

Mapping the UK interbank system

Sam Langfield,⁽¹⁾ Zijun Liu⁽²⁾ and Tomohiro Ota⁽³⁾

Abstract

This paper describes the features of the UK interbank system, using a new regulatory dataset on interbank exposures broken down by counterparty and instrument. To our knowledge, this dataset is the most granular representation of a large interbank market available worldwide. We show that the system clearly exhibits a 'hub and spoke', or core-periphery, structure. Most of the 176 banks resident in the UK are counterparties to a handful of core banks. But structure varies significantly by asset class. We interpret these findings in light of existing theories regarding the formation of networks and their resilience.

(1) UK Financial Services Authority and European Systemic Risk Board Secretariat. Email: samlangfield@gmail.com

(2) UK Financial Services Authority. Email: zijun.liu@fsa.gov.uk

(3) Bank of England. Email: tomohiro.ota@bankofengland.co.uk

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1 Introduction

Before 2007, financial regulation erred by insufficiently focusing on the stability of the financial system as a whole. The Turner Review identified deficient macroprudential regulation as ‘far more important to the origins of the crisis than any specific failure in supervisory process’ (FSA, 2009). One tenet of macroprudential regulation is that the structure of the financial system – particularly how banks are connected – matters for the ability of the system to contain shocks (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000). On one hand, structure might enable intermediaries to pool risk, thus reducing aggregate damage by distributing the effect of shocks more evenly across the system. On the other hand, structure might propagate and amplify shocks, leading to second-round effects which dwarf initial costs. Before the crisis, regulators and market participants placed too much faith on the benefits of risk sharing, without due consideration of the costs of risk propagation.

Structure matters for systemic resilience. But the precise structure of the UK interbank system was hitherto only partially observed. This paper fills that gap. In particular, we make four contributions to collective understanding of the UK interbank system. First, the paper is based on a newly available regulatory dataset on interbank exposures broken down by counterparty and instrument. Due to data constraints, previous studies could analyse interbank markets only by making strong assumptions regarding unobserved relationships. Second, we describe the structure of the interbank system along three dimensions: by instrument; by bank sector; and by banks’ market risks. Third, we adapt network theory to four complexities inherent in financial markets: directed links; weighted links; multiple links; and node-heterogeneity. Fourth, analysis reveals that the network of interbank exposures closely approximates a ‘hub and spoke’, or core-periphery, structure. Most banks are connected to a handful of core banks, which are strongly connected to each other.

We are motivated by three considerations. First, ‘network information is a classic public good’ (Haldane, 2009). Such information allows financial players to better understand the system in which they operate. Battiston et al (2009) purport tension between individual risk and systemic

¹ Mervyn King (2012), BBC Today Programme Lecture.

risk, since individual entities do not internalise their impact on the wider system. The first step towards internalising externalities consists in reducing information gaps with respect to those externalities. Second, information contained in this paper will inform ongoing policy debate regarding banking structure (ICB, 2011), counterparty clearing houses (Tucker, 2011) and capital surcharges for systemically important banks (BCBS, 2011). Third, this paper lies at the intersection of literature on networks and banking. Papers on financial networks have ballooned in quantity over recent years, but conclusive insights remain elusive. Our paper contributes much-needed evidence regarding the structure of the UK interbank system.

The paper is structured as follows. In the next section, we describe the new regulatory dataset. In the third section, we describe the general features of those data. The fourth section details our method, which accounts for certain complexities inherent in financial networks. Results are presented in section five, in which we first discuss network statistics, and then establish the closeness of the UK interbank system to a core-periphery model. The sixth section provides economic interpretation of these results, in light of existing theories regarding network formation and the resilience of systemic structures.

2 Data

This paper is based on a new regulatory dataset on interbank exposures in the UK. The data are collected directly from banks by the Financial Services Authority (FSA), under the authority of regulatory rules related to banks' recovery and resolution plans (FSA, 2012).² 176 UK consolidated banking groups, comprising deposit-takers and significant investment firms, report exposures to their top 20 bank and broker-dealer counterparties.³ Importantly, banks report exposures to other banks' global consolidated group. Intra-group exposures are not reported: in this analysis, we treat banking groups as single entities. Other research explores funding risk arising within banking groups (Mistrulli, 2011).

The data provide a thorough breakdown of financial instruments. Banks report their prime lending (unsecured, secured and undrawn); holdings of equity and fixed-income securities;

² For details of the data collection, see http://www.fsa.gov.uk/about/what/international/recov_res_plans/interbank-exposures-data-collection. The rules specify the precise requirements under which firms must submit the data. In particular, the data are submitted on a so-called 'best-efforts' basis for the first submission.

³ If the top 20 does not have at least six UK-based counterparties, firms are asked to report exposures to up to six UK-based counterparties in addition to the top 20. Branches of foreign banking groups in the UK are not included in the data collection.

credit default swaps bought and sold; securities lending and borrowing (gross and net of collateral); repo and reverse repo (gross and net of collateral); derivatives exposures (with breakdown by asset class);⁴ settlement and clearing lines; asset-backed securities; covered bonds; and short-term lending with respect to other banks and broker dealers. Moreover, banks report exposures with breakdown by the maturity of the instrument.⁵ Banks' internal risk management limits with respect to counterparties and instruments are also supplied.

Of the 176 UK incorporated banks in the dataset, 48 are UK banks; 47 are UK building societies; 14 are the UK regulated entities of investment banks; and 67 are the UK regulated entities of other banks resident outside of the UK. Additionally, there are 314 non-UK banks in the dataset, because the 176 UK incorporated banks report their exposures to other banks' global consolidated group. These 314 non-UK banks do not submit their own exposures to the FSA, but are counterparties to at least one of the 176 reporting banks.

We match the 490 banks with balance-sheet data obtained from two sources. First, for each of the 176 reporting banks, we obtain other regulatory data on the balance sheets of UK consolidated groups. Second, we match the full sample of 490 banks with public balance-sheet data obtained from Bloomberg, Capital IQ and Bureau van Dijk's Bankscope database. After thorough matching, we obtain complete balance-sheet information for 343 of the 490 banks: some very small banks could not be matched. The value of reporting banks' exposures to the 147 banks for which we could not obtain public balance-sheet data is just £12.3bn, or 4.6% of total interbank exposures.

The resulting dataset consists of matrices with dimensions 176 x 490, containing observations on interbank exposures; supplemented by observations on the balance sheets of 343 banks. Diagonal elements in the former matrix are equal to zero, since banks do not report intragroup positions. High-impact banks (of which there are 91) submit interbank exposures under 163 variables (comprising different instruments and maturities). The remaining 85 reporting banks submit a reduced template with 58 variables.⁶ The full dataset therefore comprises [(163 x 91) +

⁴ The breakdown covers interest rate derivatives; credit derivatives; equity derivatives; foreign-currency derivatives; commodities derivatives; and other derivatives. In the case of derivatives, requested types of exposure include net mark-to-market (before and after collateral); exposure at default; potential future exposure; and trade count.

⁵ Categories of maturities are open; less than three months; between three months and one year; between one year and five years; and more than five years. Derivatives are not reported with a maturity breakdown.

⁶ Definitions of high- and low-impact banks are based on the FSA's definition. This definition is based on size and other variables.

$(58 \times 85)] \times 490 = 9.7$ million elements in the cross-section. In practice, the matrices are sparse. Most banks are small players in the interbank market: 3.2% of all possible links are complete. But most links are relatively small. In weighted terms, the network is 0.00003% complete.⁷

The new regulatory dataset on interbank exposures has clear advantages over those analysed in the extant literature, in terms of both coverage and granularity. In the UK, prior research has used data from the large exposures regime (Wells, 2004; Alessandri et al, 2009). This regime requires banks to report exposures to counterparties when the value of that exposure exceeds 10% of regulatory capital. In the new regulatory dataset, 81.5% of observations, amounting to £200bn (or 75.8%) of interbank exposures, fall below 10% of own regulatory capital, and therefore would be ignored by the large exposures regime. Previously, analysts often filled gaps in observed networks using techniques such as maximum entropy, which spreads residual exposures evenly across remaining counterparties (Upper and Worms, 2004; Wells, 2004; Degryse and Nguyen, 2007; Alessandri et al, 2009). Using real data, Mistrulli (2011) shows that maximum entropy techniques tend to underestimate the extent of contagion in the case of interbank markets, although van Lelyveld and Liedorp (2006) consider the approach adequate. Either way, observing the network of interbank exposures directly, as we do with the new regulatory dataset, is a great improvement.

In order to implement maximum entropy, partially observed bilateral data must be combined with complete aggregate data. In the UK, the Bank of England collects data on the balance sheets of UK monetary and financial institutions (MFIs). The data aggregate all inter-MFI exposures, but with no counterparty breakdown. Most of the interbank activity recorded in these data refers to transfers within banking groups, which often occur as part of banks' day-to-day asset-liability management. In particular, some banks located in the UK typically 'upstream' funding to parent entities resident outside of the UK. Unsecured lending by UK MFIs to UK-resident banks, excluding intra-group transactions, amounted to £95.3bn, or 1.1% of total assets, in Q4 2011. Including intra-group transactions, the number is £625.7bn, or 7.7% of total assets. The new regulatory interbank exposures data show that unsecured lending by UK banks to other banks globally totalled £58.9bn at the end of Q4 2011. Of this, £40.1bn (68%) is lent by UK

⁷ Weighted network completeness is defined as
$$= \sum_{i=1}^{176} \left[\frac{Strength_i}{Market\ size} * \frac{1}{26 * Relative\ strength\ concentration_i} \right]$$
 in the *exposures* network. Component terms are defined in section 4.2.

banks to other UK-resident banks.⁸ Notably, the scale of interbank unsecured lending (excluding intra-group) has reduced significantly since 2007, from over 2% of total assets in 2007 to around 1% in 2011. Over the same period, intragroup unsecured lending has increased (see figure A3 in the appendix).

Interbank exposures data have been studied in some other European countries. Centralised credit registers of banks' loan- or borrower-level exposures are maintained in Austria, Belgium, France, Germany, Italy, Lithuania, Portugal and Spain (ECB, 2003). Some of these credit registers have been used to observe interbank networks. Cocco, Gomes and Martins (2009) extract overnight interbank loan data from the Banco de Portugal's *Central de Responsabilidades de Crédito* to analyse borrower-lender relationships. Iazzetta and Manna (2009) exploit data from the *Centrale dei Rischi* of the Banca d'Italia to describe the network topology of the Italian interbank market. Craig and von Peter (2010) use the Deutsche Bundesbank's *Gross- und Millionenkreditstatistik* to show that the German interbank is tiered, with a small number of core banks intermediating between peripheral banks.

For the purposes of financial network analysis, the credit registers used in these three papers have pros and cons compared with the new regulatory dataset on UK interbank exposures. In particular, the credit registers benefit from longer time series. The Portuguese data start in 1997; the Italian data in 1990; and the German data in 1999. With such data, one can observe variation over time in borrower-lender relationships; portfolios by asset class; and overall network structure. Panel data structure also facilitates more robust causal inference, deployed for example in Cocco, Gomes and Martins (2009).

But the new regulatory dataset on UK interbank exposures is much richer in the cross-section. The European credit registers typically record only unsecured and secured lending. But these categories comprise just 28% of interbank exposures in our dataset, since the latter contains more asset classes. Breakdown by asset class permits us to distinguish instruments which imply that bank i is exposed to bank j from instruments which imply that bank i funds bank j . This distinction is a key innovation of our paper.

⁸ The discrepancy between the Bank of England's MFI data and the new regulatory interbank data is mainly due to technical differences in definition and scope. For example, deposit-taking branches of foreign banking groups are included in the Bank of England MFI dataset but not in the new regulatory dataset.

There are two limitations of the new regulatory dataset on UK interbank exposures. The first limitation is that banks report only those positions held on their UK consolidated balance sheet. We therefore do not observe interbank positions held by UK banks off their UK consolidated balance sheet – just as all national datasets only record exposures held nationally. 101 of the 176 reporting banks are resident in the UK. For these 101 UK-resident banks, total assets of the UK consolidated group account for 90.1% of total assets of the global consolidated group on average. For the remaining 75 reporting banks not resident in the UK, the UK consolidated group accounts for 40.6% of total global assets on average. In addition, we do not observe interbank positions held by banks with no regulated entity in the UK. This unobserved portion of the full global network of interbank exposures is most substantial. From the point of view of UK financial stability, one would ideally observe interbank funding obtained by UK banks from banks not regulated in the UK. This data constraint will be relaxed for globally systemically important banks by the Financial Stability Board’s forthcoming data collection.⁹

The second limitation is that UK banks report exposures to their top 20 bank and broker-dealer counterparties. Exposures to counterparties beyond the top 20 are not observed. In the data submitted at the end of 2011, 62 of the 176 UK banks reported exposures to fully 20 counterparties. The total value of the 20th exposure across these 62 banks was £2.3bn, or 0.9% of total market size. However, this £2.3bn is not evenly distributed across the 62 banks and it is likely that a few very large banks will have some significant counterparty exposures not captured in the top 20. Additionally, only a few of the 176 UK banks reported exposures to fully six additional UK counterparties. So our dataset captures the majority of the UK-to-UK interbank market (excluding foreign branches) and UK banks’ exposures to non-reporting foreign banks except for a few very large banks.

3 Description of the Interbank Market

The UK banking sector is one of the largest in the world. UK banks’ claims are worth over £8tn: more than 500% of annual UK output. Size ballooned over the pre-crisis years. Between 2005 and 2008, UK banks’ credit claims on the real economy rose by around 50%, while intra-financial sector assets increased 260%. The sector is also very concentrated. The largest six banking groups account for over 80% of UK consumer lending and deposits.

⁹ See http://www.financialstabilityboard.org/publications/r_1203281.pdf.

Banks intermediate savings and investment in the real economy. Banks also intermediate credit between themselves. In doing so, they form a network of connections: that is, the interbank system. At the end of 2011, UK banks reported interbank exposures of £264bn, representing 3.1% of total assets and 78.5% of core tier one capital of the UK consolidated groups of reporting banks. In the dataset, we also observe £192bn of interbank funding, representing 0.4% of the total global consolidated liabilities of both reporting and non-reporting banks.

3.1 *The Interbank Market by Instrument*

We divide links into two categories: exposures and funding (see figure 1). The *exposures* network is relevant for solvency: it includes unsecured interbank lending, marketable securities, net CDS sold, securities financing transactions (after collateral), and off-balance sheet derivatives exposures. The funding network is relevant for liquidity: it includes unsecured interbank lending and repos (before collateral). Debt instruments are not included in the funding network, because exposures reported by banks are net of longs and shorts and so might not be equal to the actual amount of funding provided. More details on these categories are provided in section 4.1.

Derivatives are the largest category of exposures, accounting for 44%. Derivatives are measured by exposure at default (EAD), which incorporates an estimate of potential future exposure. In contrast, other exposures in interbank lending and marketable securities are measured by mark-to-market value.¹⁰ Securities financing transactions, which are measured net of collateral received, account for 11% of total exposures. When measured before collateral in the funding network, repos are the largest category, accounting for 66%.

¹⁰ The mark-to-market value of derivatives after collateral measures the exposure if the counterparty defaults today. However, the mark-to-market value of derivatives is very sensitive to the market value of the underlying instruments and can exhibit large fluctuations within a short time period. Therefore, regulatory measures of derivatives exposures (EAD) include the currency mark-to-market value as well as an estimate of potential future exposure. The latter is typically six times the current mark-to-market value based on our dataset.

Figure 1: Instrument Breakdown of the Interbank Market

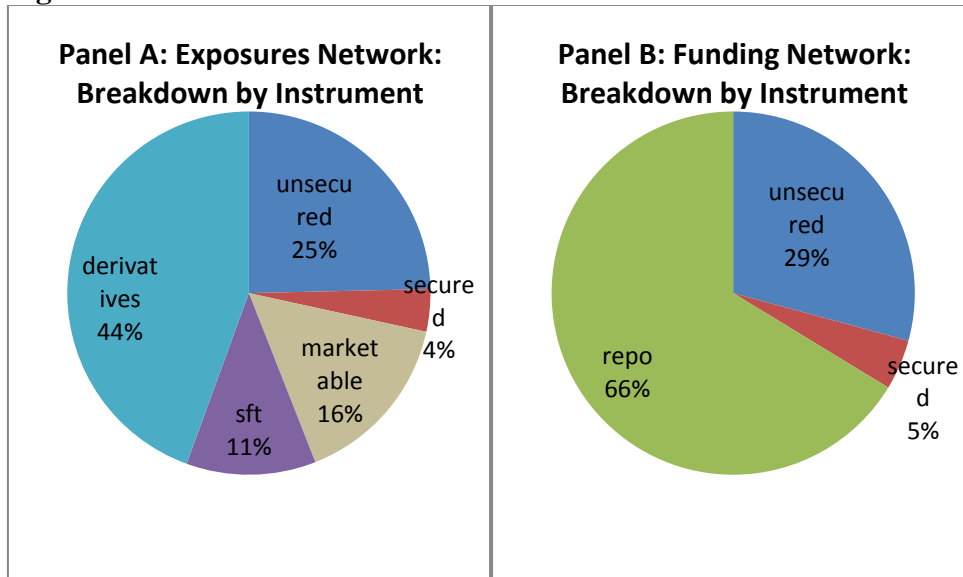


Figure 2 shows the maturity breakdown of lending instruments (including repo and interbank lending) and marketable securities (including equity and debt securities). The majority of lending instruments (69%) have an outstanding maturity of less than 3 months; only 13% mature in over one year. The share of marketable securities with maturity above one year is somewhat higher, at 33%.

Figure 2: Maturity Breakdown of the Interbank Market

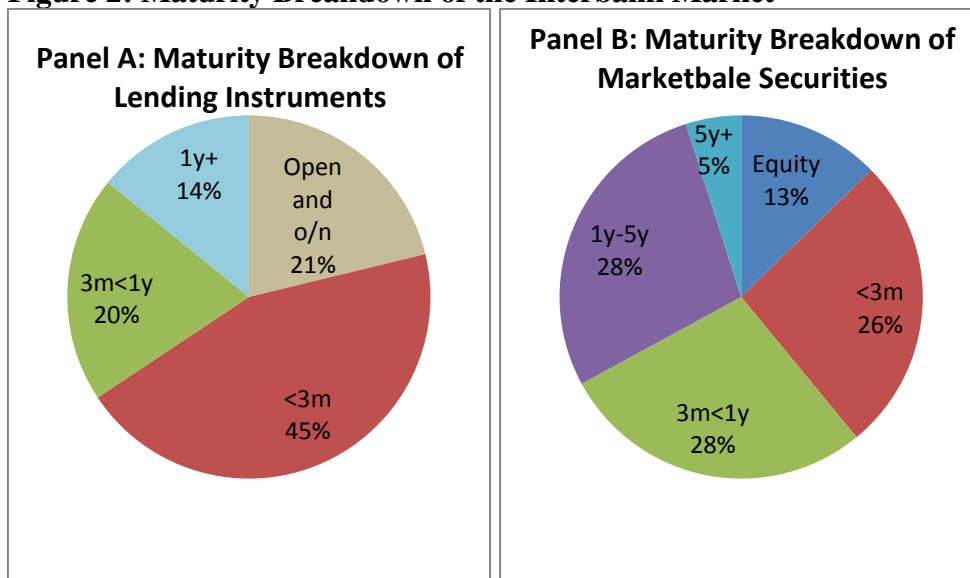
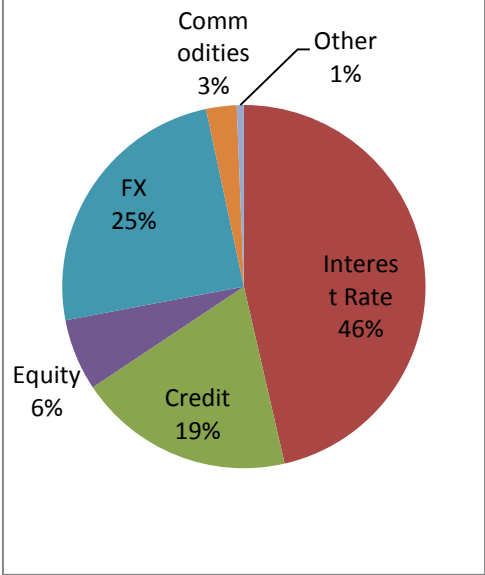


Figure 3 shows the breakdown of derivatives exposures by asset class, including equity, FX, credit, interest rate, commodity and other derivatives. The largest category is interest rate derivatives, followed by FX and credit derivatives, reflecting demand for hedges against latent

interest rate, currency and credit risks. Exposures in equity and commodity derivatives are relatively small.

Figure 3: Derivatives Breakdown by Underlying Asset Class

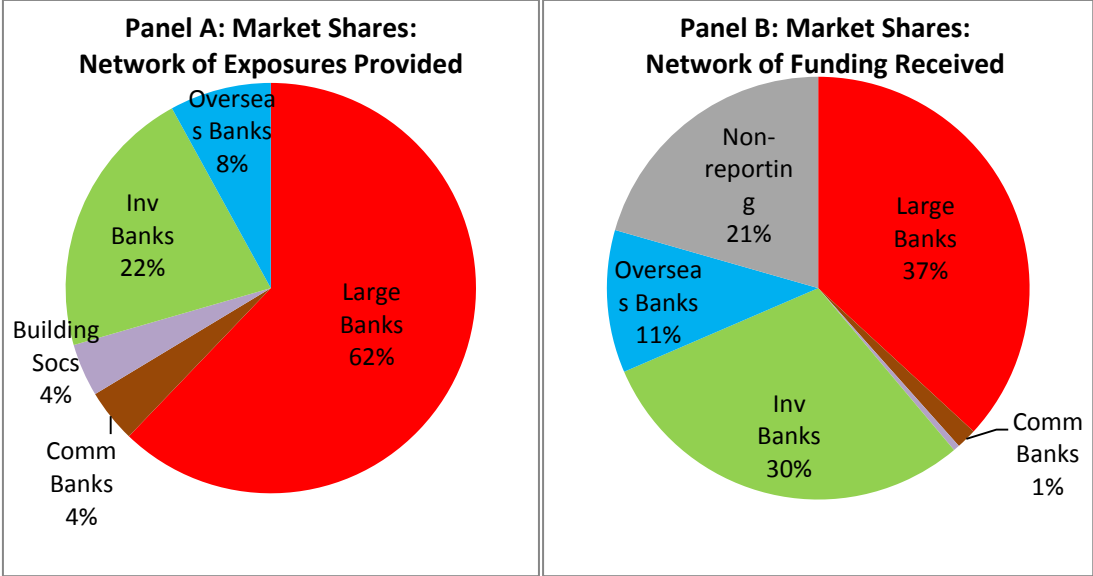


3.2 The Interbank Market by Bank Sector and Country

We now cut the exposures and funding networks by bank type. We classify banks as the eight largest UK banks; other UK banks; building societies; foreign investment banks with UK subsidiaries; other overseas banks with UK subsidiaries; and non-reporting foreign banks with no UK subsidiary. As shown in figure 4, 62% of exposures are reported by large UK banks, followed by investment banks (22%). In the funding network, 37% of funding is provided to large UK banks, followed by investment banks (30%) and non-reporting banks (21%).

Building societies reported the highest interbank exposures relative to their total core tier one capital (214%); the figure is 72% for UK commercial banks, 70% for large UK banks, 88% for investment banks and 138% for overseas banks. Globally, large banks are most reliant on interbank markets, with 0.9% of their global liabilities comprising obligations to other UK banks. The corresponding figures are 0.8% for building societies; 0.7% for investment banks; 0.4% for commercial banks; 0.2% for overseas banks; and 0.2% for non-reporting banks.

Figure 4: Market Share Breakdown by Bank Type



In the following, we use network graphs to illustrate exposures between different sectors. In the exposures network (figure 5), large UK banks are the core sector in the network, with significant exposures to investment banks, non-reporting banks and large UK banks. A large part of the exposures of large UK banks arise from derivatives transactions with UK branches of foreign banking groups. In the funding network (figure 6), large UK banks seem to rely heavily on funding from investment banks, mostly via repos. Other UK commercial banks and building societies are pure lenders in the interbank market. Overall, the UK interbank market is dominated by large UK banks that are very active in the derivatives market. In addition, these large UK banks receive unsecured funding from small banks and building societies, and secured funding from investment banks. Investment banks are net lenders in the funding network, and probably rely on intragroup funding from overseas parents.

Figure 5: Exposures Network by Bank Type (arrows point from banks holding exposure)

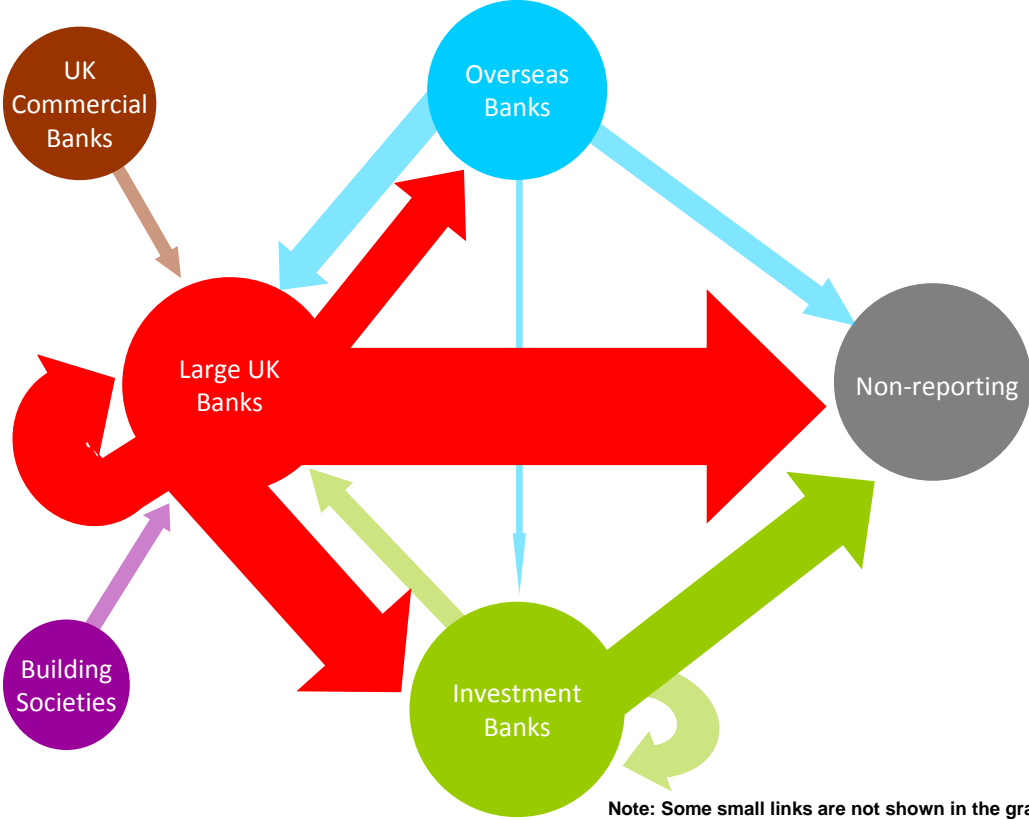


Figure 6: Funding Network by Bank Type (arrows point from banks providing funding)

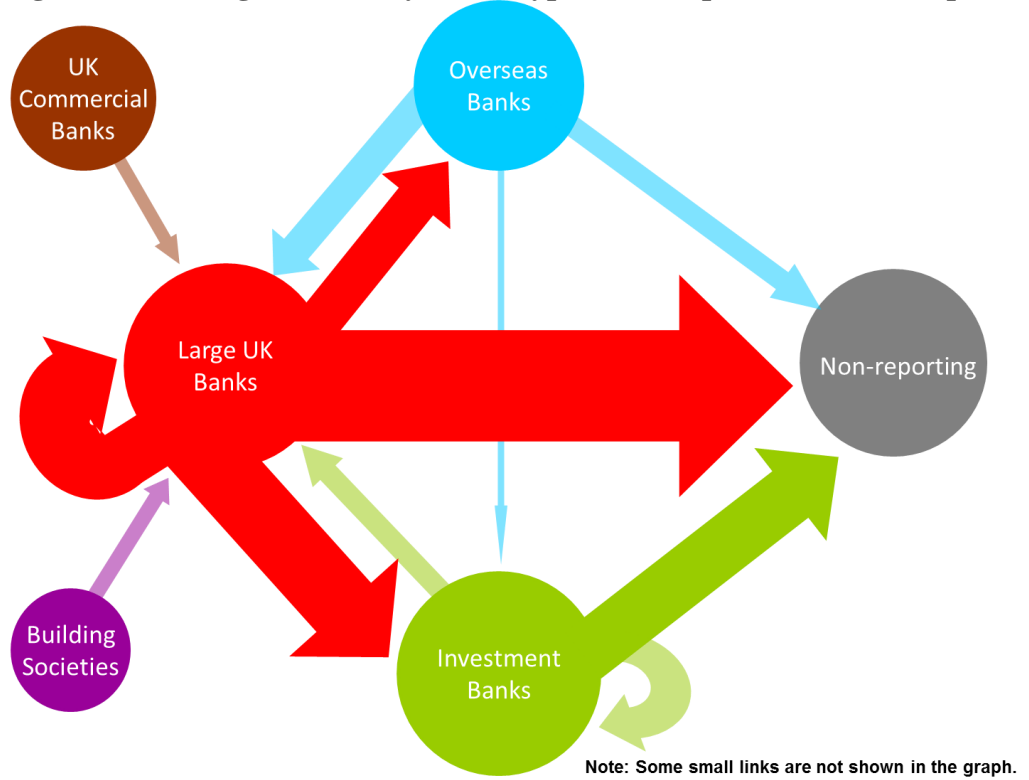
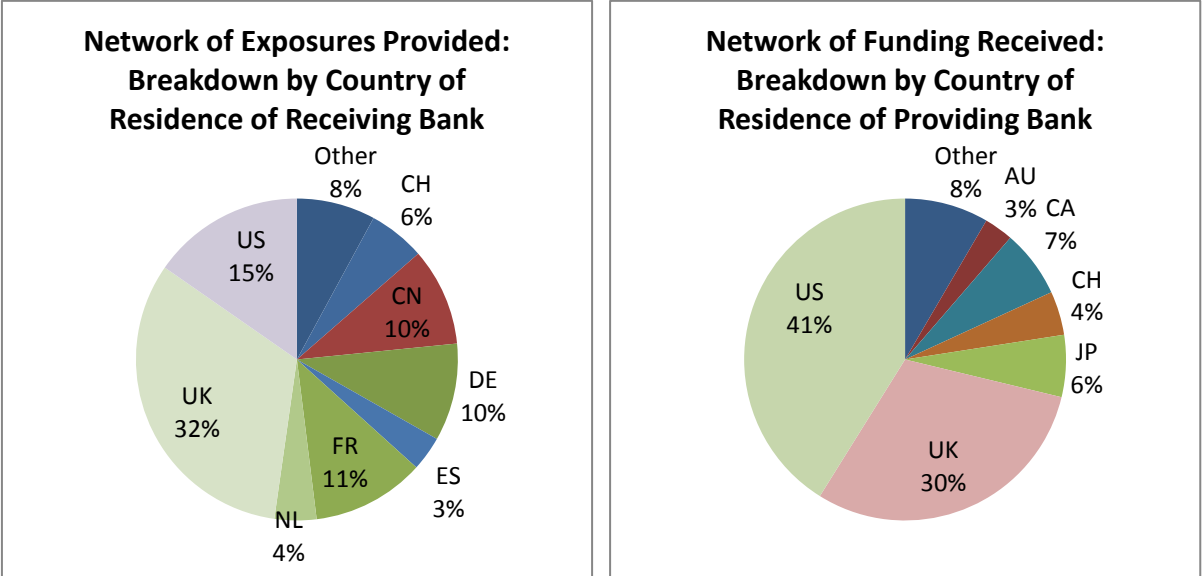


Figure 7 illustrates the decomposition by country of banks' headquarters. 68% of interbank exposures are to banks headquartered outside of the UK, topped by the US, France, Germany and China. In the funding network, US banks are more predominant, providing 41% of total interbank funding.

Figure 7: Market Share Breakdown by Country



3.3 The Interbank Market by Banks' Market Risks

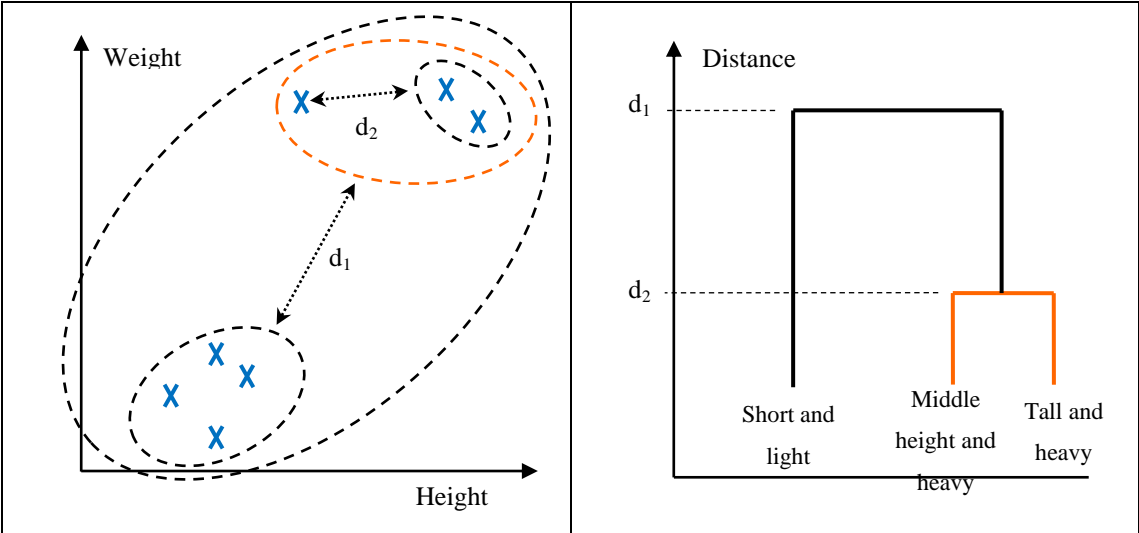
We observed the network of intersector exposures in the previous section. But sectoral categorisation does not necessarily reflect banks' business models or risk characteristics. In this section, we categorise banks by their risk characteristics in order to identify groups with common exposures to distinct market risks. These market risks include unsecured loans, secured loans, market products, derivative and others. We categorise banks by risk characteristics using cluster analysis, which helps us to infer groupings (clusters) from multivariate data. Cluster analysis has been used in other fields of finance: Ang and Longstaff (2011), for example, use the method to identify asset price comovement.

Cluster analysis works as follows. Suppose that we categorise people jointly by height and weight. To do this, we calculate distance between people across the two dimensions of height and weight. The definition of distance is illustrated by d_1 and d_2 in the left-hand panel of figure 8. Based on this distance, we bundle nearest people to create a cluster. In the next step, we

calculate distance between these small clusters; the closest clusters are again bundled into a larger cluster. This process continues until all people are merged into one big cluster.

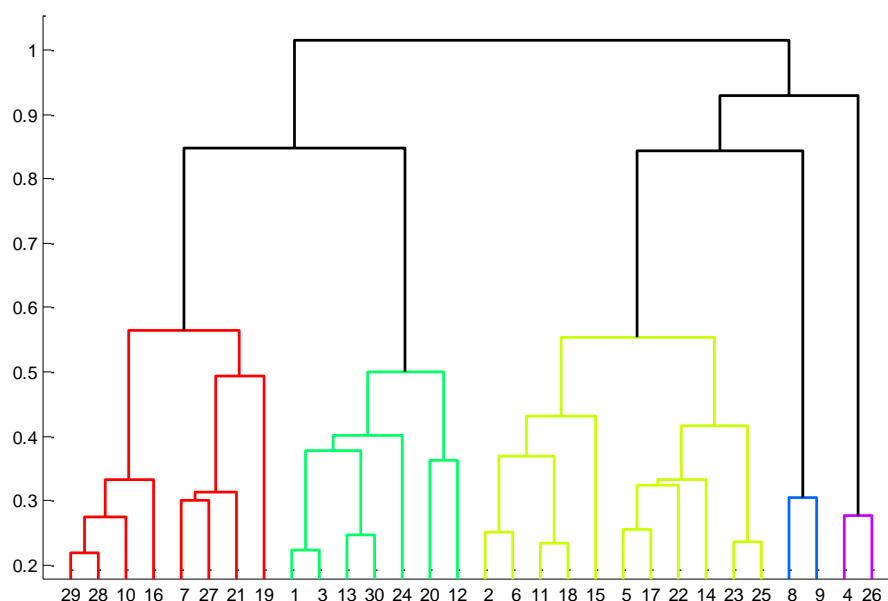
The sequential process of bundling creates a hierarchical structure of clusters of different sizes. The dendrogram on the right of figure 8 clarifies the hierarchy. The vertical axis is the ‘threshold of distance’ between clusters. For example, a cluster of two people who are ‘tall and heavy’ is separated from another cluster of ‘middle height and heavy’ people by d_2 . Further up the hierarchy, these ‘tall and heavy’ and ‘middle height and heavy’ people form a single cluster, which is separated from the ‘short and light’ cluster by d_1 . Thus, the distance d quantifies the difference between clusters. The dendrogram therefore provides different categorisations for different sizes of clusters.

Figure 8: Overview of Cluster Analysis and Dendrogram



We identify clusters of reporting banks based on the instrument breakdown of their interbank exposures. For each of the 176 reporting banks, we calculate their proportions (relative to total interbank exposures) of holdings of unsecured loans, secured loans, marketable securities, net CDS sold, securities financing transactions (SFT) and derivatives. These six instruments create six dimensions of banks’ risk characteristics. In this set-up, two banks with concentrations of exposures in unsecured interbank lending have low relative distance and therefore tend to be assigned to the same cluster early in the sequential process. In contrast, if one bank primarily holds unsecured loans and another mostly bonds and derivatives, those two banks have different business models. This difference is elicited by cluster analysis. The resulting dendrogram for the interbank exposures network is shown in figure 9.

Figure 9: Dendrogram for the UK Interbank System



Categorising banks by their market risk characteristics leads to significantly different groupings than those obtained from a sectoral breakdown. Table 1 shows the eight major clusters identified and the composition of clusters' exposures.¹² Overall, we find that banks can be usefully divided into six groups: unsecured lenders; secured lenders; marketable securities holders; derivative houses; SFT specialists; and banks with no interbank exposures. In addition, the group of marketable securities can be divided into two sub-groups depending on the degree of their exposure in unsecured lending, and the group of derivative houses can be divided into two sub-groups depending on their diversification of exposures across instruments.

Table 1: Exposures in different instruments as % of total (within-cluster average)

	Unsecured lending	Secured lending	Marketable securities	Net CDS sold	SFT exposures	Derivatives exposures
Securities holders (more unsecured lending)	51%	0%	41%	0%	1%	6%
Securities holders (less unsecured lending)	18%	1%	71%	0%	6%	5%

¹² The major clusters are identified by setting a threshold of distance between sub-clusters. Since this analysis first identifies small clusters close to each other, the distance between them becomes longer as the algorithm identify larger clusters. Once the distance between clusters exceeds a threshold, those clusters are defined as major clusters. The threshold is set to be 50% of the longest distance.

Unsecured lenders	92%	1%	5%	0%	1%	1%
Secured lenders	26%	66%	1%	0%	0%	7%
Derivative houses (less diversified)	6%	0%	7%	-1%	8%	80%
Derivative houses (more diversified)	25%	5%	12%	2%	16%	40%
SFT Specialists	8%	0%	10%	1%	70%	11%

These six groups have the following characteristics:

- *Securities holders cluster.* This cluster includes banks with exposures primarily in marketable securities (issued by banks) but also in unsecured interbank lending. Banks in this cluster are mainly small UK banks, building societies and overseas banks, but a small number of large UK banks also fall under this category. Within the cluster, we can identify two sub clusters: some banks have concentrated exposures in marketable securities (groups 7, 19, 21, 27) and the others have balanced exposure between unsecured loans and marketable securities (groups 10, 16, 28, 29).
- *Unsecured lenders cluster.* This includes banks with exposures concentrated in unsecured interbank lending. More than half of reporting banks fall into this cluster; the majority of small UK banks, building societies and overseas banks. A few investment banks are included in the green cluster, since some investment banks conduct their main business via their UK branches (which do not report exposures to the FSA) rather than subsidiaries. Within this cluster, some sub-clusters have balanced exposures in secured lending (eg groups 12, 20), while the others have significantly concentrated exposures in unsecured lending.
- *Secured lenders cluster.* This is a small group of a handful of banks, which have the majority of their interbank exposures in secured lending.
- *Derivative houses cluster.* This cluster captures mainly banks with large derivatives exposures. Most large UK banks and half of investment banks are included in this cluster. A few small UK banks and building societies also have significant exposures in derivatives. This cluster can be divided into two sub-clusters: one which has most interbank exposures in derivatives (groups 2, 6, 11, 15, 18), and the other which has relatively diversified exposures in unsecured lending, marketable securities and SFTs, in addition to derivatives (group 5, 14, 17, 22, 23, 25). Around half of large UK banks are in the former category, with heavily concentrated exposure in derivatives. The latter

more balanced category consists of most investment banks and a small number of large UK banks.

- *Securities financing transactions (SFT) specialists cluster*. This is a small group of SFT specialists. Due to the secured nature of SFTs, exposures arising from SFTs are typically much smaller than those from other instruments, despite the large scale of the activity.
- There are around 20 banks with no interbank exposures, which are not categorised in any of the clusters above.

Figures 9 and 10 illustrate the network of inter-cluster exposures.¹³ Derivative houses are split into two sub clusters – ‘pure derivative houses’ and ‘diversified banks’ – since otherwise the derivative houses cluster predominates (accounting for more than 80% of total exposures). Secured lenders and SFT specialists are merged since those clusters are small. The size of circles represents each cluster’s total core tier one capital, while the size of arrows represents the size of exposures.

Pure derivatives houses are at the core of the exposure network. This cluster is characterised as a group of dealers with significant exposures to securities holders, diversified banks, and other banks in their own cluster, mostly in the form of derivatives. They are exposed to securities holders most likely because these banks provide derivatives to hedge price risks, while they have mutual exposures with more diversified banks as a result of market-making activities.

¹³ Small links (less than 2% of exposures/funding) are not shown in figures 9 and 10.

Figure 9: Network of Inter-Cluster Exposures

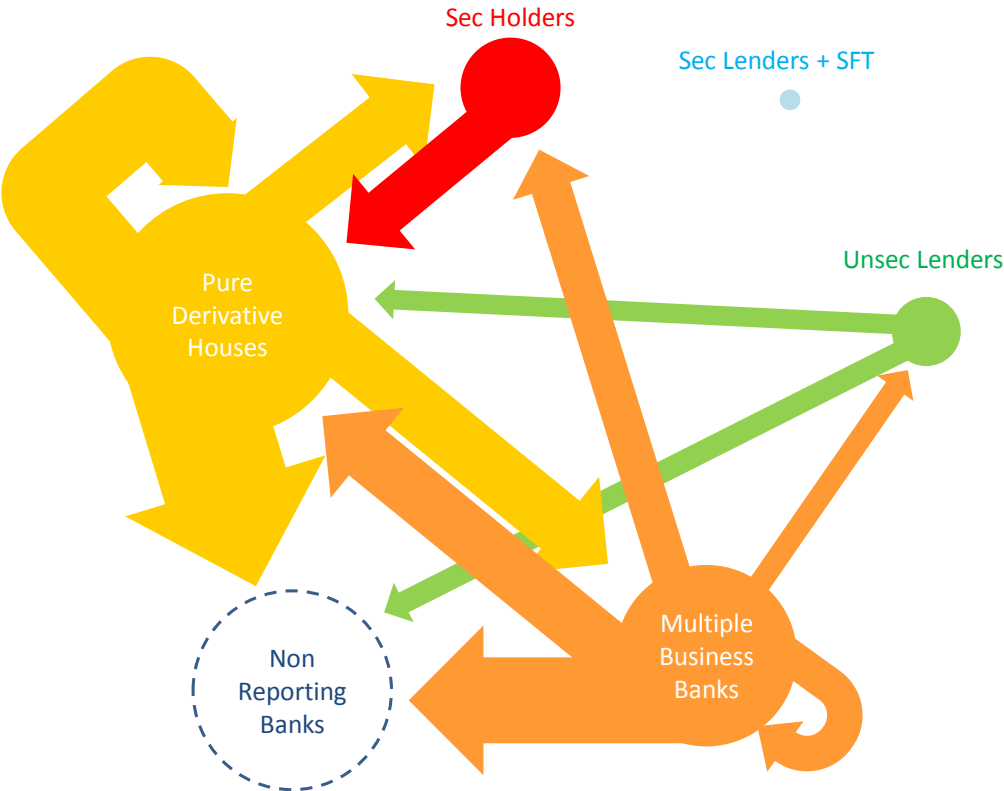
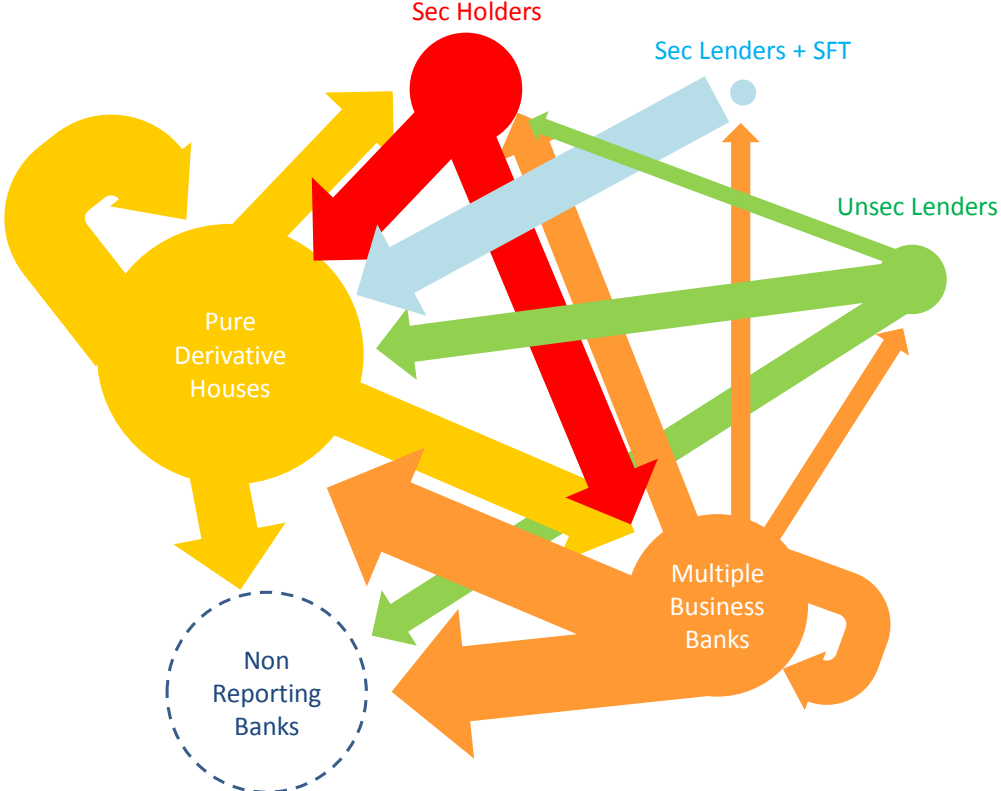


Figure 10: Network of Inter-Cluster Funding



These two sub-clusters of derivative houses also have different funding structures. All domestic unsecured funding is concentrated in the pure derivative houses, which are net borrowers in the network. Diversified banks, on the other hand, are net lenders: foreign investment banks in the cluster probably obtain funding from other countries, including their parents. The diversified banks also provide significant quantity of secured funding to pure derivative houses. If the UK were to experience liquidity shortage triggered in foreign countries, this cluster would act as the transmission mechanism. The shock would then propagate to all clusters since these diversified banks provide liquidity to all clusters. Considering the connection to the international market, the diversified banks are a key cluster in the UK funding network. Note also the intensive mutual finance between securities holders, pure derivative houses and diversified banks. These three clusters form a ‘core’ of the UK funding market, and their interdependence merits further analysis.

4 Method

4.1 *The Complexities of Financial Networks*

The new regulatory dataset is complex. We adapt our analysis to four complexities specific to financial networks: directed links; weighted links; multiple links; and node heterogeneity.

First Complexity: Directed Links

A given link between two banks has a single direction. For example, if bank i lends money to bank j , the link is directed from bank i to bank j . In networks jargon: the link is outgoing from bank i and ingoing to bank j .¹⁵ Each link is outgoing from one bank and ingoing to another. In the prior example, one could say that bank i provides a loan to bank j , and that bank j receives a loan from bank i . However, it is not always true that both the outgoing and ingoing sides of a given link are economically interesting. Consider that bank i additionally sells to a third party credit protection against bank j 's default. In this case, bank i assumes exposure to bank j , but bank j does not receive funding from bank i . Here, one should consider only the outgoing side of the link from bank i , and ignore the ingoing side of the link to bank j . In general, the economic

¹⁵ Note that there is inconsistency in the extant literature regarding interpretation of outgoing and ingoing links. Some papers, such as Boss et al (2004), define bank i 's exposure to bank j as an ingoing link of bank i from j (ie bank i lends money to bank j). On the other hand, Iori et al (2008) defines bank i 's exposure to bank j as an outgoing link of bank i , as bank i lends money to bank j . We use the latter definition, since we consider it more intuitive.

relevance of the outgoing and ingoing sides of a given link depends on the type of financial instrument which characterises the link.

Second Complexity: Multiple Links

The new regulatory dataset on interbank exposures provides a comprehensive breakdown of financial instruments. Large banks report interbank exposures under 163 types of instruments; smaller banks report 58 types. Multiple potential links between two given nodes amount to a multiplicity of networks. As a first step, we render the data more tractable by defining a total *exposures* network and a total *funding* network as follows. In sections 5.2 and 5.3, we extend the analysis to consider instrument categories separately.

Exposures network

$$\begin{aligned} &= \text{Total Prime Lending} + \text{Total Issuer Risk} \\ &+ \text{Total Securities Financing Transactions (SFT) Exposure} \\ &+ \text{Total Derivatives EAD} + \text{Total Shortterm Lending} \end{aligned}$$

Funding network

$$\begin{aligned} &= \text{Total Prime Lending} + \text{Total Reverse Repo Gross Notional} \\ &+ \text{Total Shortterm Lending}^{16} \end{aligned}$$

Recall that each link is outgoing from one bank and ingoing to another. To sharpen our exposition, we focus only on the outgoing side of links in the *exposures* network, and on the ingoing side of links in the *funding* network. In doing so, we hone in on those banks which hold interbank claims and those banks which borrow from other banks. Alternative analysis could consider also the ingoing side of links in the *exposures* network and the outgoing side of links in the *funding* network. For example, measures of a bank's systemic importance could depend on the extent to which other banks are exposed to that bank, and on the extent to which that bank funds other banks. We leave such extensions to future research.

¹⁶ We did not include debt instruments in the funding network, because the exposures reported by banks are net of longs and shorts and hence may not be equal to the actual amount of funding provided.

Third Complexity: Weighted Links

A given link between two banks has a pound-sterling quantity. If bank i lends money to bank j , we observe precisely how much money is lent. This point is simple, but often neglected in the general networks literature. In many non-financial networks, the weight of links is either not present or not observed. Matrices are instead binary: elements equal one if a link between two nodes is observed; and zero otherwise. Network metrics which account for weighted links have been elaborated only recently: see, for example, Barthelemy et al (2005), Fagiolo (2007), Saramaki et al (2007) and Opsahl, Agneessens and Skvoretz (2010).

Fourth Complexity: Node Heterogeneity

We have matched the regulatory dataset on interbank exposures with banks' balance sheet data. Banks (nodes) have heterogeneous characteristics. These balance-sheet characteristics can be interacted with links to generate additional economically interesting network metrics. In this paper, we generate two networks using balance-sheet data, in addition to the simple *exposures* and *funding* networks. First, we generate the *exposures divided by core tier one (CT1) capital* network, where the exposure of bank i to bank j is divided by the core tier one capital of the UK consolidated group of bank i . If bank j defaults on its obligations to bank i , the difference between recovery value and prior book value detracts from bank i 's loss-absorbing capital. The *exposures divided by core tier one (CT1) capital* network therefore gauge the extent to which banks can absorb direct losses on interbank positions. Second, we generate the *funding divided by liabilities* network, where the funding provided by bank i to bank j is divided by the global consolidated liabilities of bank j . This network gauges the extent to which banks are reliant on other banks for funding.

4.2 *Defining Network Metrics*

In this section, we define several network metrics, which are used throughout the paper to describe the features of the interbank system.

First, we establish some notation. E_{ij} is the weighted adjacency matrix, the elements of which represent the absolute value (in millions of pounds sterling) of a directed link from bank i to counterparty bank j . We also define unweighted adjacency matrix a_{ij} , the elements of which

take the value 1 if $E_{ij} > 0$ and 0 otherwise. We can therefore define *Market Size* as the total strength of all links in the network. Since 176 banks report exposures to up to 26 counterparties, we compute

$$\text{Market Size} = \sum_{i=1}^{176} \sum_{j=1}^{26} E_{ij}.$$

Counting the number of links gives the unweighted degree. We define *Unweighted Degree* for both outgoing and ingoing links:

$$\text{Out unweighted degree}_i = \sum_{j=1}^{26} a_{ij}$$

$$\text{In unweighted degree}_i = \sum_{j=1}^{26} a_{ji}.$$

But each link takes a pound-sterling quantity. We compute bank-level *Strength* by summing the strength of individual links:

$$\text{Out strength}_i = \sum_{j=1}^{26} E_{ij}$$

$$\text{In strength}_i = \sum_{j=1}^{26} E_{ji}.$$

In much of this paper, we normalise *Strength* by *Market Size*. The result is *Market Share*:

$$\text{Out Market Share}_i = \frac{\text{Out strength}_i}{\text{Market size}}$$

$$\text{In Market Share}_i = \frac{\text{In strength}_i}{\text{Market size}}.$$

Finally, we can measure the extent to which a bank is reliant on a small number of other banks, or whether its interbank positions are diversified across many counterparties. We define *Relative Strength Concentration* as:

$$\text{Out Relative Strength Concentration}_i = \sum_{j=1}^{26} \left[\frac{E_{ij}}{\text{Out strength}_i} \right]^2$$

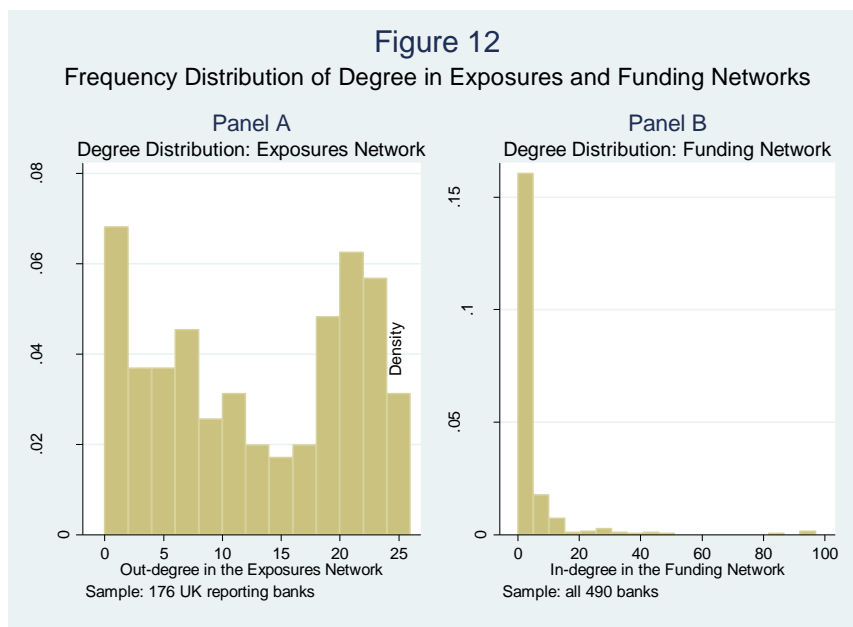
$$\text{In Relative Strength Concentration}_i = \sum_{j=1}^{26} \left[\frac{E_{ji}}{\text{In strength}_i} \right]^2.$$

5 Network Properties of the Interbank System

Our aim is to establish a set of stylised facts about the systemic properties of the UK banking system. In doing so, we draw on the budding literature on (financial) network analysis.

5.1 Network Statistics

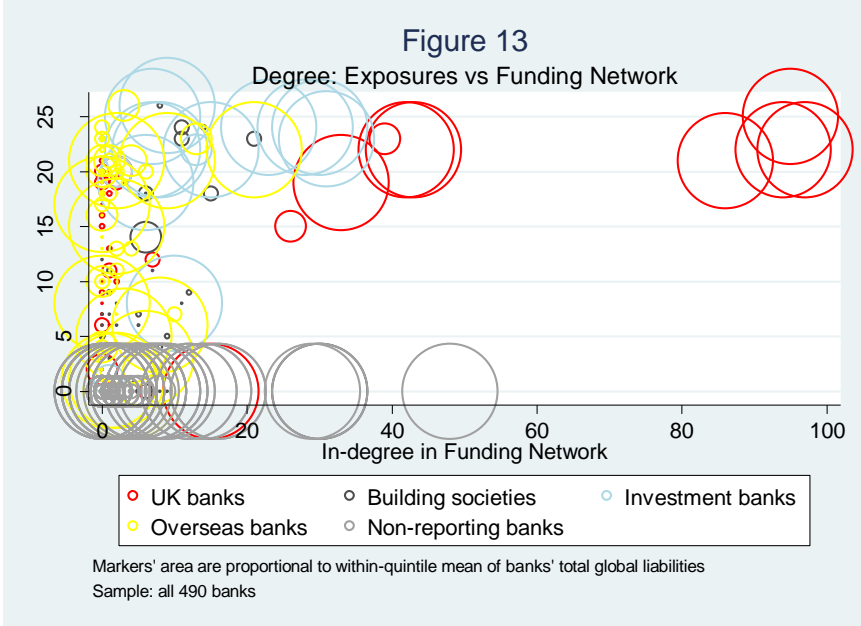
The distribution of degree in the *exposures* network exhibits almost zero skewness: mean degree is 12.3; the median is 12.5 (panel A, figure 12). This finding is largely an artefact of the data. 62 of the 176 reporting banks report exposures to 20 out of 20 possible counterparties: the maximum out-degree of these banks thus has an artificial hard ceiling of 20-26.¹⁷ In contrast, the distribution of in-degrees in the funding network is heavily right-tailed, with positive skewness of 6.2 (panel B, figure 12). Mean in-degree is 3.6; median in-degree is 1.0. These central tendencies are much lower than those reported for the *exposures* network, largely because the *exposures* network is confined to the 176 reporting banks, whereas the funding network captures all 490 banks. The maximum observation is 115: unlike the out-degree, the in-degree does not have an artificial upper bound.¹⁸ At the other end of the distribution, 73 banks have zero in-degree. All of these 73 banks are UK reporting banks.



¹⁷ Recall that if the top 20 does not have at least six UK-based counterparties, firms are asked to report exposures to up to six UK-based counterparties in addition to the top 20.

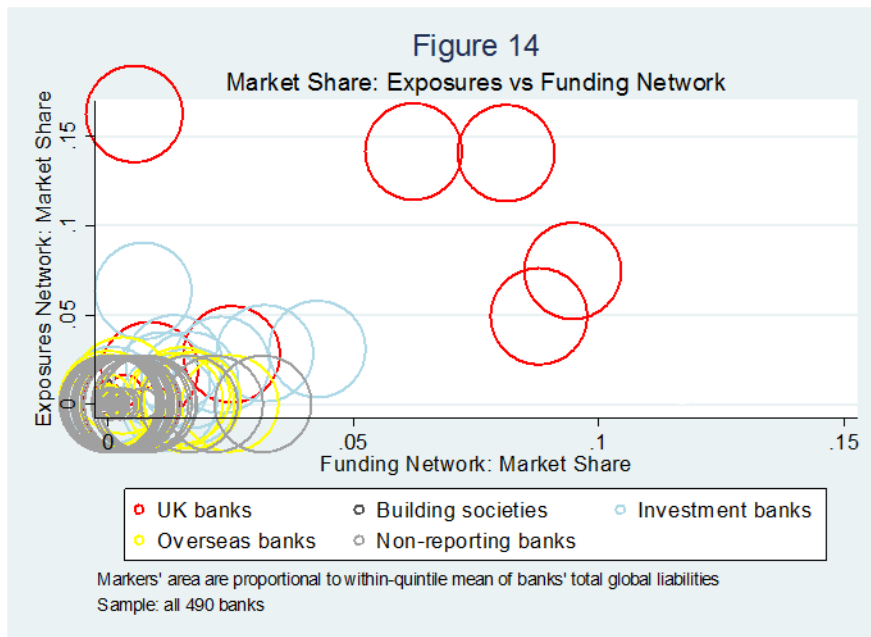
¹⁸ In fact, the upper bound of the in-degree is 176, equal to the number of reporting banks.

Figure 13 is a scatterplot of out-degree in the *exposures* network (the number of banks a given bank is exposed to) against in-degree in the *funding* network (the number of banks providing funding to a given bank). Most large banks are exposed to 20 or more counterparties (except non-reporting banks and a few overseas banks). However, only a few large UK banks receive funding from more than 50 banks in our sample. In this representation, four large UK banks (top right of figure 13) clearly emerge as significant players in the interbank market, with in-degree near 100 and out-degree at the upper bound.

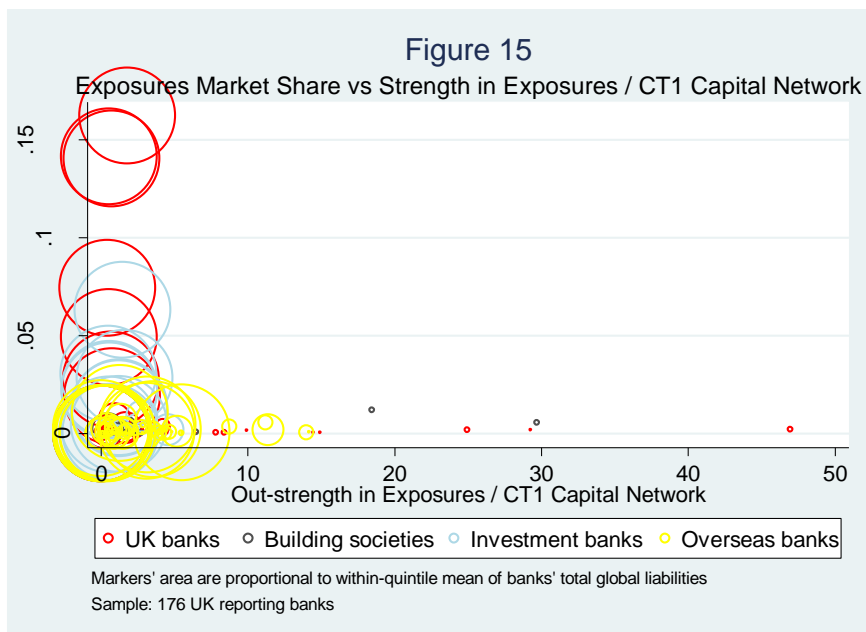


The picture changes substantially when we account for the weight of links between banks. Recall that out (in) strength is the sum of the value of links from (to) a given node to (from) all other nodes. To obtain the market share of each bank, we normalise bank-level strength by total strength in the interbank market. The distribution of out-market share in the *exposures* network and in-market share in the funding network is right-tailed in both cases, with positive skewness of 5.8 and 8.1 respectively. 10 of 176 banks account for 74% of the market in the *exposures* network. The funding network is somewhat less concentrated, with the most active 10 banks accounting for 60% of the total market.

Again, four UK banks stand out as the largest players in the interbank market, together taking 40.5% of market share in the *exposures* network and 32.6% of market share in *funding* network (figure 14). But some additional insights emerge from the weighted approach which were obscured by simple unweighted degree (figure 13). Beyond the large UK banks, approximately six investment banks play a significant role in both the exposures and funding markets.

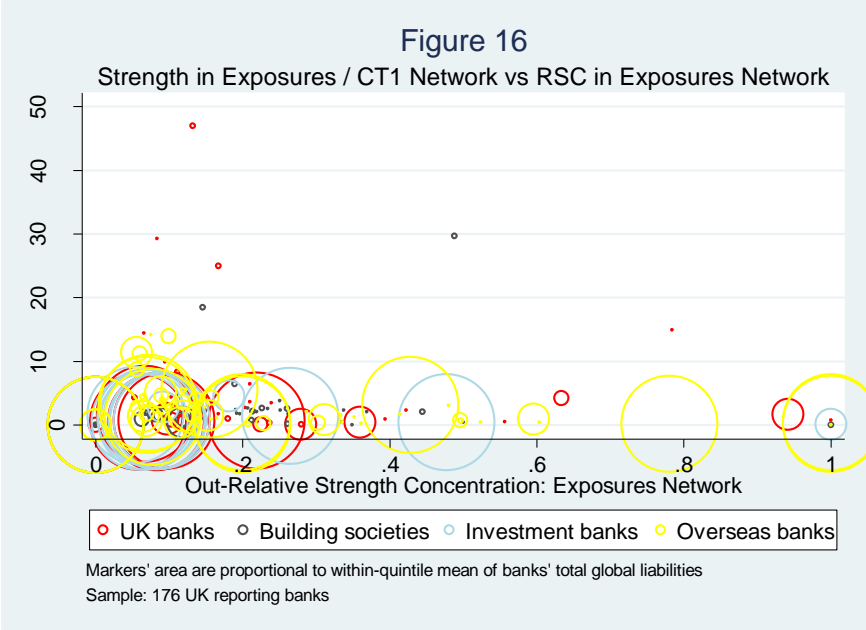


As described in section 4, we can also interact links with banks' balance sheet characteristics. Of particular interest is banks' out-strength in the *exposures* network divided by own core tier one capital. This is illustrated in figure 15, which shows that large banks tend to have large nominal exposures (vertical axis) and small banks often have large exposures relative to own capital (horizontal axis).



Out-relative strength concentration in both the *exposures* network and the *exposures divided by CT1 capital* network is below 20% for 75% of the banks (the two measures are identical by construction), indicating that most banks have relatively diversified interbank exposures, while a

handful of banks have concentrated exposures. Figure 16 shows that banks with concentrated exposures typically have small interbank exposures relative to capital (bottom right).



We can also see that the in-relative strength concentration of the *funding network* is above 50% for over half of the bank in the sample, implying concentrated funding sources. Banks that are most reliant on interbank funding have reasonably diversified funding sources, apart from a few small banks.

5.2 Structure of the Interbank System

The UK interbank market is highly concentrated. Most banks have small exposures to other banks: mean strength in the *exposures* network is £119 million. But some banks have large exposures to other banks. The distribution of strength in the *exposures* network is therefore right-tailed, with positive skewness of 5.8. The market is concentrated in a few banks: the Herfindahl-Hirschman index of concentration in the *exposures* network is 0.08.

Intuitively, the concentrated UK interbank market appears to mimic a ‘hub and spoke’ structure. Figures A1 and A2 in the annex convey this impression graphically. Informally, banks in the central hub are strongly connected to other hub banks and possibly also to banks on the periphery; in contrast, peripheral banks are weakly connected to other peripheral banks. This topology has pedigree in the extant networks literature. In Borgatti (1999), the ‘hub and spoke’, or core-periphery, structure is exemplified by a core perfectly connected to itself: in matrix

terminology, a block of ones. In contrast, the periphery is perfectly disconnected from itself: periphery-to-periphery elements form a block of zeroes. These stylised features are summarised in figure 15. In this formulation of the stylised core-periphery matrix, we are agnostic with respect to linkages between the core and periphery. Elements in the core-periphery and periphery-core blocks can take any value in this stylised core-periphery structure. In financial networks, it is not clear *a priori* how the core should connect with the periphery in the stylised core-periphery structure; hence our agnosticism. But Craig and von Peter (2010) argue that a core bank should lend to at least one and borrow from at least one peripheral bank. Their intuition is that core banks should play an intermediation role not limited to their activity within the core block. In practice, this additional constraint never binds in our data. On the contrary, core banks play a strong intermediation role between peripheral banks.

Figure 17: Stylised Core-Periphery Matrix Structure

	Core block	Periphery block
Core block	Block of ones	Agnostic (blank)
Periphery block	Agnostic (blank)	Block of zeroes

Defining the stylised core-periphery structure allows us to test how closely the interbank network approximates such a structure. Formal testing facilitates greater precision than may be achieved from general inferences regarding strength distributions and market concentration. Borgatti (1999) quantifies the degree of fitness using a Pearson correlation between the stylised matrix (figure 15 adapted to the dimensions of our data) and the observed matrix of interbank exposures. This approach has the virtue of simplicity and transparency. Moreover, Pearson correlation accounts for weighted links by construction. Although the stylised core-periphery matrix of figure 15 remains unweighted – elements are either zero, one or blank – the Pearson correlation tests the extent to which the mean of elements in the core block is significantly greater than the mean of elements in the periphery block, relative to within-block variance. The Pearson correlation coefficient, r , is given by:

$$r = \frac{\sum_{i=1}^{176} \sum_{j=1}^{26} [(E_{ij} - \bar{E})(X_{ij} - \bar{X})]}{\sqrt{\sum_{i=1}^{176} \sum_{j=1}^{26} (E_{ij} - \bar{E})^2} \sqrt{\sum_{i=1}^{176} \sum_{j=1}^{26} (X_{ij} - \bar{X})^2}}$$

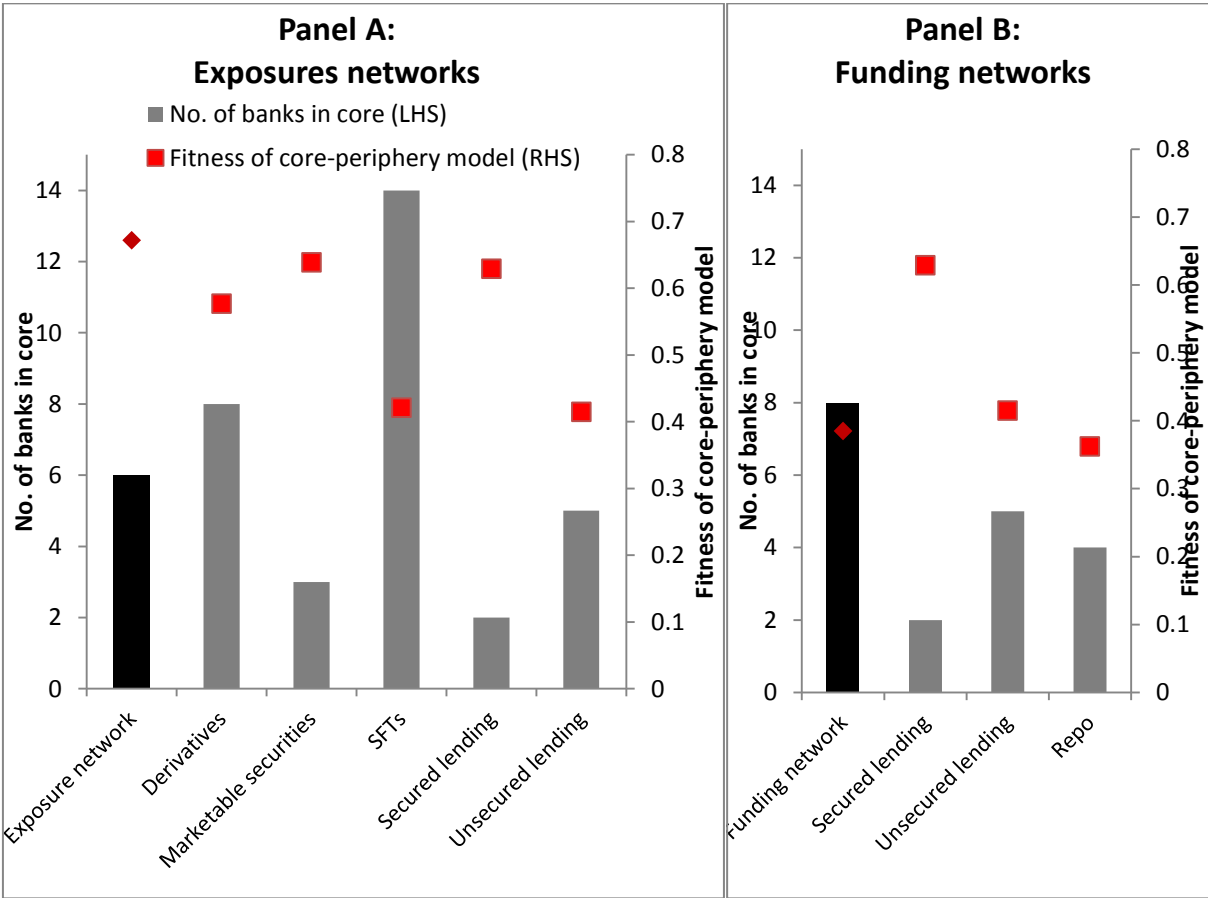
where X_{ij} denotes the elements in the stylised core-periphery matrix.

The next step is to define the composition of the core and periphery blocks. We exploit an algorithm developed by Borgatti, Everett and Freeman (2002). In short, the (genetic) algorithm searches for a core-periphery division of banks to maximise fitness between the observed matrix of interbank exposures (thus divided into core and periphery) and the stylised core-periphery structure. The resulting categorisation of core and periphery is therefore optimal, in the sense that it is the categorisation which for that observed matrix approximates most closely the stylised core-periphery structure.

We implement the algorithm on the *exposures network* for a square 176x176 matrix. That is, we drop exposures from reporting banks to non-reporting banks. For this network, the algorithm finds the optimal core to comprise seven banks; the remaining 169 banks therefore comprise the periphery. Fitness between the *exposures network* and the stylised core-periphery structure is 0.672, suggesting economically significant fitness. In contrast, the *funding network* comprises an optimal core of nine banks and exhibits fitness of 0.385 with respect to the stylised core-periphery structure.

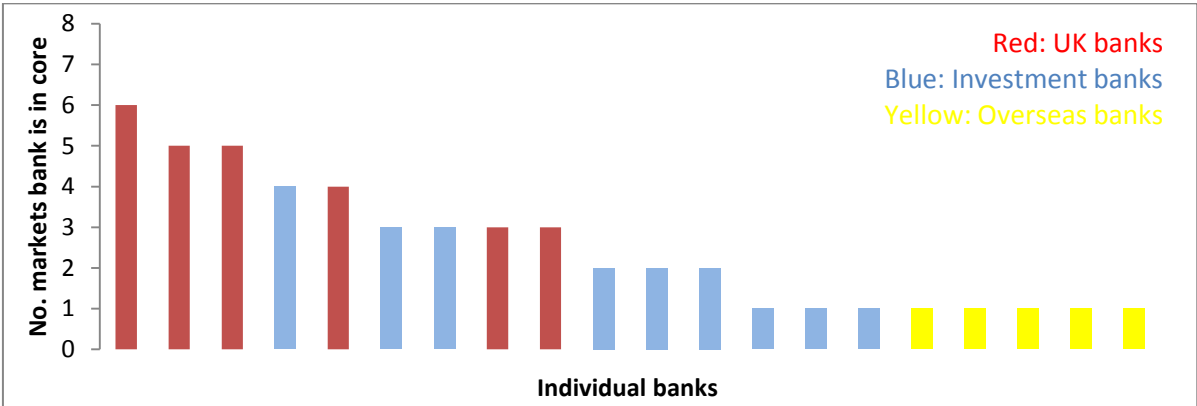
We can investigate coreness in more detail by implementing the algorithm on different link types. The results indicate that the closeness of the observed unsecured lending and repo networks to the stylised core-periphery structure is relatively low, with fitness of 0.415 and 0.362 respectively. Given that repo is 66% of the total *funding network* (figure 1), fitness of 0.362 drives relatively low fitness of 0.385 in the overall *funding network*. In contrast, fitness in the derivatives and marketable securities networks, which comprise part of the overall *exposures network*, is relatively high, at 0.577 and 0.639 respectively. We interpret these results in section 6.1.

Figure 18 – (Weighted) Fitness of Core-Periphery Model by Instrument



Another interesting facet of these instrument-specific results is how the composition of the core changes by instrument. Figure 16 shows core-periphery results based on eight different networks: total exposures, derivatives, marketable securities, securities financing transactions, secured lending, unsecured lending, repo and total funding. The sum of all cores is 54, but many banks comprise part of the core in more than one network. Figure 17 shows that one bank comprises part of the core in six of the eight sub-networks considered here. 11 other banks comprise part of the core in at least two sub-networks. All of these core banks are either large UK banks or investment banks. Finally, eight banks appear in the core only once: these banks may be thought of as product-specialists, which are significant from a systemic perspective only in one particular market.

Figure 19 – Composition of the Core by Bank Type (Weighted Fitness)



Some subtleties of these results are sensitive to the definition of fitness. So far, we have defined fitness as the Pearson correlation between the stylised core-periphery matrix and the observed matrix of interbank exposures. This approach explicitly allows for weighted links in the observed matrix. For robustness, we implement an alternative approach suggested by Craig and von Peter (2010). Their measure of fitness is a simple count of the number of elements in the observed matrix which are not equal to the respective element in the stylised core-periphery matrix. This approach therefore ignores weighted links.

We run the algorithm again, using Craig and von Peter’s ‘error count’ approach. Results are shown in figure 18, with the new core composition illustrated in figure 19. Several differences are worth highlighting. First, the ‘error count’ approach suggests that the secured lending network approximates a core-periphery structure much more strongly than any other network (figure 18). In contrast, the Pearson correlation approach found that fitness in the secured lending network was similar to fitness in the derivatives and marketable securities networks (figure 16). Second, the ‘error count’ approach defines the optimal core to be larger than that found using the Pearson correlation approach in every network except that of securities financing transactions. Third, in terms of ‘product specialists’ the ‘error count’ approach defines four building societies and one overseas bank as part of the core in one or two networks, whereas the Pearson correlation approach identified no building society and five overseas banks as part of the core in one network. In the latter case, building societies might have many links with other core banks, but these links are relatively small in value: hence they are excluded from the core in the Pearson approach, but included in the ‘error count’ approach.

Figure 20 – (Unweighted) Fitness of Core-Periphery Model by Instrument

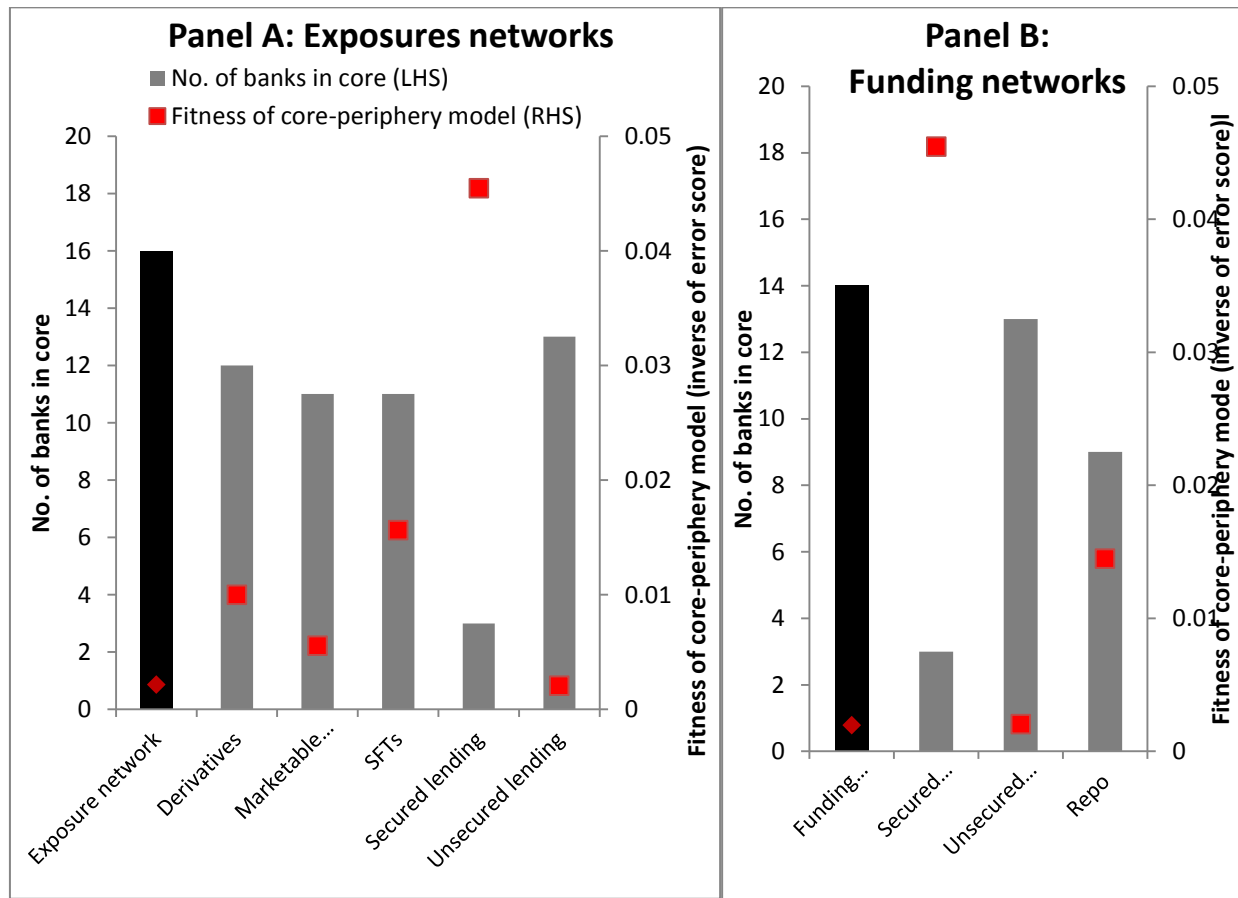
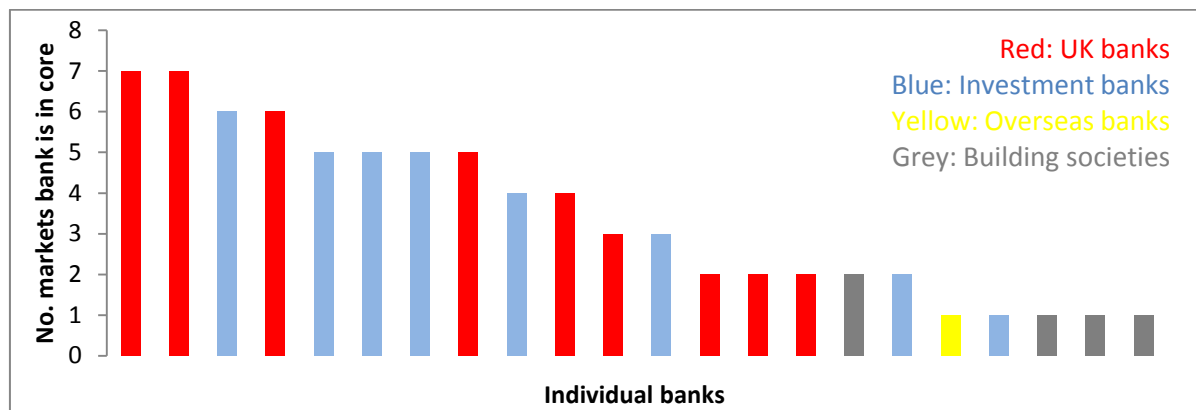


Figure 21 – Composition of the Core by Bank Type (Unweighted Fitness)



Notably, both the Pearson and the ‘error count’ approach identify similar banks which comprise the core in at least three networks. The Pearson approach finds that six UK banks and three investment banks comprise the core in at least three networks, while the ‘error count’ approach identifies six UK banks and six investment banks. Despite some important differences between the Pearson and ‘error count’ approaches, the central finding with respect to the ‘most core’ banks is robust to the definition of fitness.

6 Interpretation

We have observed that the UK interbank system clearly exhibits a 'hub and spoke', or core-periphery, structure. In this section, we draw on the extant banking and networks literature to explain why such a network structure might emerge from interbank transactions, and to infer implications for the stability of the financial system as a whole.

6.1 *Theory of Network Formation*

Incompleteness and high concentration is a common feature of modern banking systems, including Belgium (Degryse and Nguyen, 2010), Germany (Sacks, 2010; Craig and von Peter, 2010) and Italy (Fricke and Lux, 2012). Degryse and Nguyen (2010) and Mistrulli (2011) show that the core periphery structure emerged in the middle of 1990s, from a near-complete network structure. This is the first paper to reveal the core periphery network structure of the UK interbank system directly.

Although the core periphery structure has been observed in many banking systems, theoretical literature studying the economics of network formation remains scarce. Nevertheless, we can leverage insights from broader fields of banking theory. From the viewpoint of costly state verification, it is optimal to delegate monitoring activities to one agent who becomes a monitoring specialist. Thus banks specialise in monitoring activities, rather than all depositors (Diamond, 1984). In a similar vein, centralised intermediation in the interbank market could reflect optimal specialisation in monitoring activity. As Diamond and Dybvig (1983) argue, banks collecting deposits from many depositors can achieve socially optimal intertemporal consumption allocation, when depositors do not know their optimal consumption timing *ex ante*. Even though those studies consider the relationship between banks and depositors, it is not unrealistic to assume that we can observe a similar relationship between core banks and peripheral banks, given the complexity of financial markets. And it is also not unrealistic to consider that core banks would have similar vulnerability to banks being exposed to depositors' run, *a la* the roll-over risk discussed by Acharya, Gale and Yorulmazer (2011).

The theory of finance also discusses the core-periphery structure of financial markets in the context of price-setting behaviour of market-makers. This body of literature typically assumes a monopolistic specialist filling a gap between demand and supply: Garman (1976) considers a

market maker broking final buyers and sellers arriving randomly (the so-called inventory management approach); Glosten and Milgrom (1985) consider a dealer broking between informed traders and uninformed traders (the asymmetric information approach). More recently, Duffie, Garleanu and Pederson (2005) discuss the relationship between the bid-ask spread and the cost of searching counterparties in the over-the-counter derivatives markets. They argue that smaller investors tend to have few connections with other banks, which lowers searching efficiency when they want to trade, and receive less favourable prices.

The centralised network can be explained with reference to post-trade activities. If all traders clear their trades via a central agent (a so-called central clearing counterparty), the traders can net out more offsetting counterparty exposures than if they were to clear trades bilaterally (Duffie and Zhu, 2010).

In general, the ‘star-shape’ network structure is thought to be efficient and stable. Jackson and Wolinsky (1996) show that the star-shape network is efficient if the cost of making links is intermediate. At the extremes, a complete network structure is efficient if the cost of forming links is sufficiently low; while a perfectly incomplete network structure is optimal if this cost is prohibitively high. Many relatively minor transaction costs in financial markets, such as settlement operations, could help to explain the formation of star-shape networks. In addition, Bala and Goyal (2000) argue that network structure converges to the star-shape from arbitrary networks in the context of social learning.

Moreover, we have seen in Section 5.2 that the fitness between the stylised core-periphery structure and different observed networks varies substantially by instrument. This may be largely explained by the microstructure of the different networks. For example, in the derivatives network, dealer banks tend to have large mutual exposures (that is, high core-to-core fitness), since both parties of a derivatives transaction often have large uncollateralised exposures to each other (despite having collateral agreements in place), whereas non-dealer banks typically do not have derivatives exposures between themselves (that is, high periphery-to-periphery fitness). Given that derivatives account for 44% of total interbank exposures, this implies a high fitness in the *exposures* network. On the other hand, funding instruments (except secured lending which account for only 5% of the funding network) tend to have a different pattern. First, the number of banks borrowing via unsecured lending or repos is relatively large, partly due to the need of both lenders and borrowers to diversify their exposures and funding

sources (that is, low coreness for core banks). Second, most banks do not have mutual funding arrangements as funding flow is typically one-way (that is, low core-to-core fitness). Therefore the funding network has a relatively low fitness with the stylised core-periphery structure as compared to the *exposures* network.

6.2 *Financial Stability Implications*

Although the core-periphery structure has been observed in several interbank systems, theoretical literature studying vulnerabilities underlying such structure remains relatively scarce. Exceptions are Allen and Gale (2000), Freixas, Parigi and Rochet (2000) and Battiston et al (2009). But the conclusions of these papers vary, such that the extant literature is ambiguous with respect to the qualitative relationship between a core-periphery network structure and the resilience of the system. It is therefore difficult to extract straightforward implications. For example, Allen and Gale (2000) show the risk of contagion in incomplete networks; while Battiston et al (2009) argue that a highly connected network could amplify the effect of an initial negative shock, triggering systemic risk. In this vein, Gai and Kapadia (2010) find that while the probability of contagion is decreasing in connectivity, the impact of contagion should it occur is increasing in connectivity.

Freixas, Parigi and Rochet (2000) is one of few theoretical studies considering the core-periphery structure explicitly. They consider a stylised structure in which two peripheral banks connect with a ‘money centre’ bank, and find three different patterns of contagion. First, no contagion occurs if banks’ debt is sufficiently small. Second, if the debt size is large, then the insolvency of the money centre bank renders the other two banks insolvent, but not vice versa: the core bank is resilient against a peripheral bank’s default. Third, if debt is sufficiently large, a peripheral bank’s insolvency triggers all banks’ default.

The the core bank’s relative resilience is explained as follows. In the model of Freixas, Parigi and Rochet (2000), banks are connected by commitment lines; insolvency shocks are propagated across banks since depositors of failed banks withdraw cash from connected banks. This withdrawal forces connected banks to fire-sale assets at a loss, which triggers their own depositors’ run. When a peripheral bank goes bankrupt, the withdrawal from the core bank (and the loss from fire-sale) is contained since the line is diversified to two banks. The peripheral banks are thoroughly exposed to the core bank and thus vulnerable to its failure.

Since their model is highly stylised it is difficult to test. But we observe several interesting features in our dataset which relate to Freixas, Parigi and Rochet (2000). Core banks indeed have many connections with peripheral banks. The average in-degree of cores from peripherals in the *exposures network* is 89, and the average out-degree of cores to peripherals is 22.

However, Nier et al (2007) argue that the connectivity between core and peripheral banks is not monotonic. If a core bank is connected to few peripherals then the default of that core bank is likely to trigger peripheral banks' default. But if a core bank is connected with many peripheral banks, the insolvency shock is diluted and is less likely to create a systemic problem. The result follows from simulations which assume homogeneous banks. But this paper has shown that banks are highly heterogeneous in terms of both balance-sheet characteristics and levels and types of activities in the interbank markets.

It is therefore important to interact balance-sheet characteristics and interbank market activity in a way which captures banks' heterogeneity. To do this, we use a metric suggested by Amini, Cont and Minca (2011), Contagious Link, to incorporate peripherals banks' heterogeneity. The metric defines vulnerable links as those where the exposed bank goes bankrupt when the receiving banks becomes insolvent. In the first instance, we assume that the exposed bank goes bankrupt when the exposure is larger than the exposed bank's loss-absorbing capital. In the new regulatory dataset on interbank exposures there are 67 such contagious links; approximately 70% of the links are from core banks to peripheral banks. If we define the link as the exposure is larger than 50% of exposed banks' capital, the number of links increases to 173, and again 70% of the links are from core to peripherals (the others are between peripherals). Irrespective of the connectivity, some peripherals are indeed vulnerable against cores. The number of contagious nodes, exposed to contagious links, is 65, of which all are peripheral banks.

Some empirical studies, such as Degryse and Nguyen (2007), capture the core-periphery structure from the viewpoint of size. The authors show by simulation that the share of large banks' exposure (out of total exposure) is negatively correlated to aggregate loss of capital, especially when cores are well-capitalised. In short, the core-periphery structure lowers systemic risk if systemically important banks are well capitalised. The core banks that we identify using the new regulatory dataset on UK interbank exposures have a similar market share of approximately 70%.

In the core periphery structure, systemic shocks can propagate between core and peripherals, or between core and core. By construction, the core-to-core block is nearly complete. Typically this structure is considered to be resilient, as Allen and Gale (2000) argue. In addition, Sacks (2010), using German data, considers the vulnerability of core banks in the context of a core-periphery network structure. She finds both that core nodes connected with many other nodes and core nodes connected with smaller nodes are more resilient. But Battiston et al (2009) argue the opposite: a complete network structure could amplify default risks.

A central finding of this paper is that the UK interbank market closely approximates a core-periphery structure, but that the closeness of this approximation, and the composition of the optimal core, changes significantly across market instruments. This finding has potentially important implications, hitherto untapped by the extant literature. Stress is liable to propagate across interbank markets, particularly in the presence of strong confidence effects and information asymmetries. Product specialists which comprise part of the core in only one or two networks might not commonly be considered systemically important, but their centrality in certain categories of interbank markets might spill-over to other markets. For example, American International Group (AIG), the insurance company, was not considered by some observers to be a systemically important financial institution before the financial crisis. However, it was a significant player in both the CDS market and the securities lending market (Harrington (2009)). At that time, the CDS market may be characterised as a high-fitness network with AIG being one of the critical participants (because AIG was significant both as a CDS seller and a reference entity),¹⁹ whereas the securities lending market may be characterised as a low-fitness network with AIG being one of the core banks (because AIG was a significant securities lender but the borrowers are collateralised and typically non-systemic institutions). As we have seen during the crisis, the failure of a core participant in one particular network, as is the case of AIG, may have contagious effects on the whole financial system. Better understanding of the structure of different networks and the links between them would enable us to assess systemic risk more accurately.

¹⁹ We have not computed the core-periphery fitness of the CDS network in this paper, due to the fact that a CDS contract involves three banks and the resulting difficulty in defining the core.

Appendix: Network Graphs
Figure A1: Exposures Network

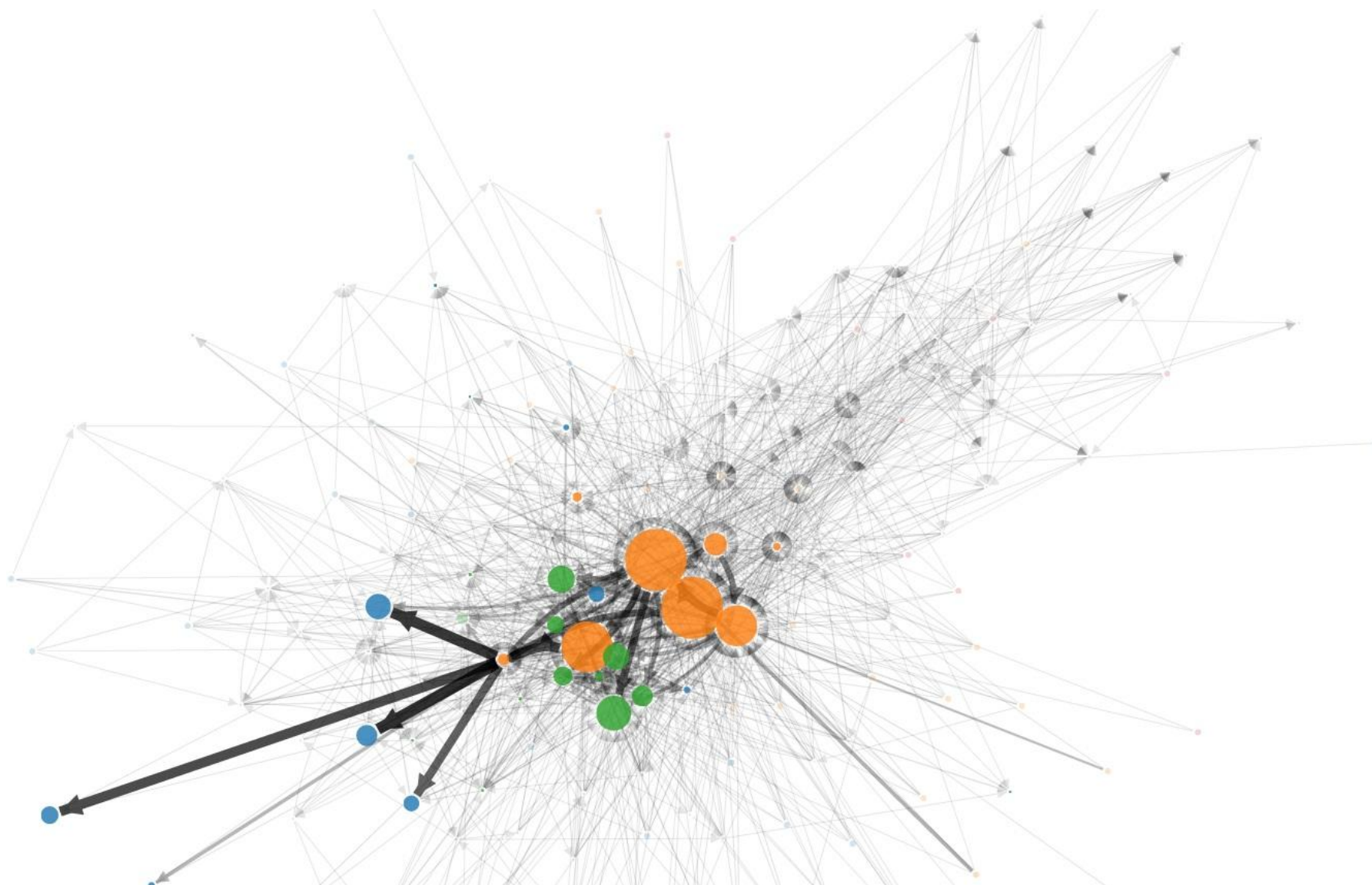


Figure A2: Funding Network

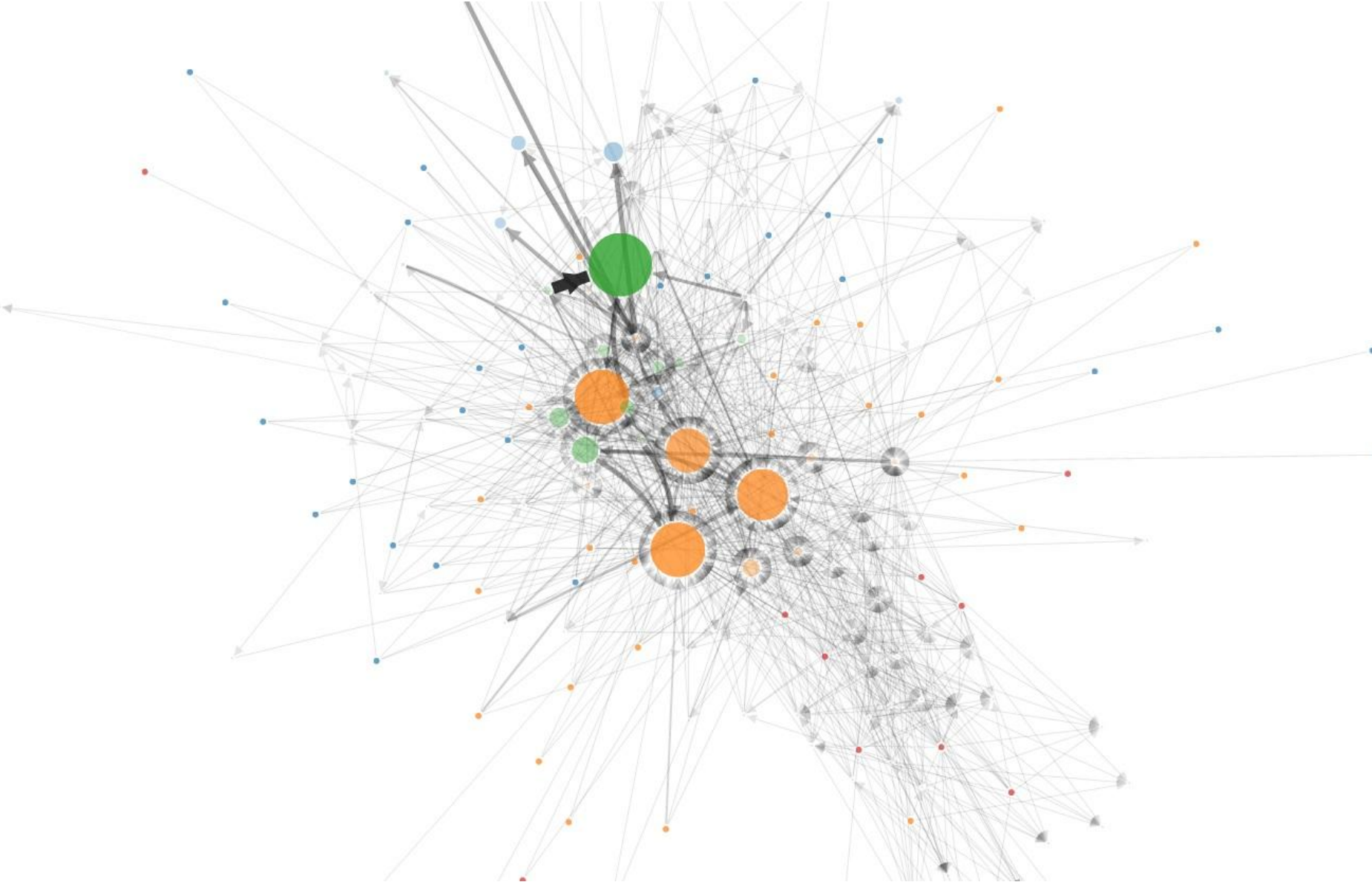
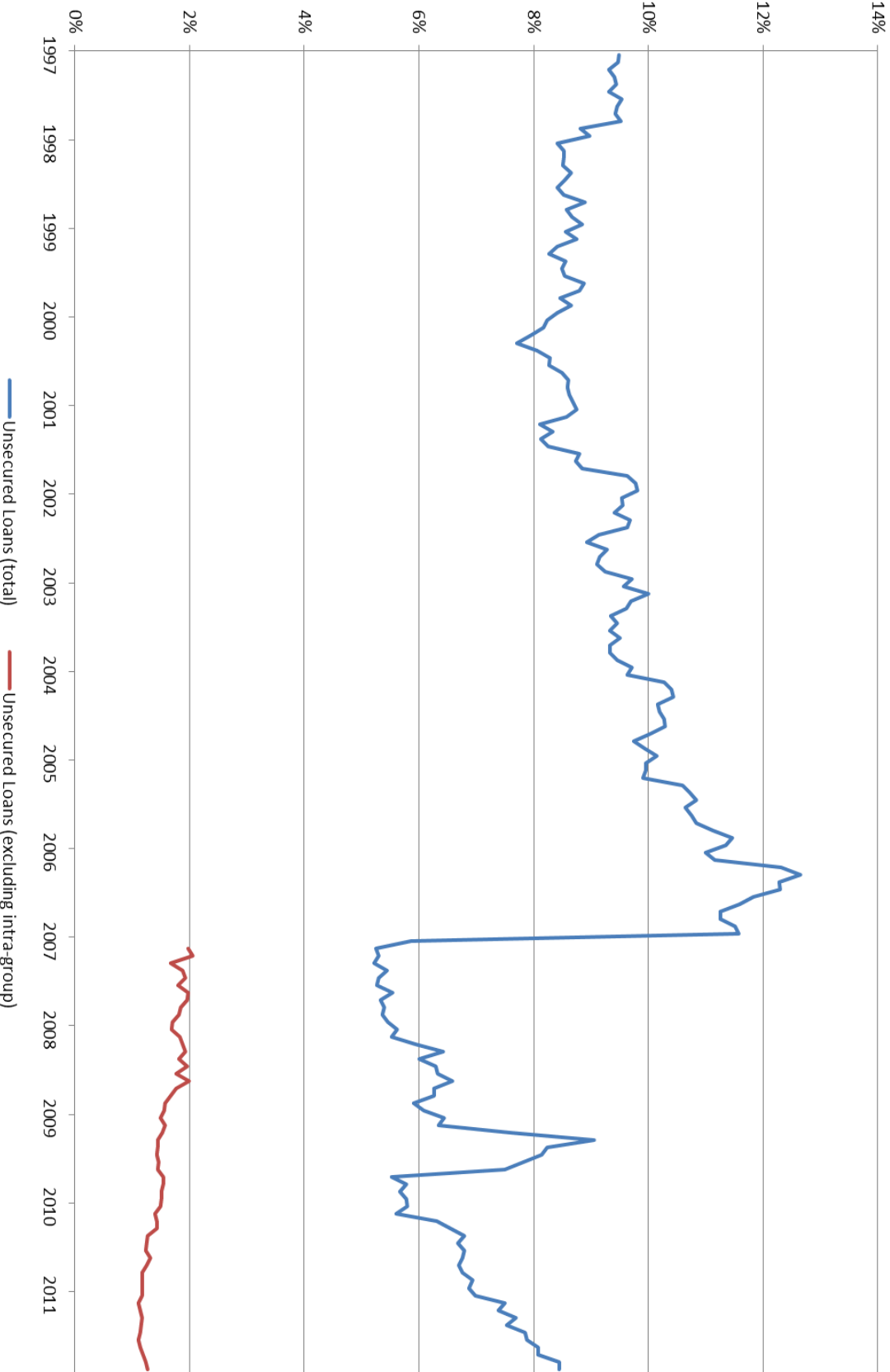


Figure A3: Unsecured Interbank Lending (Source: Bank of England)



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