALSE	0	3
Liechtenstein	0.0007	0.0000	0.0040	0.0037	0.509	FALSE	0	0
Lithuania	0.0007	0.0000	0.0041	0.0038	0.509	FALSE	0	3
Luxembourg	0.0007	0.0000	0.0072	0.0082	0.527	FALSE	1	2
Macao SAR	0.0007	0.0000	0.0041	0.0037	0.511	FALSE	0	3
Macedonia	0.0007	0.0000	0.0041	0.0038	0.499	FALSE	0	1
Madagascar	0.0007	0.0000	0.0040	0.0036	0.499	FALSE	0	1
Malawi	0.0007	0.0000	0.0040	0.0036	0.494	FALSE	0	1
Malaysia	0.0007	0.0000	0.0046	0.0046	0.518	FALSE	0	0
Maldives	0.0007	0.0000	0.0040	0.0036	0.498	FALSE	0	1
Mali	0.0007	0.0000	0.0040	0.0036	0.479	FALSE	0	4
Malta	0.0007	0.0000	0.0043	0.0040	0.515	FALSE	0	2
Marshall Islands	0.0007	0.0000	0.0043	0.0041	0.509	FALSE	0	3
Mauritania	0.0007	0.0000	0.0040	0.0036	0.498	FALSE	0	1
Mauritius	0.0007	0.0000	0.0041	0.0038	0.509	FALSE	0	3
Mexico	0.0007	0.0000	0.0064	0.0072	0.518	FALSE	0	2
Moldova	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	1
Mongolia	0.0007	0.0000	0.0040	0.0036	0.501	FALSE	0	3
Montenegro	0.0007	0.0000	0.0040	0.0036	0.499	FALSE	0	3
Morocco	0.0007	0.0000	0.0040	0.0037	0.518	FALSE	0	0
Mozambique	0.0007	0.0000	0.0042	0.0039	0.505	FALSE	0	3
Myanmar	0.0007	0.0000	0.0040	0.0036	0.499	FALSE	0	1
Namibia	0.0007	0.0000	0.0040	0.0036	0.506	FALSE	0	3
Nauru	0.0007	0.0000	0.0040	0.0036	0.488	FALSE	0	1
Nepal	0.0007	0.0000	0.0040	0.0036	0.501	FALSE	0	3
Netherlands	0.0475	0.0612	0.0098	0.0118	0.601	TRUE	1	2
New Caledonia	0.0007	0.0000	0.0040	0.0036	0.483	FALSE	0	1
New Zealand	0.0007	0.0000	0.0066	0.0072	0.523	FALSE	0	2
Nicaragua	0.0007	0.0000	0.0040	0.0036	0.499	FALSE	0	1
Niger	0.0007	0.0000	0.0040	0.0036	0.481	FALSE	0	1
Nigeria	0.0007	0.0000	0.0041	0.0037	0.514	FALSE	0	0
North Korea	0.0007	0.0000	0.0040	0.0036	0.487	FALSE	0	3

vertex_id	CheiRank	CheiRank-0	PageRank	PageRank-0	closeness	cvpcore	maxclique	newman
Norway	0.0007	0.0000	0.0056	0.0058	0.526	FALSE	0	2
Oman	0.0007	0.0000	0.0041	0.0038	0.509	FALSE	0	3
Pakistan	0.0007	0.0000	0.0041	0.0037	0.514	FALSE	0	0
Palau	0.0007	0.0000	0.0040	0.0036	0.468	FALSE	0	1
Palestinian Territory	0.0007	0.0000	0.0040	0.0036	0.465	FALSE	0	4
Panama	0.0007	0.0000	0.0045	0.0043	0.522	FALSE	0	2
Papua New Guinea	0.0007	0.0000	0.0040	0.0037	0.499	FALSE	0	3
Paraguay	0.0007	0.0000	0.0040	0.0036	0.507	FALSE	0	3
Peru	0.0007	0.0000	0.0043	0.0040	0.514	FALSE	0	3
Philippines	0.0007	0.0000	0.0042	0.0040	0.514	FALSE	0	2
Poland	0.0007	0.0000	0.0062	0.0066	0.519	FALSE	0	2
Portugal	0.0083	0.0045	0.0048	0.0048	0.681	TRUE	1	2
Qatar	0.0007	0.0000	0.0042	0.0039	0.519	FALSE	0	2
Republic of Congo	0.0007	0.0000	0.0040	0.0036	0.489	FALSE	0	4
Romania	0.0007	0.0000	0.0052	0.0051	0.518	FALSE	0	2
Russia	0.0007	0.0000	0.0054	0.0057	0.522	FALSE	0	2
Rwanda	0.0007	0.0000	0.0040	0.0036	0.499	FALSE	0	1
Samoa	0.0007	0.0000	0.0040	0.0036	0.482	FALSE	0	1
San Marino	0.0007	0.0000	0.0040	0.0036	0.489	FALSE	0	1
Sao Tome and Principe	0.0007	0.0000	0.0040	0.0036	0.406	FALSE	0	6
Saudi Arabia	0.0007	0.0000	0.0043	0.0041	0.519	FALSE	0	2
Senegal	0.0007	0.0000	0.0040	0.0036	0.510	FALSE	0	3
Serbia	0.0007	0.0000	0.0044	0.0041	0.515	FALSE	0	0
Seychelles	0.0007	0.0000	0.0040	0.0036	0.513	FALSE	0	3
Sierra Leone	0.0007	0.0000	0.0040	0.0036	0.483	FALSE	0	1
Singapore	0.0007	0.0000	0.0069	0.0080	0.522	FALSE	0	2
Sint Maarten	0.0007	0.0000	0.0040	0.0036	0.472	FALSE	0	1
Slovakia	0.0007	0.0000	0.0049	0.0049	0.513	FALSE	0	2
Slovenia	0.0007	0.0000	0.0042	0.0039	0.518	FALSE	0	0
Solomon Islands	0.0007	0.0000	0.0040	0.0036	0.451	FALSE	0	0
Somalia	0.0007	0.0000	0.0040	0.0036	0.468	FALSE	0	1
South Africa	0.0007	0.0000	0.0047	0.0047	0.522	FALSE	0	2
South Korea	0.0070	0.0025	0.0059	0.0065	0.768	TRUE	1	3
Spain	0.0428	0.0463	0.0082	0.0097	0.745	TRUE	1	0
Sri lanka	0.0007	0.0000	0.0041	0.0038	0.509	FALSE	0	3
St. Helena and Dependencies	0.0007	0.0000	0.0040	0.0036	0.387	FALSE	0	2
St. Vincent and the Grenadines	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	1
St.Lucia	0.0007	0.0000	0.0040	0.0036	0.494	FALSE	0	1
Sudan	0.0007	0.0000	0.0040	0.0036	0.490	FALSE	0	3
Suriname	0.0007	0.0000	0.0040	0.0036	0.468	FALSE	0	1
Swaziland	0.0007	0.0000	0.0040	0.0036	0.487	FALSE	0	1
Sweden	0.0200	0.0197	0.0057	0.0059	0.719	TRUE	1	0
Switzerland	0.0438	0.0587	0.0066	0.0074	0.537	FALSE	1	2
Syria	0.0007	0.0000	0.0040	0.0036	0.467	FALSE	0	4
Tajikistan	0.0007	0.0000	0.0040	0.0036	0.480	FALSE	0	4

vertex_id	CheiRank	CheiRank-0	PageRank	PageRank-0	closeness	cvpcore	maxclique	newman
Tanzania	0.0007	0.0000	0.0040	0.0036	0.505	FALSE	0	3
Thailand	0.0007	0.0000	0.0044	0.0043	0.511	FALSE	0	0
The Gambia	0.0007	0.0000	0.0040	0.0036	0.472	FALSE	0	1
Timor Leste	0.0007	0.0000	0.0040	0.0036	0.406	FALSE	0	7
Togo	0.0007	0.0000	0.0040	0.0036	0.492	FALSE	0	1
Tonga	0.0007	0.0000	0.0040	0.0036	0.412	FALSE	0	5
Trinidad and Tobago	0.0007	0.0000	0.0041	0.0037	0.507	FALSE	0	3
Tunisia	0.0007	0.0000	0.0040	0.0036	0.511	FALSE	0	3
Turkey	0.0030	0.0011	0.0062	0.0065	0.599	TRUE	1	2
Turkmenistan	0.0007	0.0000	0.0040	0.0036	0.476	FALSE	0	4
Turks and Caicos Islands	0.0007	0.0000	0.0040	0.0036	0.495	FALSE	0	1
US Pacific Islands	0.0007	0.0000	0.0040	0.0036	0.482	FALSE	0	1
Uganda	0.0007	0.0000	0.0040	0.0036	0.500	FALSE	0	3
Ukraine	0.0007	0.0000	0.0041	0.0038	0.513	FALSE	0	3
United Arab Emirates	0.0007	0.0000	0.0051	0.0052	0.523	FALSE	0	2
United Kingdom	0.1244	0.1395	0.0268	0.0361	0.792	TRUE	1	3
United States	0.1502	0.1748	0.0355	0.0483	0.876	TRUE	1	1
Uruguay	0.0007	0.0000	0.0040	0.0037	0.513	FALSE	0	0
Uzbekistan	0.0007	0.0000	0.0040	0.0036	0.502	FALSE	0	3
Vanuatu	0.0007	0.0000	0.0040	0.0036	0.473	FALSE	0	4
Venezuela	0.0007	0.0000	0.0041	0.0038	0.510	FALSE	0	2
Vietnam	0.0007	0.0000	0.0044	0.0041	0.510	FALSE	0	3
Yemen	0.0007	0.0000	0.0040	0.0036	0.489	FALSE	0	3
Zambia	0.0007	0.0000	0.0040	0.0037	0.506	FALSE	0	3
Zimbabwe	0.0007	0.0000	0.0040	0.0036	0.502	FALSE	0	3

Appendix 3

Dependent Variable: CORE
2005-Q1 – 2014Q1

Regressors	1	2	3	4	5	6	7	8	9	10	11	12	13
Exposures	0.05**		0.00**	0.01**	0.03**				0.02**	0.00**	0.01**		0.02**
	(57.64)		(-3.70)	(23.91)	(36.25)				(34.82)	(-3.98)	(24.27)		(34.63)
Closeness			3.66			-0.16	3.44		-1.01	3.54		-0.21	-1.03**
			(95.04)			(-4.53)	(92.60)		(-24.87)	(78.86)		(-5.57)	(-24.49)
Betweenness		0.13**		0.12**		0.14**		0.13**	0.15**		0.13**	0.14**	0.15**
		(247.69)		(209.77)		(120.20)		(197.55)	133.84		187.71	120.05	133.52
PageRank					38.07**		4.19**	0.87**		4.36**	-2.04**	1.83**	0.76**
					39.76		5.06	1.91		5.26	-4.47	3.75	(1.67)
C	-0.28	0.02	-1.78	-0.05	-0.34	0.10	-1.71	0.01	0.41	-1.74	-0.04	0.11	0.42

	(-39.46)	(15.72)	(-107.95)	(-15.92)	(-50.59)	(5.56)	(-100.54)	(6.31)	(22.06)	(-94.21)	(-12.97)	(6.32)	(21.98)
R-squared	0.30	0.89	0.68	0.90	0.42	0.89	0.68	0.89	0.90	0.68	0.90	0.89	0.91
No of obs	7618	7618	7618	7618	7618	7618	7618	7618	7618	7618	7618	7618	7618