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Resilience of United Kingdom Financial Institutions to Major Uncertainty: A Network Analysis Related to the Credit Default Swaps Market

Miia Chabot¹, Jean-Louis Bertrand², Eric Thorez³

Abstract

The banking sector plays an important role in the UK economy as a whole, and investors are increasingly concerned about the ability of UK-based banks to withstand the consequences of major uncertainty such as the Brexit. This paper investigates the UK financial system resilience using networks of relationships related to the Credit Default Swap market. We propose a detailed descriptive analysis of the topology of the networks, and characterize the nature of relationships between financial institutions. We compare our results with theoretical network configurations (small-worlds, preferential attachments, etc.) to reveal the connection dynamics of the networks we identify. We then develop a panel analysis including variables of centrality and influence of banks in their networks. We identify prominent banks and groups of banks that could disrupt the system. Our results help identify priority areas of action by regulators and risk managers.

Keywords: Networks, CDS Spreads, Prominence Analysis, Brexit

JEL Codes D85, E44, G21, G28, L14.

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1. Introduction

Political uncertainty results in the weakening of the future global economic situation and the financial conditions of many companies, particularly those that rely on debt financing (Hill et al., 2019). The relationship between political uncertainty and financial markets has been widely studied from both a theoretical (Bernanke, 1983; Dixit, 1989; Bloom et al., 2007; Pástor & Veronesi, 2012) and empirical perspective (Julio & Yook, 2012; Baker et al., 2016). Extensive literature has shown that in times of major economic and political uncertainty, stock market volatility increases and impacts financial markets, causing financial difficulties and instability (Forbes & Rigobon 2002, Bloom 2009, Diebold & Yilmaz 2009, Diebold & Yilmaz 2012). For instance, the decision of the U.S. House of Representatives to reject the bailout bill to provide additional liquidity to the struggling U.S. financial markets sent the volatility of the Chicago Board Options Exchange up 17% and the Dow Jones Industrial Average Index down 778 points in less than 2 hours (Boutchkova et al., 2012). Other examples include the surprise decision by the UK government to grant operational independence to the Bank of England (Chadha et al., 2007), the German unification (Hallett et al., 1996), or more recently the Brexit that gave rise to an unprecedented political, social, and economic uncertainty (Chang W., 2017; Hill et al., 2019).

As uncertainty about whether and how Brexit will actually occur remains, there is growing concern about the level of stress the British system can face and its ability to be resilient and remain competitive (Arnold & Binham, 2017). London is Europe's leading financial center. Financial and insurance services accounted for 7.5 percent of UK value-added and 13 percent of exports in 2014 (Office for National Statistics, 2016). If the UK leaves the single market, UK-based financial institutions will face greater barriers to access EU member states (Sampson, 2017). The Financial Policy Committee estimates that the UK banking system should be strong enough to continue to serve UK household and businesses even in a disorderly Brexit (Financial Stability Board, 2018). However, recently published research suggests that caution should be exercised. Djankov (2017) for instance estimates that UK finance industry revenues could fall by up to 18%, as a number of large financial institutions are considering or have already started relocating parts of their core business

from London to rival financial hubs in Continental Europe, shifting altogether capital, liquidity and jobs (Arnold and Noonan, 2017).

The UK financial system exhibits numerous synergistic relationships among highly specialized financial activities (Jacobs, 1969; Dörry, 2017). Given the level of interaction and influence between market participants, the representation of credit issues across the financial system requires a framework that integrate micro-behaviors of the various financial actors involved (Thorne, 1969). As banks and financial institutions are mainly debt financed, the Credit Default Swap (CDS) market is a relevant measure of the level of uncertainty and the fear that financial distress of one or more market participants may spread across the financial system (Li & Mizrach, 2010; Schiereck et al., 2016; Annaert et al., 2013, D’Errico et al., 2017). A stream of research uses neo-institutionalist theories of politico-organizational change in complex governance systems (Pierson, 2004; Olsen, 2007; Hall, 2010; Henökl, 2018). Some papers offer an analysis of the causes and potential consequences of Brexit (see for instance Shaw et al., 2017 and references therein), others use case studies to evaluate how much business the UK may lose in different service industries including financial services, others again try to evaluate the output fall of the finance industry under different scenarios (Dhingra et al., 2017). Yet, to our knowledge, no paper has so far used the networks of UK-based financial institutions to study how the UK financial system may react to major uncertainty, such as the one caused by the Brexit. This is the gap we address.

We focus our empirical analysis on 5-year UK CDS spreads and produce a series of panel analyses to identify key explanatory variables. Network measures of prominence are introduced in the estimations, as well as a Brexit dummy, with a view to confirm the importance played by network components in the movements of CDS spreads over time. The questions we address are as follows: (Q1) are there any UK bank that are particularly exposed to major uncertainty? (Q2) are there any reputable banks or group of banks likely to disrupt the system? (Q3) conversely, are there any domestic bank or financial institution that are less exposed to major uncertainty? (Q4) what are the characteristics of the connections between banks in their different networks of relationships? (Q5) are network characteristics (i.e., betweenness and degree per node) significant determinants of CDS spreads?

Our network analysis offers the opportunity to visualize and discuss the location of UK banks in their networks, their influence on the financial system, as well as the consequences of a possible relocation of their activities. To the best of our knowledge, this is the first study to provide such a detailed analysis of the UK CDS ecosystem.

Our prominence analyses as well as our network representations bring a new dimension to existing approaches. Based on network theory (Douglas, 2015), our results highlight the presence of central and peripheral clusters. In particular, our results underline the influence of these clusters in the system and characterize the type of relationships among network members. Force-directed layouts prove to be particularly useful tools for emphasizing these connections. The Kamada-Kawai algorithm (1989) used for this purpose preserves the total balance of the layout so that clusters appear clearly in the graphs. The characteristics of relations between financial institutions and between clusters provide a better understanding of the evolution and dynamics of investor confidence. They also provide valuable guidance for regulators seeking to identify the most fragile institutions in the event of major uncertainty, and to take appropriate measures to reduce systemic risk.

Our paper contributes to the literature in several ways. We build on the works of Telesford et al. (2011), Brunetti et al. (2015), and Giudici et al. (2017) to propose a novel methodology that captures the specific patterns of the CDS networks. We construct correlation networks to study exposures among UK financial institutions. The topologies of the relationships are compared to small-world configurations, (Watts & Strogatz, 1998) and configurations holding preferential attachments (Barabási & Albert, 1999, Yook et al., 2001). The identification of the type of network structure in which banks or clusters of banks are connected provides new insights into the channels of distribution and the speed at which an event such as Brexit can destabilize the UK system.

The rest of this paper is organized as follows. Section 2 discusses literature. Section 3 introduces the theoretical framework of networks. Section 4 presents the methodology and the data. Section 5 discusses the results of the network analysis and the panel data analysis. Section 6 concludes.

2. Literature Review

Uncertainty about the future has real implications for economic agents' behavior (Bernanke 1983, Bloom 2009, Bloom et al., 2007, Dixit 1989). Uncertainty may be caused by what a government or a regulator is going to do, as well as what the effects of their actions are going to be (Schierreck et al., 2016). When uncertainty increases, volatility and financial stress increase, leading to potential economic disintegration.

As uncertainty rises, businesses and households tend to postpone or withdraw from new investments and purchases at times of greater uncertainty (Davig & Hakkio, 2010). The uncertainty related to the largest bankruptcy proceeding in the history of the United States (Lehman Brothers on September 15, 2008) had enormous long-term consequences for global capital markets and pushed the U.S. into its most severe recession since the Great Depression, as it was not clear whether the U.S. government was going to try to rescue the bank and whether its actions would be successful. In financial markets, uncertainty generally translates into lower stock returns, tighter credit conditions (Christiano et al., 2014; Gilchrist et al. 2014; Arellano et al. 2018), and higher volatility (Bialkowski et al., 2008; Pastor & Veronesi, 2012; Brogaard & Detzel, 2015; Boutchkova et al., 2012). This was observed in the case of the fall of Lehman Brothers and the potential end of the "too-big-to-fail". This has also been the case during reforms of the American health system, or with the tightening of financial regulations, and generally during international summits or election periods (Kelly et al., 2016). Many of those changes were unprecedented, with long-term effects that were difficult to predict in advance.

The Brexit is no exception: on 23rd June 2016, the FTSE100, the Dow Jones International and the Dax all dropped, market volatility persistently increased, and banking stocks depreciated more substantially than they did when Lehman Brothers shut down (Dao et al., 2018; Li, 2019). Opinions may be divided on the actual reasons which led English citizens to choose the Leave side rather than the Remain side during the referendum on whether or not the UK should break ties with the European Union, but the outcome came as a jolt to many across Europe (Shaw et al., 2017). Further uncertainty prevails concerning the likelihood of a "hard Brexit" that would sever financial services access between the UK and the rest of the European Union (EU). Some investors have already started to shed UK-related assets to protect themselves against the threat of potential losses if the UK crashes out of the EU with no deal, triggering further uncertainty over financial contracts (Binham & Arnold, 2017). Despite many attempts to try to analyze the ins and outs of the Brexit,

uncertainty about what the government will decide and how the world will react to it prevails (Pierson, 2004; Olsen, 2007; Hall, 2010; Henökl, 2015; Henökl & Trondal, 2015; Ringe, 2017; Henökl, 2018). In particular, there is uncertainty with regard to the future operations of banks and the regulatory environment, as it is not clear whether UK-based banks will still benefit from the same access to EU financial markets as before (Armour, 2017).

As banks largely depends on debt, the CDS market provides a very relevant a measure of uncertainty: Schiereck et al. (2016) for instance show that the Lehman Brothers bankruptcy filing, as well as the Brexit announcement, resulted in a steep increase in CDS spreads. CDS work as insurance contracts built upon the transfer of the credit risk of a specific legal entity relative to a reference from a risk seller to a risk buyer. The seller of the risk becomes exposed to counterparty risk, should the risk buyer not honor his contract. But the nature of the risk is not just bilateral as the buyer of the risk may not necessarily retain 100% of the risk. Banks in particular tend to resell risk to other market participants, generating a complex network of exposures (Peltonen, 2014). Moreover, in terms of information discovery, the use of CDS is especially relevant as the CDS market acts as a leading indicator to other markets (Li & Mizrach, 2010). This is especially true for the bond and the stock markets (Hart & Zingales, 2011). The literature on CDS spreads determinants emphasizes the importance of the characteristics of the market, the economic and financial situations, and the duration period of the analysis (Chiaramonte & Casu, 2013). Demirgüç-Kunt & Huizinga (2013) for instance find that stronger public finance positively influences CDS pricing. Yet, research dealing with the structure of the CDS networks and their determinants remains scarce (Peltonen et al., 2014).

One way to estimate the impact of Brexit on the finance industry is through case studies that analyze how much business the United Kingdom may lose in the finance sectors and subsectors. By doing so, Djankov (2017) estimates that, if the UK and the EU trade under World Trade Organization rules, finance industry revenue would fall by between 12 and 18 percent and employment would fall by between 7 and 8 percent. Dhingra et al. (2017), who base their estimates on scenario analysis, estimate that the finance industry output would fall by 6.4 percent. Whilst both approaches lead to similar results, further research on the effects of major uncertainty on UK banks is needed as neither takes into account the role that

interconnections between UK banks may play in influencing the financial distress of both individual banks and the UK financial system as a whole.

3. Theoretical Framework

Research is scarce and no predominant theoretical framework seems to prevail with respect to representing the concentration of risk in the UK financial system, investigating how uncertainty may unfold through the relationships between UK financial institutions, and identifying the weakest links, should some market participants experience financial distress. The United Kingdom has one of the most centralized and concentrated banking sectors in the OECD, its capital markets are geographically concentrated and there are still debt and equity problems to support small businesses. Given the intertwining credit issues and the complexity of the relationships between UK banks, we use a framework that integrates micro-behaviors of the various financial actors involved (Thorne, 1969). Such framework was originally introduced by Quesnay (1758) who represented the flow of funds in a system as a network. Thorne (1969) & Charnes and Raike (1966) capitalized on mathematics and algorithms to analyze the propagation of information and flows and demonstrate how the concept of networks outperforms classical matrix approaches. Other examples of mathematical programming and networks applied to financial systems are discussed in Nagurney & Ke (2006).

3.1.CDS Determinants

We consider four categories of potential CDS determinants (Table 1). The first category of determinants is accounting information (Batta, 2011). For instance, a high level of non-performing assets or inadequate Tier 1 is likely to fuel financial distress and default expectations. Also, as the ability of banks to remain competitive providers of liquidities is also of key importance (Myers & Rajan, 1998; Diamond & Rajan, 2005), other influential determinants include the amount of total loans and deposits as well as interbank assets.

A second category of CDS spreads determinants focuses on market data such as publicly traded returns, yield spreads and banks' specific credit risks (Duffie & Singleton, 1999;

Lekkos & Milas, 2001; Collin-Dufresne et al., 2001; Campbell & Taksler, 2003; Benkert, 2004; Fabozzi et al., 2007; Naifar, 2012; Drago et al. 2017). Market determinants seem to display the greatest explanatory power (Samaniego-Medina et al., 2016), but here again, the context is important.

Ordinary market circumstances must be distinguished from turbulent times, as investors focus on volatility rather than returns during periods of turmoil (Alexander & Kaeck, 2008; Galil et al., 2014). Industry and liquidity factors as well as interest rates are expected to play a key role in the evolution of spreads over time (Benbouzid & Mallick, 2013; Shahzad et al., 2017), but theoretical determinants are also worth studying. For this, forward-looking default probabilities, whose estimates rely on Merton (1974), Altman & Sabato (2005), Bharath & Shumway (2008) and Altman (2010), are meaningful. Distance to default measures and insolvency proxies assess the soundness of capital structures in the overall financial system. The uncertainty that followed the Brexit vote is also reflected in the UK national currency and the returns observed in the UK financial market.

Macro-economic variables make the third category of CDS spreads determinants (Shahzad et al., 2017; Benbouzid et al., 2017). Macro-economic variables are expected to have a significant influence at times of high volatility and turbulence. This was the case since the subprime crisis (Baum & Wan, 2010; Di Cesare & Guazzarotti, 2010). In line with this literature, we used real GDP, inflation and the Herfindahl-Hirschman coefficient (sector concentration index) in our analysis. Then, with the aim of reporting on the effect of uncertainty within the system, we also included indicators of economic surprise and investor confidence.

INSERT TABLE 1 ABOUT HERE

The fourth category of determinants includes measures of banks' prominence in their different networks of relationships (Torri et al., 2018). We used betweenness coefficients and degree per nodes (banks' interconnectedness).

3.2. Networks Analysis

Our networks are constructed following the propositions of Giudici et al. (2017) and Brunetti et al. (2015). Instead of using matrices of bilateral exposures (BEM), our adjacency matrices are constructed using correlation matrices. These ‘correlation’ networks are viable alternatives to classical networks because they address common exposures among institutions (Giudici et al., 2017).

We selected and analyzed four correlation networks. The first network is based on CDS spreads’ correlations. The other three correlation networks focus on non-performing assets, interbank assets and default probabilities, which have been identified as powerful drivers of CDS spreads over time in our panel estimates. Each of these networks has been analyzed separately. We then rely on edge filters and use prominence analysis to further investigate the connections (Castren & Rancan, 2014; Douglas, 2015). The use of edge filters allows us to focus on the most important banks or clusters of banks, without altering the inherent characteristics of the network. This approach is similar to Sun & Shenoy (2007). In their analysis of bankruptcy filings, the authors measure partial and total correlation threshold to eliminate redundant and less relevant variables.

One of the most important issues in a network is to identify important key nodes. The accepted approach for ranking nodes is to use centrality measures (Freeman, 1978) in order to select and rank prominent or dominant nodes (de Blas et al., 2018). Following Douglas (2015), we selected an edge filter that focuses on the closest (immediate neighborhood) and most important (degree per node) banks and clusters⁴. The network characteristics (clustering and average path length between nodes) are then compared with those of known theoretical networks.

In the case of a regular network, each bank is connected to its nearest neighbor. In the case of a random network, connections are completely random. Regular and random networks are useful benchmarks for assessing clustering thresholds and geodesics. In the case of a small-world network, the average distance between banks is small, and the clustering is high (Watts & Strogatz, 1998). In these networks, highly interconnected institutions are organized into two different groups where smaller institutions connect with larger

⁴ This entails selecting the edges for which a bank displays at least 50% correlation with its connections

organizations. Our analysis addresses the common exposures among the institutions and involves flows of information (Gómez et al., 2013).

The average distance (path Length) between banks in the network is given by the coefficient L . It measures the number of steps required to move, on average, from one bank to another. The shorter the distance, the faster the information will flow. The average number of neighbors that banks have in their network gives an idea of the different possible relationships that they could develop in their environment. The number of incoming and outgoing links or edges (Degree) observed provides further insight into how banks interact with each other. A large number of neighbors does not necessarily imply a large number of ins and outs. The clustering coefficient (C) gives the proportion of relations organized in closed triangles compared to all relations organized in the form of open and closed triangles. A high level of clustering implies specialization between banks, as the proportion of closed triangles of relationships is greater.

In a small-world network, for instance, the smaller the distance (L) between two banks (nodes), the faster information about a default spreads from one bank to another. This phenomenon is all the more true as the clustering coefficient (C) is high (Gómez et al., 2013; Lozano & Calzada-Infante, 2018). In this paper, we also use the Telesford ratio (Telesford et al., 2011; Humphries et al., 2008) to confirm small-world networks. If the Telesford ratio is equal to zero, we can confirm the presence of a small-world network. Finally, Density measures the proportion of existing connections between banks relative to the total number of connections that could be made in a network. A very strongly connected network is characterized by a density close to 100%.

The robustness of a network cluster can also be measured by the connectivity between the nodes. Connectivity being defined as the existence of a path between every two nodes, the shorter the path between every pair of nodes, the more robust the network structure.

The robustness of a network also depends on the number of distinct paths between every pair of nodes to ensure that the network cluster stays connected even if some nodes disappear from the network (Veremyev & Boginski, 2012). For their part, Barro & Basso (2010) rely on entropy spatial interaction models to evaluate how financial distress or bankruptcy of one network participant can affect the rest of the network. A comprehensive

review of bankruptcy determinants for financial institutions and techniques deployed to estimate the likelihood of bankruptcy is provided in Kumar & Ravi (2007).

We evaluate the preferential attachment using scale-free models (Barabási & Albert, 1999; Yook et al., 2001) and verify if the clustering (C) and average path length (L) of our empirical networks match those of a scale-free configuration with similar characteristics (number of nodes, power of attachment, and number of ins and outs). Preferential attachment results should be taken with caution. Indeed, to verify the presence of reputable (prominent) banks, it is necessary to study the coefficients C and L by adding one bank after the other in the network. A new bank should connect first to those with the most connections and the observed distances between institutions should be small. After 10 vertices, adding one bank at a time, we check if the new banks tend to connect to the banks having large degrees but also high betweenness scores. Betweenness is a measure that was first proposed by Freeman (1977). Once analyzed, our networks are visualized using a Kamada-Kawai (1989) algorithm.

4. Methodology and Data

Our database gathers 43 Monetary Financial Institutions (excluding the Central Bank) operating in the United Kingdom over the period 1999-2016 (see list in appendix A1). The data was collected with a Bloomberg terminal. The calculations are performed under the R statistical programming environment.

4.1. Model

The identification of the determinants of CDS spreads in the UK financial system is done on the basis of the following model:

$$CDS_{it} = \alpha(x_i)_t + \beta(y_i)_t + \gamma(z_i)_t + \delta(n_i)_t + \varepsilon_t \quad (1)$$

Where

CDS_i is the 5-year CDS spreads of bank (i) (UK banks or UK-based banks) involved in the panel.

x_i is a vector gathering bank (i) individual characteristics: non-performing assets, total loans, total deposits, Tier 1, and interbank agreements.

y_i is composed of financial market information: 5 years forward default probability, FTSE 100, 3 month treasury bills, 3 month LIBOR, 30 year Treasury bills and the GBP currency.

z_i gathers macro-level information: real GDP, Bloomberg Economic surprise index, Investors' Confidence index, Inflation, Herfindahl-Hirschman index.

n_i gathers the information concerning the prominence of banks in the networks. Measures of betweenness as well as degree per node are used.

ε_t is the disturbance term.

The detailed definitions of the explanatory variables retained in Equation 1 are listed in Table 1, section 3.1. We used Panel OLS (fixed effects -FE and random effects -RE) to estimate several variants of Equation (1).

The model estimate (1) is consistent with similar studies (Houston et al., 2018). Given the panel nature of our sample, we use a fixed effects model and a random effects model to fit these specifications. The Lagrange multiplier test (Breush-Pagan) carried out on the estimates of the random model showed that the random model was not appropriate for our data. The fixed effect was then estimated using different approaches (Fixed effect within group model, fixed effect first difference model) and testing each approach against the random effect using Hausman test, our results revealed that the random effect was inconsistent in all the tests. The fixed effect model was more appropriate for the data studied.

In addition, we tested for panel cross-section dependencies in the residuals. When testing cross-section heteroscedasticities in our residuals, we computed Breush-Pagan (1980), Pesaran Scaled Lagrange Multiplier (2004), and Baltagi, Feng & Kao (2012) scaled Lagrange Multiplier tests. We also tested for panel period heteroscedasticities in our residuals.

The results presented in Tables 3a, 3b, 3c, 4, 5a and 5b are the estimates obtained for fixed effect models. They are accompanied with the Hausman test results.

A first step of our work has consisted in considering banks' individual characteristics as determinants for CDS spreads (table 3a). A second step introduces financial markets data (table 3b). The third step consists in controlling for macroeconomic variables (table 3c).

Then, in order to check for the presence of national belonging effects, we have split domestic banks from banks operating in the United Kingdom (table 4). The last step of our work entailed to test for the relevance of the betweenness and the connectedness (degree) of the banks in their different networks (tables 5a and 5b). A Brexit dummy has also been added to control for the effect of the referendum on UK Banks' CDS spreads.

4.2.Data: Daily CDS Spreads in the face of the Brexit referendum

Figure 1 and 2 plot the evolution of daily CDS spreads of the three most influential domestic banks (Standard Chartered Bank, HSBC and Royal Bank of Scotland) and non-domestic banks (Bank of America, Banco Bilbao Viscaya) resulting from our network analyses (see detailed results available in section 3.1). Three different crises are highlighted in both figures. The first crisis covers both the housing bubble and the global financial crisis. During this period, the impact on daily CDS spreads was significant.

The second crisis period that affected CDS spreads extends from 2011 to 2013. It corresponds to the country's debt explosion (sovereign crisis) and the UBS scandal. This is the strongest impact observed in the spreads. After the results of the Brexit referendum in 2016, the spreads reacted rapidly, but the increases remained moderate. The reactions in the spreads are clearly visible on a daily frequency. In the panels' estimations that follow (section 3.3), the frequency is annual so that balance sheet elements can be considered for analysis. The introduction of crisis dummies (housing bubble, global financial crisis, sovereign crisis and Brexit) into the models has not lead to significant results. CDS spreads respond rapidly to shocks on a daily basis, but these movements are not necessarily confirmed with annual data. This echoes the results obtained by Schiereck et al., (2016).

INSERT FIGURE 1 & 2 ABOUT HERE

5. Results

In the context of Brexit, a better understanding of how and to what extent UK-based banks are connected to each-other can help the regulator in evaluating the potential consequences of future restructuring actions. This is one of the main reasons why we investigate the presence of banks or groups of banks that have most influence in the system.

Our detailed study of the characteristics of the networks of the main financial institutions operating in the UK offers two advantages: (1) understanding the structure of the relations and dependencies that exist in the British economic and financial area; (2) evaluating the extent to which these elements have an impact on the CDS spreads market.

5.1. Network Characteristics

Table 2 summarizes descriptive statistics on networks of relationships involving credit default swaps (CDS), interbank assets (Itb A.), non-performing assets (Np. Assets) and default probabilities (Dflt Prb) in the UK financial system (Q4). Descriptive statistics include clustering coefficients (C), the average distance between banks which we term “path length” (L), the number of incoming and outgoing links (Degree), and the ratio between existing connections and total possible connection (Density). The clustering (C) and average path length (L) coefficients are defined as:

$$C = \frac{2e_i}{d_i(d_i-1)}; L = \frac{1}{n(n-1)} \sum_{i \neq j} P_{ij} \quad (2)$$

where C is the ratio of edges (connections, noted e_i) between the neighbors of a node (bank) i relative to the total number of possible ins and outs (degree, d_i) between these neighbors. A high level of clustering entails a strong interconnectedness between the banks. L is calculated as the average of the shortest path distance between all possible pairs in the network, with n being the number of banks in the network. The shortest series of steps between i and j is noted P_{ij} . When L is small, information spreads rapidly.

The closeness and betweenness centrality coefficients used in the search of prominent institutions are defined as:

$$Cl_i = \left(\sum_{j=1}^g ds_{ij} \right)^{-1}; Bt_i = \frac{\sum_{j < k} P_{jk(i)}}{P_{jk}} \quad (3)$$

The closeness coefficient is the inverse of the sum of all the distances (d_s) between a bank and the others in a network. It represents bank’s proximity to other banks. The betweenness

coefficient measures the extent to which a bank sits between pairs of other banks such that a path between the other banks has to go through that bank. This coefficient represents the reputation a bank holds in a network. In being an unavoidable node to others, it can exert a control on the flows of information that others could possibly exchange in the network.

$P_{jk}(i)$ is the shortest distance between j and k that contain bank i .

A first step in our analysis consists in comparing our empirical networks with the following theoretical network structures: a regular network of relationships where banks connect with their closest neighbor, a random network of relationships where banks connect randomly to each other, a small-world configuration where small clusters of banks have solid connections, and a network with preferential attachments (scale-free configurations) where reputed banks attract others and benefit from central locations in the networks of relationships.

Empirical networks are characterized by comparing clustering and path length to those of theoretical networks (Humphries & Gurney, 2008; Douglas, 2015). In the case of small-world configurations, Telesford et al. (2011) have however shown that these comparisons were sometimes misleading.

To allow more relevant comparisons with regular (regular clustering, noted C_{reg}) and random theoretical networks (random path length, noted L_{rand}), they proposed the following ratio:

$$\omega = \frac{L_{rand}}{L} - \frac{C}{C_{reg}} \quad (4)$$

A small-world configuration is confirmed when ω is equal to zero. A negative value of ω means a regular configuration, whilst a positive value of ω reflects a random configuration of connections (Telesford et al., 2011). The analysis of our empirical networks shows that the financial networks in the UK are highly interconnected. The density observed in our networks is generally very close to 100%, and it is consequently difficult to identify core institutions and relationships in these configurations. When the network is close to a complete configuration (every bank holds a connection with others), small-world or scale-free configurations cannot be easily observed. This is the reason why we introduced an edge attribute filter that allows focusing on the most important relationships between banks (Douglas, 2015).

Our prominence analysis offers the opportunity to highlight several particularities (Table 2). The clustering coefficients are not identical from one network to another. The two networks constructed on the basis of CDS spreads and non-performing assets hold the highest densities (73.23% and 71.65%), and the highest clustering (0.86 and 0.84).

INSERT TABLE 2 ABOUT HERE

The average path distance observed between the banks of these networks are also the smallest (1.27 and 1.28). This entails that information spreads faster than in any other networks. As a result, a shock affecting CDS spreads could very quickly affect all actors in the system. This raises the question of whether stress testing alone will be sufficient to reassure investors about the ability of UK-based banks to absorb a shock as important as the Brexit.

Another important feature observed in CDS and non-performing assets networks is that the way entities connect leads to preferential attachment for larger banks (average length paths are close, and when a new bank is added to the network, it connects those with the highest degree). In such a situation, reputed banks attract smaller institutions and constitute unavoidable points that may concentrate investors' concerns in case of distress. Our analysis of the topological characteristics of these networks allows us to identify (Q1) these banks (Figure 3, 4 and 5).

In contrast, the network of interbank assets exhibits a low level of clustering (0.61). Yet, the clustering is higher than in a regular situation ($C_{reg} = 0.55$) or in a small-world configuration ($C_{small-world} = 0.39$). The average number of immediate neighbors is however quite low (12). In this network, the information spreads steadily: the average path length is the longest (1.84) and is comparable to a regular situation ($L_{reg} = 1.88$). This network is less responsive in the event of a shock. It reacts less rapidly and involves a limited number of institutions.

The defaults network exhibits a high density (53.47%). The strong interconnections between the institutions are also confirmed by the clustering threshold (0.75). The presence of preferential attachments to reputable banks is not verified, but HBSC (Figure 3.b, HSBA) exhibits one of the highest levels of betweenness (Bt coefficient, Eq.3). HSBC is a prominent institution within the network that links 5-year forward probable bank defaults.

For each of these networks, the betweenness measures are used to identify prominent institutions (Figure 3). Prominent institutions hold a key role in the networks, as they are able to control the flow of information (highest betweenness scores) and have central locations in the systems (closeness coefficients). In Figure 3, several British Institutions exhibit strong and central locations, but non-domestic banks operating in the UK exert a stronger influence: Bank of America (BAC) is a ‘super node’, with the highest scores in all the networks studied (Q2).

In this context, reassuring investors on the capacity of the sole domestic institutions to remain resilient and be competitive providers of services is not enough. The forthcoming Brexit may urge some reputable institutions to leave the country or reorganize their activities, both decisions having potential material consequences. The dependence of other banks on prominent nodes in the network must be taken into account. Further, the ability of the UK financial system to remain stable in terms of its network structure and the volume of services provided goes beyond domestic banks. This is where our network analysis offers the opportunity to identify the institutions that play a major role in the UK financial system.

5.2. Network visualizations

The force-directed layouts (Figures 4 and 5, see appendix A1 for mnemonics) provide additional evidence. For example, British institutions do not hold the same influence as Bank of America (BAC), but they are always located in the very center of the networks (Standard Chartered Bank STAN, HSBC Holdings HSBA, Lloyds LLOY, Royal Bank of Scotland RBS, Bank of Ireland BKIR). UK financial institutions are highly dependent on reputed nodes, and exposed to changes in their immediate neighborhood (Q1).

INSERT FIGURE 3 ABOUT HERE

INSERT FIGURE 4 ABOUT HERE

In Figure 4, Standard Chartered Bank (STAN), Lloyds Bank (LLOY), Royal Bank of Scotland (RBS) and HSBC (HSBA) hold solid levels of closeness. Bank of America (BAC) and Banco Bilbao Vizcaya (BVA) are reputed nodes (highest betweenness). These two banks benefit from a preferential attachment in the network.

INSERT FIGURE 5 ABOUT HERE

In Figure 5, the force-directed layout reveals a strongly connected cluster, as already noted in Table 2. HSBC (HSBA) and Royal Bank of Scotland (RBS) are located in the very center of this network (Q1). Increasing probabilities of default could rapidly spread and affect primarily the banks located in the circle. Note that Lloyds Bank (LLOY) does not appear in this cluster of banks (Q3).

These results raise several questions. How can the regulator protect the system from a relocation of Bank of America (BAC)? How can the regulator ensure that HSBC Holdings (HSBA) and Royal Bank of Scotland (RBS) will be ready to withstand major uncertainty? How has Lloyds Bank (LLOY) succeeded in staying outside the cluster of banks exposed to defaults, while being a reputed node in the CDS network? Finally, as building societies are less exposed than other institutions, is their business model an example to follow?

5.3. Panel Data Analysis using Network Measures

Analysis of the topological characteristics of the networks reveals very different relationships between UK-based financial institutions depending on the network under consideration.

In the context of the uncertainty generated by the upcoming implementation of Brexit, the main objective of this section is to show that while the determinants of CDS highlighted in the literature apply to British banks, the measures characterizing the relationships between financial institutions within their networks provide an equally essential complementary perspective.

The estimates on the influence of traditional explanatory variables on CDS are presented in Tables 3.a, 3.b and 3.c. Bank soundness is a key variable. The sensitivity of five year CDS spreads to the Tier 1 capital ratio is confirmed in estimations (5) to (15). Enhanced levels of Tier 1 reassure investors as they are accompanied by a decrease in CDS spreads (negative impact in models 3 to 13). Table 3.a. shows that an increase in NPAs leads to a rise in CDS spreads, and an increase in interbank assets leads to a fall in CDS spreads. We also note that Total loans (TL) do not seem to impact CDS spreads, unlike Tier One capital ratio (T1) and Total Deposits (DEP). Enhanced T1 and DEP leads to a decrease in CDS spreads.

The importance of bank soundness is confirmed in particular by the significance of non-performing assets in the models. When the banks exhibit abnormally high levels of non-performing assets, CDS spreads rise in all models tested. Default probabilities also have a considerable influence, as demonstrated by the high values of the t-tests in models (6) to (15). This is consistent with Christiano et al. (2014), Gilchrist et al. (2014), and Arellano et al. (2018) who show that uncertainty is associated with tighter credit conditions and financial stress. We note the importance of the investors' confidence index in model (15): increased concerns about the country's overall situation lead to an increase in CDS spreads. Again, this is consistent with Bernanke (1983), Bloom (2009), Dixit (1989) and Davig & Hakkio (2010), as uncertainty rises, confidence drops and economic agents tend to postpone or cut down on new investments.

The general situation of the economy and financial markets has no direct influence on CDS prices (FTSE 100, GBP, real GDP, inflation, liquidity or yield spreads). This is not inconsistent with prior research which shows that uncertainty translates into lower stock returns and higher volatility. This is not what our results intended to investigate. What our results say is that stock returns, inflation, exchange rates and other economic variables do not explain UK-based banks CDS spreads fluctuations.

Furthermore, we find that the high level of concentration in the UK banking sector negatively affects CDS spreads. This last result confirms the market power-stability assumption (Lapteacru, 2017): greater concentration allows the system to improve its capital buffers and profits, which leads to a decrease in CDS spreads.

In table 3.b., we note that the inclusion of financial market data in the estimations does not alter the significance of NPAs, Tier 1 and Total Deposits. The probability of default over 5 years (Dprob) is highly significant: the more likely a bank is to default, the greater the CDS spreads. The FTSE 100 (Ftse) and the national currency (GBP) apparently do not influence CDS spreads. Finally, our results show that Liquidity and Yield have no influence on CDS spreads. Macroeconomic data have only a limited and weakly significant impact; Real GDP (Rgdp) and the economic surprise indicator (Ecosurpr) do not affect CDS spreads (Table 3.c.). The Herfindhal-Hirschman index (Herf) is only significant at the .05 level.

We then investigated possible differences between domestic and non-domestic banks. We produced separate estimates (Table 4). In both groups, the roles played by non-performing assets and the default probability are confirmed. Tier 1 capital ratio is however only significant in the case of non-domestic banks. The presence of specific credit institutions such as building societies in our UK panel may explain this result. Building societies do not manage risks in the same way as other banks, because of their special status and role in the UK (Bàtiz-Lazo and Noguchi, 2014). Building societies fall in fact outside of the graphical representations as a result of being less exposed (Q3). If we exclude building societies from our Panel, Tier 1 is significant.

Similarly, in both groups, non-performing assets and probabilities of defaults have a significant influence on CDS spreads (Table 4). There are interesting differences between domestic and non-domestic banks when considering Tier 1 and Total Deposits. These variables are only significant in the panel involving non-domestic banks. Overall, we find that there are no major differences between the two groups. This is not surprising inasmuch as the majority of the banks in the sample are global institutions, with significant activities outside of the UK.

INSERT TABLES 3.a., 3.b., and 3.c. ABOUT HERE

INSERT TABLE 4 ABOUT HERE

When it comes to estimating network variables, we used a similar approach to Embree & Roberts (2009), who investigated the networks associated with the Canadian large-value transfer system. They demonstrated the presence of influential clusters within their networks, but failed to highlight the relevance of centrality variables through their panel estimates. In the case of the UK-based banks, we also validate the presence of influential clusters, and we demonstrate the significance of betweenness and degree per nodes coefficients (Q5).

A significant body of literature on networks focuses on interbank assets (Aldasoro et al., 2017; Langfield et al. 2014; Craig & Von Goetz, 2014). In the case of our study of the UK-

based financial institutions, we confirm the existence of similar configurations, but we extend the scope of the analysis to other types of networks so as to consider a wider set of banking relationships. Moreover, our results demonstrate that centrality variables in interbank networks are not necessarily the most relevant measures to explain the fluctuations of CDS spreads.

Our results also extend the findings of Torri et al. (2018). They studied the weekly time series of CDS spreads (5-year maturity) of 31 European banks in 12 countries over the period 2009-2016, and focused on centralization measures (Freeman centralization, coreness, modularity, clustering, and assortativity) to compare them to random theoretical configurations. In our study, we compare our results to a wider range of theoretical configurations (Table 2, Section 5.1) and propose a new network metric (Telesford Ratio). Network representations are often described in the literature as irrelevant because they are based on unrealistic assumptions (Torri et al., 2018). On the contrary, with our approach focused on the most important relationships and using simple topology metrics, we demonstrate that it is possible to provide explicit and clear visualizations of UK-based banks networks using the Kamada-Kawai algorithm (see section 5.2).

Another key issue is to understand to what extent prominent banks in their networks may impact the system. To this end, we have introduced the betweenness (B) in the different networks (Tables 5.a and 5.b.). This coefficient measures the influence exercised by banks in their networks. We also introduced a measure of the number of incoming and outgoing links per institution in the different networks (degree per banks, D). We show that B and D play a significant role in CDS spreads (Q5), although this influence varies from one network to the other.

Models (1) to (13) show that betweenness and degree per node in the non-performing assets network are significant determinants of UK CDS spreads: a rise in the prominence of the banks (B_NPA) holding non-performing assets leads to an increase in CDS spreads. This confirms the hypothesis that prominent banks with impaired resilience could impact the entire financial system. It is corroborated by the relevance of the degree per banks (D_NPA). In models (10) to (13), the number of links that banks have in this network is positively associated with changes in CDS spreads.

The significance of the betweenness observed between banks in the default network (B_DPROB) is verified in models (7) to (13). The variable has a negative effect. The more reputable nodes banks form in this network, the more CDS spreads decrease. This is an illustration of the 'too big to fail' principle (see Demirgüç-Kunt & Huizinga, 2013). Investors are convinced that large and reputed banks will be rescued in case of distress, so that the system is preserved. However, when the banks' default probability increases (DPROB), investors' concerns translate into enhanced CDS spreads, which is consistent with empirical evidence and academic research (Bialkowski et al., 2008; Pastor & Veronesi, 2012; Brogaard & Detzel, 2015; Boutchkova et al., 2012). In addition, we note that prominent banks in the network of CDS do not benefit from lower spreads: the higher the coefficient (B_CDS), the higher CDS spreads. This reflects investors' mistrust who would prefer a bank to increase the number of its relationships (D_CDS) than see this bank become the unavoidable partner in the event of future Brexit negotiations. In terms of adapting regulation in the context of Brexit, our results offer the regulator the ability to select priority areas for action.

INSERT TABLES 5.a. and 5.b. ABOUT HERE

5.4. Robustness

We performed three types of robustness tests. First, we tested the presence of network effects before and after the subprime crisis, as the financial crisis may have transformed the form of networks and the way banks exercise their influence within these networks. During turbulent times, banks are likely to rely more on strong existing relationships. At the same time, shared information within existing connections may be dramatically reduced (Houston, 2018). We therefore divided our sample into two periods to study the topology of banking relationships before and after the crisis. We estimated fixed effect models over these two sub-periods. Our results show that the crisis did not reduce the number of connections between the banks. After the financial crisis, the distance between banks in the different networks decreased. The clustering increased. The post-crisis reaction of the UK banking system is therefore a strong concentration of relations. This dynamic is confirmed by the

estimates of fixed effect models. Before the crisis, the influence of banks (betweenness) was only marginally significant.

Only connections between banks (degree) were relevant. After the crisis, the coefficient of betweenness becomes an essential variable in most of the networks of relationships studied (Non-performing assets, Distances to default, CDS spreads).

The second robustness test is related to the independence of betweenness and degree per nodes variables. Our results provide strong evidence that these variables have opposite effects. Higher levels of betweenness (B_CDS) entail higher CDS spreads, while higher connectedness (D_CDS) entail lower CDS spreads (Table 5b). Besides, the correlation between these two categories of variables is relatively low (see Table A2 in appendix).

The third type of robustness test relates to the issue of reverse causality. Our results are not driven by reverse causality, namely that the credit default swap spreads would allow the bank to increase its network centrality. For verification purposes, we followed the proposals of Houston et al. (2018) and Hochberg et al. (2007). We used new centrality measures for betweenness and degree per nodes, based only on the ties formed 5 years before. The significance of these variables confirms the robustness of our results to reverse causality.

6. Concluding remarks, theoretical contribution and policy implications

Our paper investigates the exposure of the UK financial system to major uncertainty using the CDS spreads market. We obtain five key results. First, we show that prominent institutions all experienced an increase in daily CDS spreads following a major uncertainty, such as the Brexit vote. This reflects investors' concern about the ability of UK financial institutions to withstand unprecedented political, social and economic uncertainty. Second, we identify reputable banks and groups of banks that could disrupt the system, namely Société Générale, Unicredit Bank AG and Bank of America. Third, we note that a number of UK banks (for example HSBC or Royal Bank of Scotland) are particularly at risk in the event of distress in the system, an obvious example of which would be a hard Brexit. Fourth, building societies, and to lesser extent Lloyds Bank are the least exposed as they all stand at a “safe” distance in the networks. Finally, our last finding concerns the significance of network measures of centrality and influence in our panel analyses. We show that the

influence of banks in their networks of relationships has a significant influence on the fluctuations of CDS spreads.

While a significant part of the literature on networks is based on the study of interbank assets and measures of centrality, we open up new research opportunities by analyzing multiple networks that demonstrate that centrality variables in interbank networks are not necessarily the most relevant measures to explain uncertainty and fluctuations in CDS spreads in particular.

Our results also contribute to research on network graphical representations. While graphical representations are criticized and often considered irrelevant because of the unrealistic assumptions required to build them, we propose a method that avoids such assumptions and produces simple and clear graphs by focusing on the most important relationships and using simple topology metrics.

This study has important implications for regulators and policy makers. The first policy implication concerns the influence of non-domestic institutions. In the face of Brexit, and considering their prominent influence in the UK financial system, The Bank of America, Société Générale and Unicredit Bank AG are institutions whose relocation of all or part of their activities could have a major effect on their direct relationships and the UK financial system as a whole. Close monitoring and potential contingency plans may be considered to either prevent them from relocating or mitigate the consequences of such relocation on their UK-based partner banks.

A second policy implication relates to the exposure of domestic institutions that excessively rely on non-domestic banks. This is notably the case of Standard Chartered, HSBC, Royal Bank of Scotland or Bank of Ireland that are all overly exposed to a potential restructuring of the UK financial system.

The third policy implication concerns the networks for which interconnections are the densest. The risk and speed of contagion are higher than anywhere else. The main networks involve CDS, non-performing assets and probable defaults. One way for the regulator to reduce the strength of these connections is to increase competitiveness within the system as a whole. In this context, a strict and demanding disclosure policy for investors and financial markets is of the utmost importance. In a context of increasing uncertainty, regulators must

be able to put in place effective channels of trust to stem excessive market reactions that could lead to economic disintegration.

7. References

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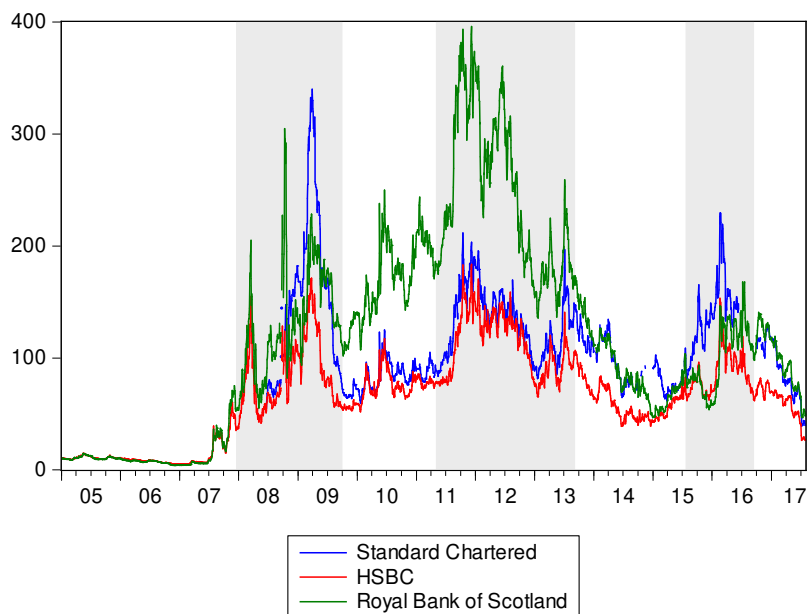
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Appendix

INSERT TABLE A.1. ABOUT HERE

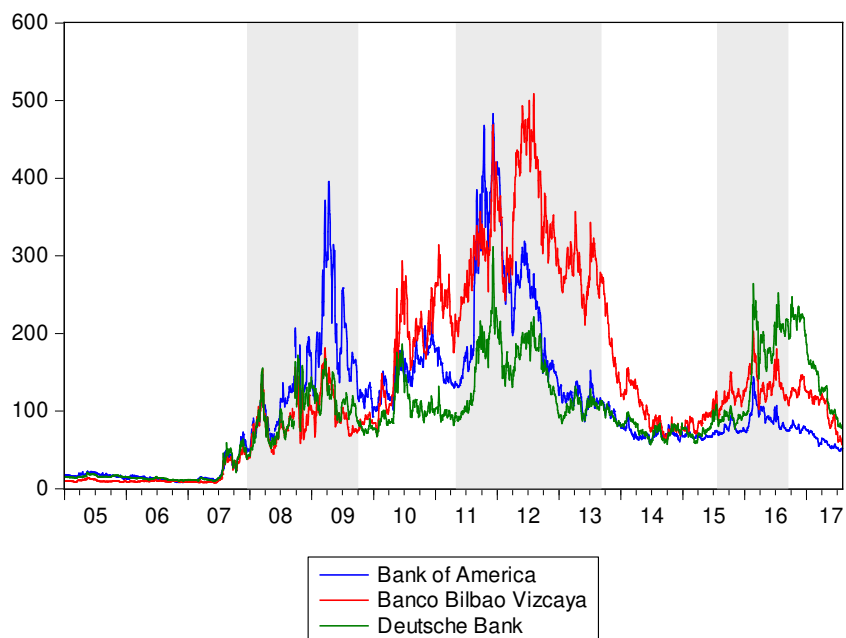
INSERT A.2. ABOUT HERE

Figure 1. Prominent British Institutions, 5 year CDS spreads, daily bps.



Colors should be used in print for Figure 1

Figure 2. Prominent non-domestic banks, 5 year CDS spreads, daily bps.



Colors should be used in print for Figure 2

Figure 3. Prominent Institutions: Highest Betweenness Scores

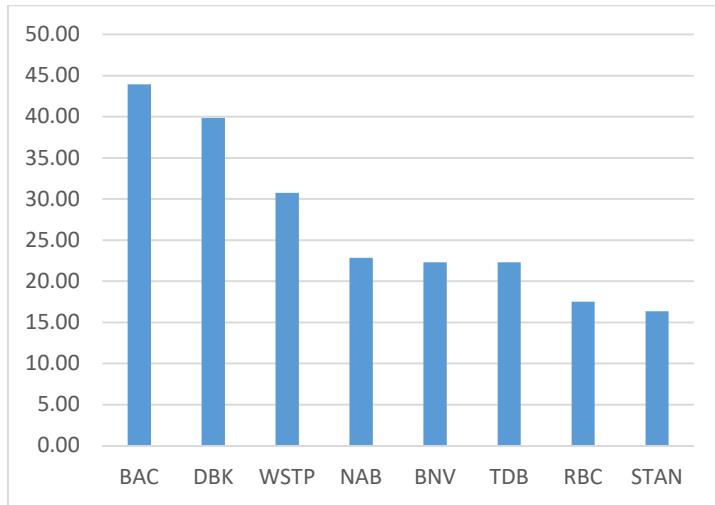


Figure 3.a Interbank Agreements Network

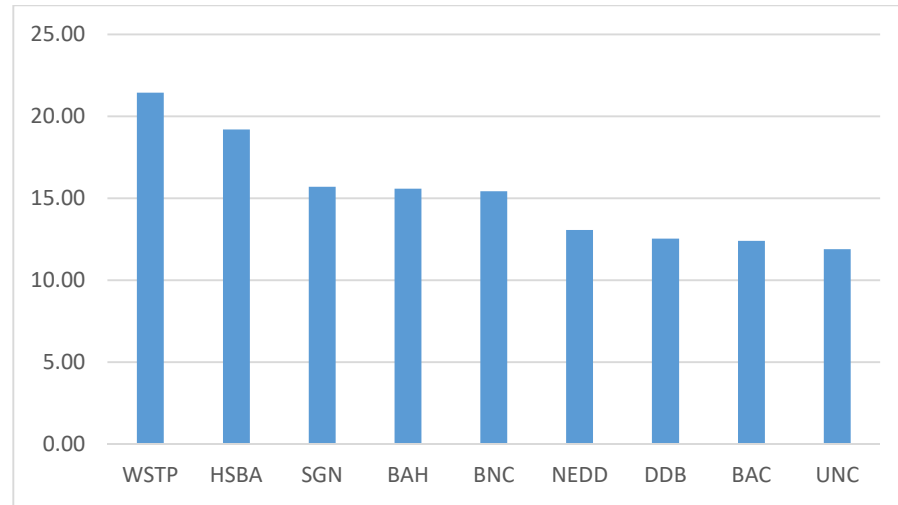


Figure 3.b Defaults Network

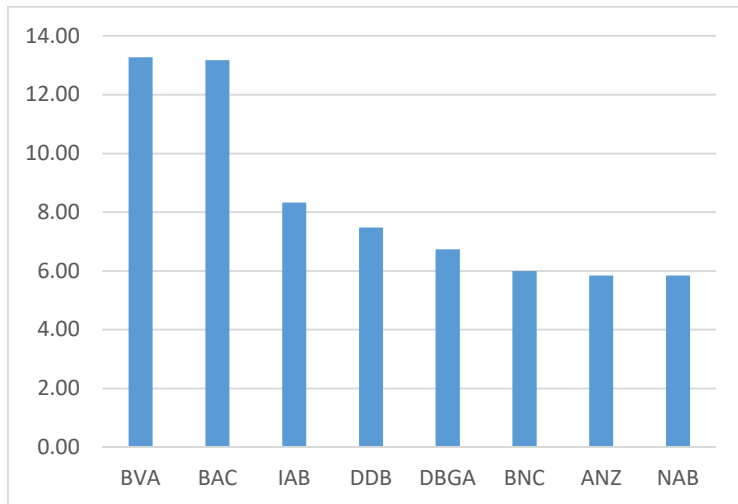


Figure 3.c Non-Performing Assets Network

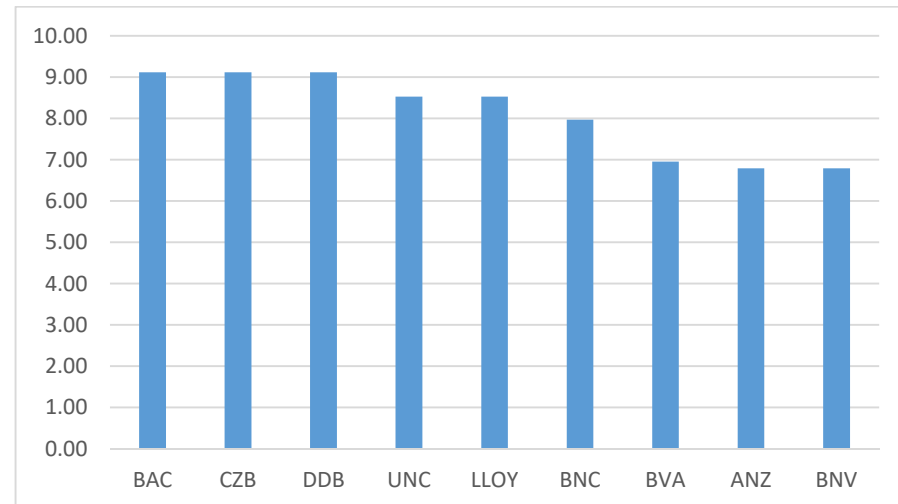


Figure 3.d Credit Default Swaps Network

Figure 4. Prominent Banks in the Non-Performing Assets Network

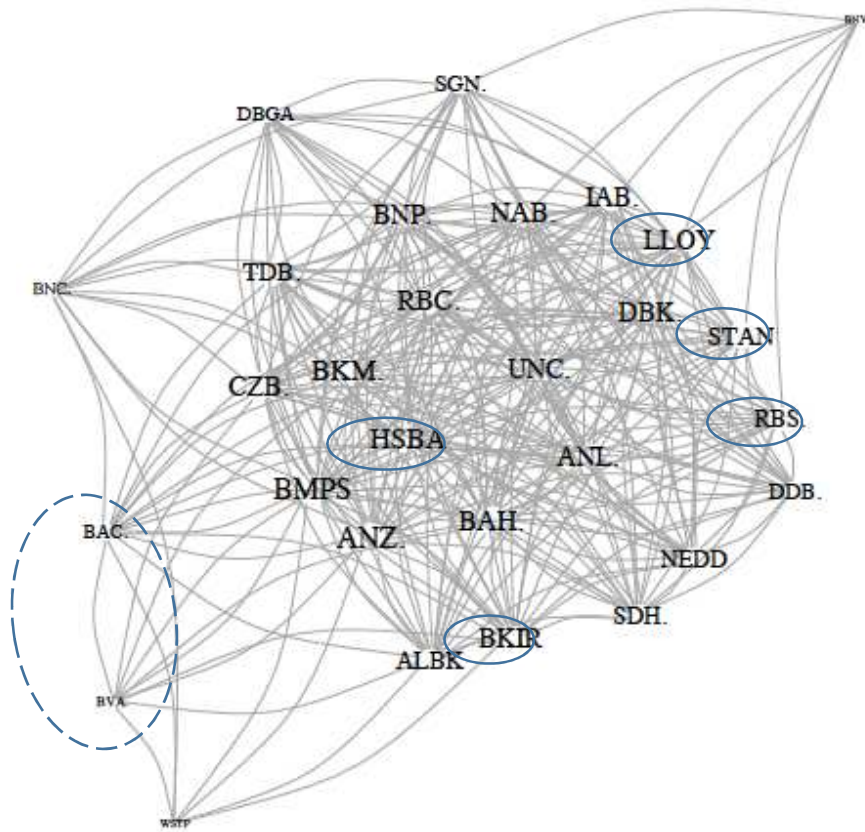


Figure 5. Prominent Banks in the Defaults Network

