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The Structure and Resilience of the European Interbank Market

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This paper summarises the work of the ESRB's Expert Group on interconnectedness.

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Executive summary

Financial institutions are connected to each other by a series of bilateral transactions. In normal times, institutions' connections may result in efficient risk transfer. But in crises, connections can facilitate contagion – as initial problems lead to chains of defaults and liquidity shortages – sparked by shocks which might arise within the financial system or from the real economy.

Institutions are also interconnected in indirect ways, since they are exposed to common risk factors that can result in concurrent losses. For example, most banks extend loans secured by real estate: they are thus collectively exposed to falls in house prices. Resulting bank distress can then exacerbate initial problems: banks might simultaneously sell collateral (houses), thus worsening downward price spirals. Less tangibly, institutions can also be connected through perceptions of counterparties' creditworthiness. Given uncertainty, financial institutions may in general become reluctant to lend to each other and hoard liquidity.

Potential for contagion due to interconnectedness is a key component of systemic risk. As a first step towards understanding the mechanisms of contagion, this paper abstracts from complex indirect connections between banks, and rather focuses on direct linkages between 53 large EU banks, based on unique data on interbank exposures collected by national regulators as of the end of 2011.

Section 1 of the paper reviews the extant literature on financial network analysis. The review identifies two distinct approaches: static network analysis and dynamic network analysis, which are respectively deployed in sections three and four of this paper. Static analysis describes the structural properties of financial networks, without assuming mechanisms for the transmission of shocks. These analyses provide useful information on the characteristics of network structure, and provide ways to identify central players within systems. Dynamic analysis explicitly assumes transmission mechanisms in order to test the resilience of a network under certain stress scenarios. Such analysis often entails simulation: initially local shocks propagate through the rest of the system via contagion channels, impacting individual institutions' balance sheets. These channels of contagion can be purely mechanical, or they can incorporate assumptions about institutions' behavioural responses.

Section 2 describes the dataset on interbank exposures, on which the remainder of the paper is based. Exposures are reported on a consolidated basis under the following categories of instruments: (i) assets (broken down into credit claims, debt securities and other assets); (ii) derivatives; and (iii) off-balance sheet exposures. Exposures are also broken down by residual maturity (sight; overnight and up to one year; more than one year). At the end of 2011, the 53 reporting banks held €1.7 trillion of interbank exposures, equivalent to 6.4% of their total assets. The largest exposures arise from holdings of debt securities, interbank deposits and derivatives.

Section 3 describes the characteristics of this interbank market and analyses measures of network fragility. The large EU banks display high connectivity, and the density of the network is typically very high. A highly connected and dense network implies that credit and funding events are likely to be widespread, as no single institution is remote from the others. But the systemic impact of these events critically depends on the size of the interbank exposures, banks' capital and liquidity levels, and the extent to which interbank funding can be substituted. The section also identifies banks which are important within the network using measures of centrality and cluster analysis. The cohesion of the interbank market is also analysed in order to highlight the policy relevance of correctly identifying communities in the interbank market.

Section 4 provides a dynamic network analysis of the interbank market, with the objective of assessing the potential consequences of solvency and liquidity contagion on the European banking system.

The solvency default simulation works as follows. First, all banks are hit by a common exogenous shock (varying in severity between 1% and 4% of all banks' non-interbank assets). Second, an individual bank is assumed to fail, due to an idiosyncratic loss on its non-interbank assets which erodes all of that bank's capital. The failure imposes a loss rate (between 0% and 100%) on that bank's creditors, some of which are other banks. These counterparties incur the loss caused by the defaulting bank, in addition to losses caused by the initial common exogenous shocks. If each of the remaining banks has positive capital after these losses, the simulation stops. Alternatively, if at least one remaining bank has no capital, the simulation resumes: creditors to that bank incur losses (in proportion to the asset value of the defaulting bank), and so on.

The liquidity channel of contagion is also modelled. There are two potential channels of liquidity contagion: fire sales, which affect the liquidity of assets; and wholesale funding supply, which affects banks' ability to roll-over liabilities. This paper focuses on the latter channel. In particular, banks with low regulatory capital ratios are assumed to face difficulties rolling over some of their short-term interbank funding. These banks attempt to meet this funding gap through new repurchase agreements. However, if holdings of liquid securities are inadequate, these banks will default, triggering the solvency contagion mechanism.

Results for the combined solvency and liquidity simulation suggest that there is a low likelihood of contagion with smaller common shocks. When the common shock is set to 1% of non-interbank assets, contagious defaults only occur for values of loss given default above 80% even in the most conservative setting (with the critical threshold for the liquidity channel of contagion set at a 7% Tier 1 capital ratio). However, the number of contagious defaults increases non-linearly when the common shock increases from 2% to 3% of non-interbank assets.

Overall, results may be sensitive to particular features of the data and analysis. First, analysis is conducted on a cross-section of interbank exposures at the end of 2011, when risk aversion and perceptions of bank-counterparty risk were high, and volumes of non-repo cross-border interbank lending were around one-third lower than in 2007 (ECB, 2012). Results could change substantially if the size or distribution of interbank exposures were to change. Second, the data capture only large cross-border banks; effects of shocks on smaller banks therefore cannot be considered. Third, other mechanisms of contagion could be modelled, such as behavioural responses (including confidence effects in the presence of asymmetric information) and market characteristics (such as margining, collateral availability and common exposures).

In conclusion, this paper represents an important contribution to collective understanding of the European interbank market. Further work could provide more insights regarding systemic fragility and resilience. Such extensions require additional data, in order to capture the time dimension at high frequency, and improve the cross-sectional granularity of instruments (particularly with respect to derivatives exposures). These data could be merged with other channels of connection, such as CDS exposures or common exposures (for example, to sovereign bonds or real estate). With these additional data, it would be possible to explore more granular shock scenarios.

Section 1: Literature[1]

1.1. Analysing the structure and resilience of financial networks

Networks portray complex financial systems as a set of nodes connected by links. In a financial network, nodes might represent countries, regions, sectors or financial institutions. Links represent connections between these nodes, such as trade, mutual characteristics or financial transactions.

Policymakers can learn about contagion risk by analysing the channels through which shocks propagate within financial networks. Thus the robustness and resilience of a network can be tested and systemically important nodes identified. Network analysis also provides an evidence-based setting in which to test the effectiveness of macroprudential policies.

The financial system is composed of many networks. Defining the network of interest entails specifying nodes and the types of links between them. Specifying nodes as individual banks requires detailed information on bilateral exposures; such data, however, are typically only available nationally. But interlinkages often transcend national boundaries: this mismatch between the geographies of national sovereignty and financial activity frustrates holistic analysis of cross-border financial networks.

Moreover, data constraints typically imply that observed financial connections based on exposures are limited to single markets.[2] Most national credit registers capture prime lending between banks, but ignore other instruments such as derivatives. Overnight interbank loans can be inferred from payments systems using algorithms (Furfine, 1999), which have been applied to TARGET 2 (Arciero et al., 2013) and Fedwire (Soramäki et al., 2007; Kuo et al., 2013).[3]

Complete datasets are therefore rare. But data completeness is important: Gauthier et al. (2010a) find that banks' probabilities of default change when the network is expanded from interbank deposits to all interbank exposures (including cross-shareholdings and derivatives). Incomplete data can therefore lead to severe underestimation of systemic risk.

The literature on financial networks takes two distinct approaches. The first approach describes network structure using topological indicators. The literature often relates these indicators to 'model' graphs from network theory. This approach does not assume a mechanism by which shocks are transmitted within the network, and thus is referred to here as *static network analysis*.

The second approach subjects the observed financial network structure to shocks, in order to assess the strength of contagion channels and the resilience of the network. As the introduction of a shock

[1] The main contributors to this chapter were Stijn Ferrari, Pietro Franchini and Guillaume Vuillemey.

[2] The regulatory 'large exposures' report captures aggregate counterparty exposure across multiple products, but only for exposures greater than 10% of institutions' own funds.

[3] Alternative approaches use prices rather than quantities. For example, Mantegna (1999) and Barigozzi et al. (2013) study interconnectedness in the context of correlation networks, in which the strength of connections between two nodes is based on the (time-varying) correlation of prices (such as bank equity prices). However, this approach relies on the quality of information contained in market prices. In the presence of incomplete and asymmetric information, prices might be noisy.

assumes a specific transmission mechanism (e.g., the default of one or several market participants), it is referred to here as *dynamic network analysis*.[4]

1.2. Static network analysis: describing and explaining network structures

Characteristics of financial networks

The first strand of the financial networks literature describes interconnectedness through measures of density, concentration and clustering (among others). Common network metrics are described in, for example, Newman (2010). These network metrics provide useful information about the stability of the network structure and allow analysts to identify central nodes which are more likely to propagate shocks.

The literature on static networks suggests that national interbank networks tend to be tiered: that is, they comprise a few central nodes and many less significant nodes. Such networks exhibit low density and a distribution of exposures concentrated in a few nodes. For example, based on the Austrian central credit register, Boss et al. (2004) and Puhr et al. (2012) find that the Austrian interbank market is tiered and that banks within subsectors tend to cluster together.

The tiering of core banks and peripheral banks is confirmed for several national interbank systems.[5] However, Langfield et al. (2013) find that the strength of the core-periphery structure varies significantly by asset class: the observed interbank network fits the core-periphery model more strongly for derivatives and marketable securities than for unsecured lending and repurchase agreements.

Other studies consider changes in the network topology of the financial system before, during and after financial crises. This new body of literature helps to gauge the effects of crises on dynamic link formation. Garratt et al. (2011) and Hale (2012) show that the structure of global banking networks varies over time and responds to economic and financial shocks. Nevertheless, the strength of core-periphery structures in national interbank markets tends to be stable over time (Craig and von Peter, 2010; Fricke and Lux, 2012; Puhr et al., 2012). The number of core banks and the aggregate level of interbank activity may vary over time, however. For example, Puhr et al. (2012) document decreasing network density between 2008 and 2010, with central nodes becoming more important. In contrast, Fricke and Lux (2012) find that network density was fairly stable in the Italian interbank market over 1999-2010. They also present some evidence that the 2008 financial crisis constituted a structural break in interbank intermediation: core banks tend to rely on the liquidity of periphery banks during crises, whereas in normal times they tend to be net providers of liquidity to the system.

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[4] Recent papers have analysed which financial network indicators resulting from static network analysis best explain the outcomes (in terms of the banks' impact on the system and/or fragility in the case of a stress scenario in the system) of dynamic network analysis (see, for example, Cont et al., 2012; and Puhr et al., 2012).

[5] Belgium (Degryse and Nguyen, 2007), Germany (Craig and von Peter, 2010), Italy (Iori et al., 2008; Fricke and Lux, 2012), the Netherlands (van Lelyveld and in 't Veld, 2012) and the UK (Langfield et al., 2013).

Explaining financial network structure

Understanding how links form is central to explaining why particular structures are more prone to contagion. The literature has established three important insights regarding dynamic link formation:

1. *Scale-free networks are frequently observed in real interbank markets*. These networks are characterized by the presence of a few hubs, which are connected to a large proportion of other banks. Several papers provide graph models in which scale-free networks tend to be observed due to 'preferential attachment' in link formation (see Dorogovtsev and Mendes (2003) for an overview). In the theoretical networks literature, preferential attachment is based on the extent to which the would-be counterparty is already connected. In interbank markets, preferential attachment may be interpreted as relationship lending and borrowing between known counterparties.
2. *Financial systems tend to be robust yet fragile* (Gai and Kapadia (2010)). Interbank transactions lead to more efficient risk transfer, but also facilitate shock propagation (Haldane, 2009). Battiston et al. (2012a) assess how network density (the number of connecting links) relates to systemic risk in a model of the economy as a credit network. Connections between banks improve risk sharing, but connectivity also leads to trend reinforcement. When an economic agent suffers a negative shock, trade partners react by making conditions even worse. Systemic financial fragility is thus self-reinforcing. Georg (2011) shows that money-centre networks are typically more stable than random networks. Sachs (2010), by contrast, focuses on concentration, showing that asset concentration among core banks is a factor causing instability; hence, tiered networks may be less stable.
3. *Policy can help to reduce systemic risk in networks*. Nier et al. (2007) show that bank capital requirements do not adequately mitigate contagion risk. Even if banks are well capitalised, levels of interbank activity beyond a certain threshold imply elevated systemic risk. Gauthier et al. (2010a) conclude that comprehensive bank regulation should be based on a set of requirements related to capital, liquid asset holdings and short-term liabilities. Manna and Schiavone (2012) analyse the effect of capital regulation and central bank intervention on banks' deleveraging via the roll-off of interbank loans and asset disposals. When authorities intervene, unconventional monetary policies mitigate contagion, but these measures become less effective when the shock is very large.

1.3. Dynamic network analysis: assessing the resilience of financial networks

Dynamic network analysis is used to explore the resilience of a network in certain stress scenarios. This often involves simulation: the network is exposed to an external shock which propagates through the system via one or more contagion assumed channels, affecting the balance sheets of individual institutions. Box 1 summarises the main approaches taken in the extant literature.

Shocks to the banking system can be either idiosyncratic or common. Idiosyncratic shocks can simply be the (exogenous) default of an individual bank on its (interbank) liabilities (see Espinosa-Vega and Solé (2010); van Lelyveld and Liedorp (2006); Lubloy (2005); or Wells (2002)). More advanced approaches also study the impact of common shocks, which affect the value of all banks' assets simultaneously (see Elsinger et al. (2006); Gauthier et al. (2010a); or Gauthier et al. (2010b)).

Shock propagation can be mechanical or behavioural. In addition, different networks may be linked to allow for interactions among them, thereby determining contagion channels within the entire system.

Box 1: Literature review on network contagion

Reference	Initial shock	Contagion mechanism	Non-solvency contagion channel	LGD	Scope
Aikman (2010)	Common	Simultaneous	Liquidity	Exogenous	United Kingdom
Cifuentes et al. (2004)	Common	Iterative		Exogenous 100%	Brazil
Demange (2012)	Unspecified	Simultaneous		Endogenous	None
Eisenberg and Noe (2001)	Unspecified	Simultaneous		Endogenous	None
Elsinger et al. (2006)	Common			Exogenous	
Espinosa-Vega and Solé (2010)	Specific	Iterative	Fire sales	Exogenous	BIS data
Fourel et al. (2013)	Common	Iterative	Funding	Exogenous	France
Furfine (2003)	Specific	Iterative		Exogenous	United States
Gauthier et al. (2010a)	Common	Simultaneous	Fire sales	Endogenous	Canada
Gauthier et al. (2010b)	Common	Simultaneous	Fire sales	Endogenous	Canada
Gourieroux et al. (2012)	Unspecified	Simultaneous		Endogenous	France
Gourieroux et al. (2013)	Unspecified	Simultaneous		Endogenous	
Karas et al. (2008)	Common	Iterative	Liquidity	Exogenous 100%	Russia
Lubloy (2005)	Specific	Iterative		Exogenous	Hungary
Memmel et al. (2012)	Specific	Iterative		Exogenous	Germany
Upper and Worms (2004)	Specific	Iterative		Exogenous	Germany
van Lelyveld and Liedorp (2006)	Specific	Iterative		Exogenous	Netherlands
Wells (2002)	Specific	Iterative		Exogenous	United Kingdom

Mechanical propagation

The mechanical treatment of a shock is restricted to automatic balance sheet adjustments by financial institutions. Shocks to the balance sheets are entirely governed by accounting equalities, and there are no behavioural reactions by institutions. For example, the idiosyncratic default of a financial institution on its interbank liabilities results in losses among other banks.[6] The losses incurred by the defaulting institution's counterparties may result in further defaults, followed by new counterparty losses, potentially new defaults, and so on.

These studies generally find limited effects of contagion stemming from losses to banks' capital. For example, Elsinger et al. (2006) find that positive correlation in the value of Austrian banks' portfolios is far more important than direct solvency contagion. While domino effects can wipe out major parts of the banking system, such effects are unlikely to occur. Martinez-Jaramillo et al. (2010) report a similar finding for Mexico: while the failure of a single small bank could result in the collapse of almost the entire financial system owing to contagion, the likelihood of this happening is very small. This is an important feature of the general 'robust yet fragile' property of financial networks.

Behavioural dynamics

The inclusion of behavioural aspects, such as management decisions taken in response to a stress scenario, provides potentially greater realism. Behavioural assumptions usually relate to banks' liquidity management, and thus to liquidity contagion, extensively discussed in Karas et al. (2008) and Aikman et al. (2010).

In response to stress, financial institutions could change the composition of their asset portfolio, alter the composition of the liability side of their balance sheet or change the currency and/or maturity structure of their balance sheets. These reactions have repercussions for other financial institutions (e.g. marking-to-market losses following fire sales; dry-up of funding owing to liquidity hoarding), in addition to the scope and potential for contagion. Coordination failures arise: individual institutions' reactions might be individually rational, but together they amount to financial instability.

Three types of behavioural effects have been considered in the literature: liquidity hoarding, asset fire sales and reinvestment decisions.

Liquidity hoarding: This behavioural mechanism relates to liquidity hoarding and dry funding markets (De Bandt et al., 2010). Two approaches can be identified. In the first approach, credit losses weaken investor confidence, resulting in general reduction in bank funding supply (Aikman et al., 2010; Gauthier et al., 2010b). The second approach considers liquidity hoarding within the network. Karas et al. (2008) consider several magnitudes of liquidity hoarding: banks may withdraw lending from infected banks only, or run on all banks indiscriminately. In Arinaminpathy et al. (2012), banks cut lending in the interbank market, according to a function which depends on banks' own health, that of their counterparties and banks' confidence in the system as a whole. Similarly, in Fourel et al. (2013), a bank curtails its overnight interbank lending, depending on that bank's capital

[6] Such empirical studies include, among others, Sheldon and Maurer (1998) for Switzerland, Furfine (1999) for the US, Wells (2002) for the UK, Upper and Worms (2004) for Germany, Lubloy (2005) for Hungary, Elsinger et al. (2006) for Austria, Van Lelyveld and Liedorp (2006) for the Netherlands, Degryse and Nguyen (2007) for Belgium, Martinez-Jaramillo et al. (2010) for Mexico, Silva (2010) for Portugal, Mistrulli (2011) for Italy and Cont et al. (2012) for Brazil.

ratio relative to regulatory minima and on the market's perception of counterparties' credit risk. Gai et al. (2012) focus exclusively on liquidity contagion, as they assume that banks which face liquidity stress hoard liquidity by withdrawing deposits held at other banks.

These studies generally find that liquidity matters for systemic stability. Failure to account for funding liquidity risk thus implies underestimation of actual default risk (Fourel et al., 2013). In this vein, Aikman et al. (2010) find that funding cost and liquidity concerns can amplify other sources of risk. Moreover, while counterparty credit risk and asset price contagion generate losses for individual banks, liquidity hoarding imposes a negative externality on the entire financial system (Arinaminpathy et al., 2012).

Fire sales: A second behavioural extension in network models incorporates fire sales of assets as a response to liquidity shortage. When banks sell illiquid assets, asset prices decrease: this causes mark-to-market losses for other banks which hold the same asset (or other assets correlated with that asset). In Alessandri et al. (2009), Aikman et al. (2010) and Arinaminpathy et al. (2012), fire sales occur only in the course of liquidation or resolution after a bank defaults, and not as a defensive action in a bid to prevent or defer failure. In addition, these models assume that asset prices recover to their pre-stress levels, such that mark-to-market losses do not persist over time.

In more general set-ups, asset fire sales occur not only in the event of outright bank default. Approaches adopted by Cifuentes et al. (2004) and Gauthier et al. (2010a) are somewhat less restrictive with respect to the trigger of asset fire sales. In the model of Gauthier et al. (2010a), banks sell assets to reduce their size and leverage when a pre-specified minimum capital ratio is breached.

Inclusion of the asset fire sale mechanism can materially affect model outcomes. Alessandri et al. (2009) find that the joint effect of counterparty credit losses and asset fire sales is much more substantial than the individual effects of these mechanisms. Gauthier et al. (2010a) find that the Canadian banking system is very stable in the absence of asset fire sales, but inclusion of this mechanism substantially alters results.

Reinvestment decisions: A third behavioural extension concerns banks' reinvestment decisions when profits or losses are incurred in a given period. Alessandri et al. (2009) and Aikman et al. (2010) update banks' balance sheets using mechanical reinvestment rules. Defensive actions in response to declines in capital are very limited, however, since banks are assumed not to disinvest or raise capital.

In an even more stylised framework, Aspachs et al. (2006) provide a two-period general equilibrium model calibrated to UK banking data. In the model, three banks make endogenous decisions regarding their supply of loans to the real economy; their demand for deposits from the real economy; their assets and liabilities in the interbank market; and the repayment rates to their creditors in the interbank and deposit markets. This framework entails both liquidity hoarding and reinvestment decisions, and is used to map credit risk in the interbank market as well as indirect contagion channels between the real economy and the financial sector.

Section 2: Data[7]

The following sections are based on a unique dataset on interbank exposures between 53 large EU banks as of 31 December 2011.[8] The data comprise bilateral exposures between each of the 53 banks, with breakdown by instrument and maturity. In addition, the dataset includes the 53 banks' aggregate exposure to all other European banks (by country).

2.1. Description of the dataset

In the dataset, each of the 53 banks reports its counterparty exposure to the other 52 banks. These counterparty exposures are broken down by the following instrument categories: (i) assets (with further details on credit claims, debt securities and other assets); (ii) derivatives; and (iii) off-balance-sheet exposures. Each exposure class is broken down by residual maturity into two buckets: less than one year (including on sight); and more than one year. Overall, the templates comprise 2,245 data points for each reporting bank.

The 53 banks' aggregate interbank exposure (by country) includes additional granularity. In particular, credit claims are further divided into interbank deposits, repos and other claims. Off-balance sheet exposures are split into guarantees extended, credit commitments and other off-balance-sheet items. In addition, exposures under two further categories are included: equity holdings and credit default swap (CDS) protection sold.

Banks reported their interbank exposures at the level of the banking group,[9] meaning that exposures in non-financial subsidiaries (including insurance) were excluded. Exposures to counterparties were aggregated using an accounting scope of consolidation, thereby including all subsidiaries of that counterparty (including financial and ancillary activities; domestic, EU and non-EU).

The reporting templates are mostly based on the existing EBA framework for Large Exposures[10] and FINREP,[11] using common definitions and valuation methods. In terms of valuation, on-balance sheet items, including derivatives, were reported according to the carrying amount under accounting rules (International Financial Reporting Standards). Off-balance-sheet items were required in notional amounts. Exposures were reported in gross terms, not netted against funding from counterparts,

[7] The main contributors to this chapter were Pavol Jurca and Antonio Sanchez.

[8] The dataset was created thanks to close cooperation between the ESRB, the European Banking Authority (EBA) and national supervisory authorities (NSAs). In particular, the data were collected according to the provisions in Article 15 of the Regulation (EU) No 1092/2010 of the European Parliament and of the Council of 24 November 2010 on European Union macro-prudential oversight of the financial system and establishing a European Systemic Risk Board (see http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2010:331:0001:0011:EN:PDF) and the "Agreement between the European Banking Authority and the European Insurance and Occupational Pension Authority and the European Securities and Markets Authority and the European Systemic Risk Board on the establishment at the ESRB Secretariat of specific confidentiality procedures in order to safeguard information regarding individual financial institutions and information from which individual financial institutions can be identified": see http://www.esrb.europa.eu/pub/pdf/111125_agreement_EBA_EIOPA_ESMA_ESRB.pdf.

[9] 'Banking group' is defined in Art. 73 of Directive 2006/48/EC. The consolidated nature of the data collected for this paper masks some cross-border exposures within multinational banking groups.

[10] See http://www.eba.europa.eu/Supervisory-Reporting/COREP/Common-reporting-of-LE.aspx

[11] See http://www.eba.europa.eu/Supervisory-Reporting/FINER/FINREP-framework.aspx.

except repurchase agreements and derivatives. In the latter case, banks were allowed to report values in net as well as in gross terms, with netting as the default option. All amounts were reported before applying any credit risk mitigation techniques (including collateral and other hedges).

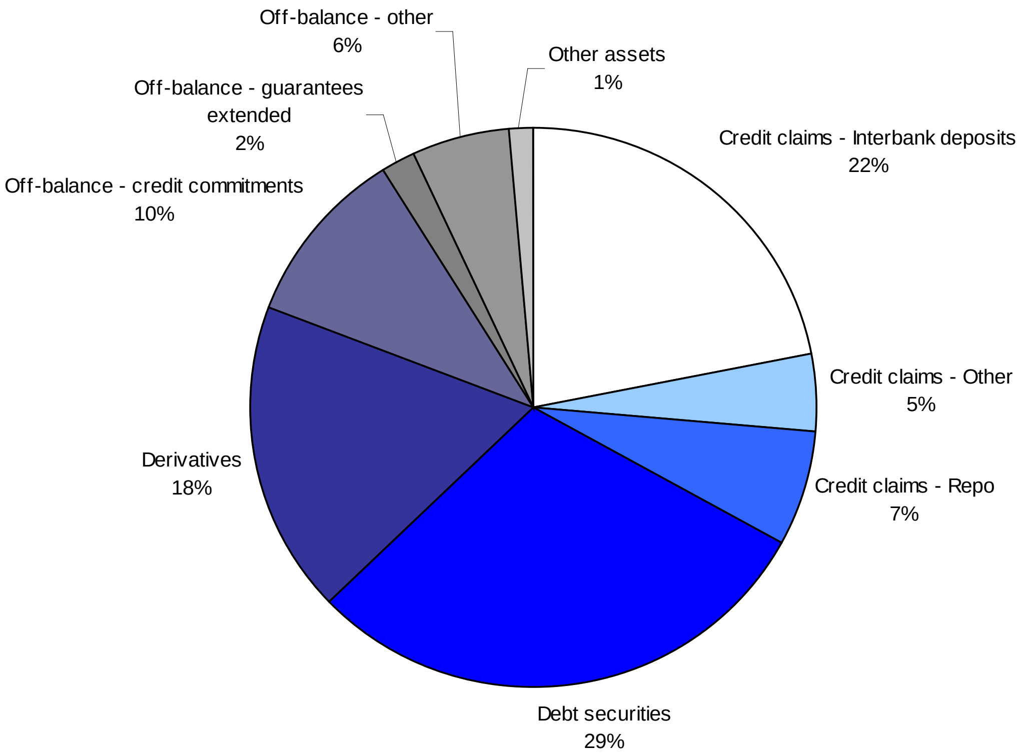
The interbank exposure data were matched with banks' balance sheet data from Bloomberg. These additional data were necessary in order to analyse the interaction of measures of network fragility with balance sheet characteristics (chapter 3) and the vulnerability of banks' balance sheets to losses on interbank exposures (chapter 4).

2.2. Descriptive statistics

The total value of all interbank exposures (including off-balance-sheet items) reported by the 53 large EU banks to all other EU banks is €1,714 billion, which represents 6.4% of reporting banks' total assets and 163% of their Tier 1 capital.

Chart 1 presents the shares of individual instruments in total interbank exposures. Interbank credit claims (34%) and debt securities (29%) account for most interbank exposures; the remainder is split among derivatives (18%) and off-balance-sheet items (18%). Interbank deposits are the largest source of credit claims (22% of interbank exposures); repurchase agreements are substantially smaller (7%). Credit commitments constitute the largest share of off-balance sheet interbank exposure (10%). All banks in the sample report relatively large amounts of credit claims and debt securities; by contrast, off-balance-sheet activities are concentrated in a few reporting banks.

Chart 1: Individual instruments as shares of total interbank exposures, end-2011 (%)

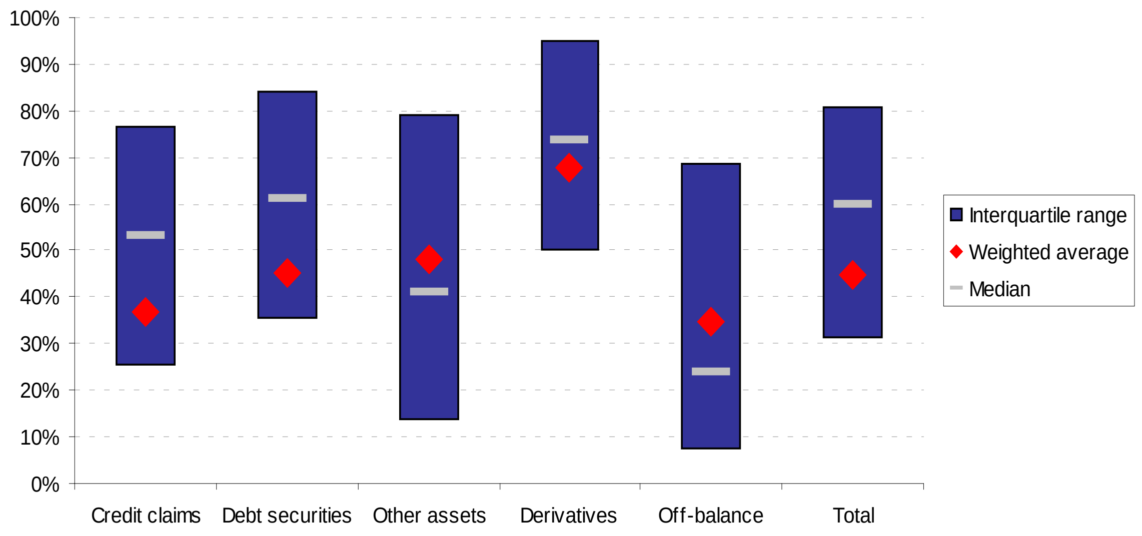


Source: ESRB, EBA and national supervisory authorities.

Exposures through equity cross-holdings and CDS protection sold on other EU banks represent 3% and 14% of total interbank exposures respectively. As with off-balance sheet activity, sales of CDS protection are highly concentrated in a few banks.

Bilateral exposures reported by the 53 banks to each other are a subset of the 53 banks' exposure to all other EU banks. Chart 2 shows averages and distributions of the proportion of the 53 banks' exposures to each other relative to all EU banks. The median share is around 60% for total exposures, with large variance across the 53 reporting banks. There is also substantial variation in the median across exposure classes. Overall, interbank exposures within the sample of 53 banks therefore represent a slim majority of total interbank exposures. Nevertheless, since we do not observe the complete bilateral network of interbank exposures, subsequent analysis might miss interesting dimensions of activity between the 53 banks and smaller banks.

Chart 2: Total exposures to major EU banks as a share of total exposures to EU banks, end-2011 (%)[12]



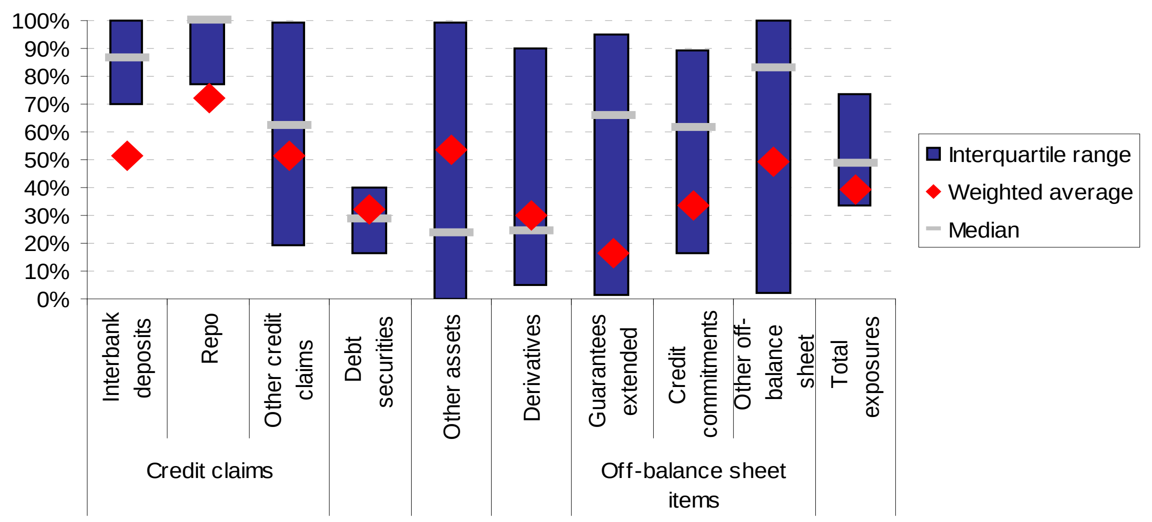
Source: ESRB, EBA and national supervisory authorities.

Breakdown by maturity permits analysis of the distribution of short-term and long-term interbank exposures across instruments. Chart 3 shows that the maturity structure varies significantly across both instruments and reporting banks. The share of instruments with residual maturity of up to one year is relatively high for credit claims, and particularly for interbank deposits and repurchase agreements. Debt securities tend to have longer maturities, and therefore represent a more stable source of funding for the receiving bank, but potentially a more illiquid asset for the providing bank. For other asset classes, the proportion of short versus long residual maturities varies across banks, with other assets and derivatives tending to be characterised by longer residual maturities for the

[12] When calculating the weighted average, the amount of total exposure to all EU countries for the given exposure class has been taken as the weight.

majority of banks, and the opposite being true for other credit claims and other off-balance-sheet items.

Chart 3: Exposures with residual maturity of up to one year as a share of total exposure, end 2011 (%)[13]



Source: ESRB, EBA and national supervisory authorities.

[13] When calculating the weighted average, the amount of total exposure to all EU countries for the given exposure class has been used. Residual (rather than original) maturity has been used.

Section 3: Network fragility measures[14]

A network provides a convenient representation of interbank systems. To infer economic meaning from networks, it is necessary to consider networks' topological structure (presence or absence of links between banks); the direction of links between banks (provision or receipt of funds); and the magnitude of those links (value of exposures). It may also be important in some contexts to distinguish relationship types by instrument and residual maturity.

The multiplicity of weighted and directed relationships is known in the literature as a *weighted and directed multiple-graph representation* of a network. This section considers distinct exposures by instrument type and residual maturity. Specific types of structural analysis – for instance, those which focus on the fragility of the interbank network with regard to fluctuations in liquidity availability or to long-term investment strategies – would deal, more appropriately, with only a subset of exposures, or account for different maturity horizons and specific asset types more explicitly.

There is no unique measure of network fragility. This section instead highlights a number of representative measures. Following a brief overview of the characteristics of the network, this section will look at measures of network fragility and their similarity, as well as whether network structure can be explained by banks' characteristics. The section concludes by grouping banks according to informal communities in which they operate.

3.1. Characteristics of the interbank network

Large European banks display high interconnectivity for most instruments and maturities (see Table 1). These banks are generally not isolated (all relationships form a 'giant component'), and the density of the network is typically very high (with completeness of 40-60% of potential links). Furthermore, there is no general difference between the graph-level degree of total exposures ('outward' linkages) and funding ('inward linkages'). By contrast – and not unexpectedly given the sample of this study – national banking systems display 'core-periphery' structures (e.g. Degryse and Nguyen (2007); Fricke (2012); Sachs (2010); and Langfield et al. (2013)), and therefore tend to be sparse.

Banks in the sample are also very 'close' to each other. Mean geodesic distance (shortest path) is rarely above two and generally close to one; thus exposure is significantly less than two banks away. This measure of closeness can be interpreted as a bank's centrality within the network, as it captures how distant its activities are from those of others. Like all centrality measures displayed in Table 1, the *global* measure is a network aggregate of the *local* centrality measures explained in section 3.2.

High density and proximity are associated with a high *transitivity* coefficient (banks linked to bank 'a' are likely to be directly connected to other banks also linked to bank 'a') suggesting large redundancy in the exposures. Transitivity also affects the power law characteristics of the degree distribution.[15] The interbank market is 'scale free', similarly to other networks observed in the literature. This

[14] The main contributor to this chapter was Ivan Alves.

[15] This is captured by the parameter α, which identifies bank connectivity that follows a power law when its values are above 2, a distribution function associated with a process with a high propensity to experience sudden changes, For a general discussion on the role of power law distributions see Newman (2006), and for details on the econometric estimation of α see Clauset et.al. (2009).

increases with aggregation of instruments and maturities, suggesting that problems are more systemic when considering a larger range of exposures. At the same time, distinct links are hidden by the aggregation of exposures, and may hide possible substitutability of specific instrument-maturity exposures.

Table 1: Summary statistics of network measures[16]

				Banks	Bilateral exposures	Value in € billion	Density	Mean geodesic distance	Graph-level degree		Exponent α, degree distr.		Transitivity	Reciprocity	Assortativity	Closeness centrality index	Betweenness centrality index	Eigenvalue centrality index
									Out	In	Out	In						
Total exposure			total, *of which*	54	1737	770.593	0.60	1.38	0.34	0.39	3.50	3.50	0.84	0.71	-0.24	0.19	0.03	0.37
			short	54	1273	336.4	0.44	1.55	0.39	0.56	3.43	3.50	0.75	0.56	-0.25	0.05	0.07	0.52
			long	54	1202	310.8	0.41	1.58	0.39	0.58	3.25	3.50	0.74	0.53	-0.25	0.08	0.10	0.55
			(no identified maturity)	54	274	140.8	0.09	1.27	0.04	0.89	3.50	1.93	0.26	0.11	-0.28	0.00	0.02	0.91
	Assets		total, *of which*	54	1410	456.3	0.48	1.51	0.41	0.47	2.72	3.50	0.79	0.58	-0.23	0.19	0.07	0.48
			short	54	1007	227.3	0.35	1.64	0.37	0.55	2.55	3.50	0.67	0.48	-0.22	0.02	0.08	0.59
			long	54	925	188.4	0.32	1.68	0.39	0.62	3.00	3.50	0.67	0.41	-0.21	0.01	0.09	0.65
			(no identified maturity)	49	161	58.1	0.07	1.10	0.06	0.72	2.08	2.36	0.14	0.00	-0.32	0.00	0.00	0.00
		credit claims	total, *of which*	54	988	211.2	0.34	1.73	0.45	0.56	3.50	3.02	0.67	0.53	-0.27	0.13	0.11	0.58
			short	54	792	116.2	0.27	1.78	0.38	0.55	3.50	3.50	0.62	0.46	-0.25	0.02	0.10	0.64
			long	50	389	64.9	0.16	1.95	0.23	0.78	3.50	3.50	0.47	0.35	-0.31	0.00	0.15	0.78
			(no identified maturity)	41	104	30.1	0.06	1.17	0.09	0.69	3.12	3.50	0.05	0.00	-0.25	0.00	0.01	0.00
		Debt securities	total, *of which*	54	1100	232.8	0.38	1.67	0.37	0.48	2.89	3.50	0.73	0.47	-0.18	0.08	0.06	0.55
			short	54	548	85.4	0.19	2.01	0.22	0.60	2.53	2.17	0.52	0.31	-0.09	0.01	0.07	0.76
			long	54	811	120.1	0.28	1.78	0.34	0.55	2.74	3.50	0.63	0.35	-0.17	0.01	0.07	0.67
			(no identified maturity)	46	141	27.3	0.07	1.09	0.07	0.73	2.15	3.50	0.14	0.00	-0.37	0.00	0.00	0.00
		Other	total, *of which*	53	226	12.4	0.08	2.02	0.19	0.82	2.92	2.71	0.27	0.13	-0.33	0.00	0.21	0.90
			short	47	121	8.3	0.05	2.12	0.12	0.60	3.50	2.49	0.16	0.08	-0.23	0.00	0.10	0.92
			long	48	97	3.3	0.04	1.62	0.06	0.89	2.69	1.89	0.12	0.06	-0.55	0.00	0.07	0.94
			(no identified maturity)	29	40	0.7	0.05	1.00	0.09	0.67	3.39	3.05	0.00	0.00	-0.42	0.00	0.00	0.00
	Derivatives		total, *of which*	54	1062	208.7	0.36	1.64	0.52	0.55	3.50	3.29	0.69	0.56	-0.33	0.15	0.12	0.56
			short	54	684	68.9	0.23	1.89	0.42	0.55	3.00	3.50	0.58	0.32	-0.27	0.05	0.18	0.68
			long	54	651	98.8	0.22	1.91	0.51	0.64	3.50	3.50	0.57	0.30	-0.29	0.02	0.22	0.70
			(no identified maturity)	50	150	41.0	0.06	1.56	0.08	0.94	2.25	3.13	0.18	0.08	-0.54	0.00	0.08	0.94
	Off balance sheet		total, *of which*	53	828	105.5	0.29	1.66	0.31	0.64	3.50	2.37	0.61	0.47	-0.32	0.01	0.07	0.64
			short	53	498	40.2	0.18	1.74	0.24	0.67	2.69	3.50	0.52	0.35	-0.31	0.00	0.11	0.75
			long	53	348	23.6	0.12	1.94	0.20	0.64	2.64	1.99	0.42	0.24	-0.31	0.00	0.08	0.82
			(no identified maturity)	52	178	41.7	0.07	1.33	0.05	0.89	3.50	2.21	0.19	0.09	-0.35	0.00	0.02	0.93
Memo:	*Credit claims*		*secured*	47	311	67.5	0.14	2.06	0.29	0.60	3.50	3.21	0.52	0.30	-0.23	0.00	0.14	0.80
			unsecured	54	720	121.1	0.25	1.69	0.33	0.64	3.50	3.50	0.60	0.40	-0.28	0.01	0.10	0.67
			(no identified maturity)	49	219	23.7	0.09	2.32	0.16	0.49	2.97	1.81	0.27	0.10	-0.14	0.00	0.13	0.88

Source: ESRB, EBA and national supervisory authorities.

Note: Summary network statistics for various levels of potential aggregation of exposures, illustrating both the type of asset underlying the exposure and the remaining maturity - more (long) or less (short) than one year.

The aggregation of exposure types also results in higher reciprocity (i.e. the number of exposures that have a corresponding counter-exposure) between any two banks. A high fraction of mutual exposures (high reciprocity) at aggregate levels suggests that systemic risk might be lower; since otherwise unbalanced specific instrument-maturity exposures are (partly) netted.

More negative values of assortativity (associated with banks' degrees) are also evident for individual asset and maturity classes, illustrating that efficient specialisation (in the manner of a core-periphery structure) is more evident in granular instrument and maturity types. At the same time, still-negative values of assortativity at aggregate levels suggest that some degree of specialisation is observable even at the aggregate.

These network characteristics illustrate that credit and funding events can be expected to be widespread in the interbank market, because institutions are close to each other and well connected. At the same time, the systemic impact of such contagion crucially depends, among other things, on

[16] Some rows show that the sample size of banks is 54. One bank did not report its interbank exposure and therefore reporting banks are only 53, on exposures on other 54 banks.

the nature of the initial shock, the size of exposures, banks' initial capital levels and the extent to which flows can be substituted.

3.2. Banks' local importance

Risk in the banking system is a summary concept, which incorporates individual facets of constituent parts' resilience and interaction. Portraying the banking system as a network of funding relationships is one way to nuance systemic risk analysis by explicitly addressing more granular sources of risk, particularly those stemming from the interaction among banks.

The centrality of a bank helps to refine the notion of its systemic importance. The distribution of banks' local centrality helps to identify particularly fragile components of the network. Many measures of banks' local centrality are available; this analysis focuses only on those measures with clear economic meaning. The Basel Committee on Banking Supervision (BCBS, 2011) has broadly characterised the relevant dimensions of systemic importance as size, interconnectedness, substitutability, each of which incorporates the idea of centrality.[17]

Centrality measures can be grouped into three categories:

1. **Connectivity**, which captures the importance of a bank's activity within the network. The most basic centrality measure is a bank's degree: the number of links from that bank to other banks. A bank's degree can be weighted in various ways, such as by the relative importance of connected banks. One notable example is PageRank centrality, which improves on the already more sophisticated measure of eigenvector centrality.[18] Additional measures take account of the role (giver or receiver) of the bank in providing funding; examples include the HITS (hyperlink-induced topic search) hub and authority centrality measures.
2. **Proximity**. When considered in relation to providers of funding, this measure captures banks' relative importance as suppliers of funding in the interbank market. In terms of banks as fund-takers, this measure accounts for the potential impact of a bank's failure, since a close bank in the 'receiving' network is more likely to generate contagion. Closeness centrality takes account of the direction and size of the exposures.
3. **Betweenness**, which captures banks' uniqueness as intermediaries between other banks, thereby proxying the extent to which a bank's intermediation is substitutable. A slightly more generalised version of this measure is load centrality.[19]

[17] The BCBS's methodology for identifying systemically important banks also refers to cross-jurisdictional activity and complexity.

[18] As intermediate notions, a node's eigenvector and alpha/bonacic centralities depend on the centrality of the other nodes to which this node is connected. As with PageRank, a bank will have a higher eigenvector/alpha/bonacic centrality when its counterparties are more central.

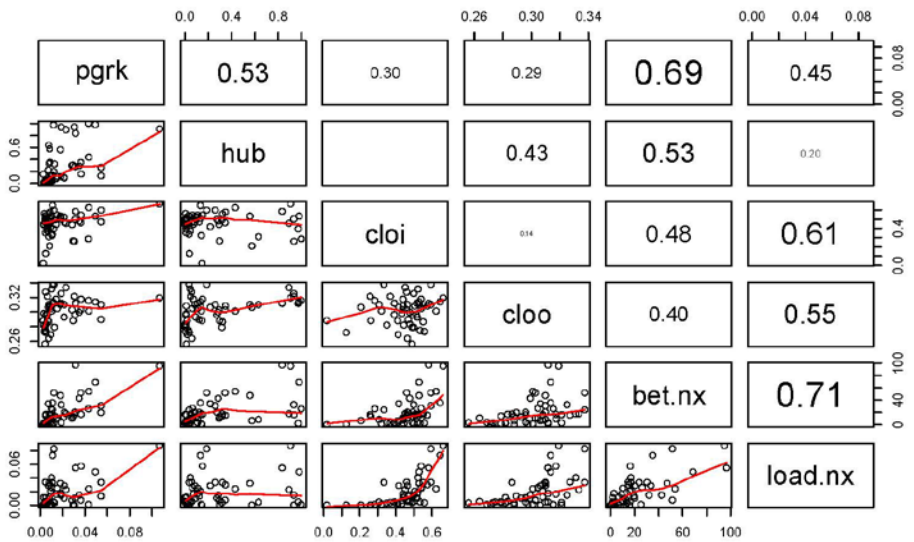
[19] Load centrality is specified via a process whereby each bank sends a unit amount of funding to each other bank. Starting from the respective source, funding is always passed to adjacent banks closest to the target, and in case there is more than one such bank, funding is divided equally among them. The total amount of funding passing through a bank during all these exchanges defines its load. See Brandes (2008).

Observable measures of centrality and a summary illustration of banks' importance

We compute several measures of centrality, along these three categories of systemic importance. A subset of six measures are selected on the basis that they are sufficiently different from each other. Chart 4 shows the remarkably correlated distributions of these measures, suggesting that they capture a common concept of systemic importance.

However, notable differences remain: some banks are central according to one measure and not another. Closeness (*cloi* and *cloo* in Chart 4), for example, is substantially different from connectivity (*pgrk*), highlighting that banks that are connected are not necessarily those that are close to one another, both in terms of exposures (*cloo*) and funding (*cloi*). A bank's closeness is more strongly correlated with its betweenness (*bet*) rather than its connectivity, reinforcing the idea that the location of a bank within the network is important. Thus both betweenness and connectivity are important within a more general measure of importance.

Chart 4: Correlation of network centrality measures



Source: ESRB, EBA and national supervisory authorities.

Note: The measures of centrality displayed for illustrative purposes are those substantially different from one another (i.e. with correlation less than 0.75). PageRank (pgrk) and the HITS hub centrality capture the magnitude of the network relationships. The inward (funding - cloi) and outward (exposure - cloo) measures represent a bank's closeness, whereas betweeness and load measure a bank's substitutability. The Pearson correlation is reported in the upper part, and the locally-weighted polynomial regression in the lower part of the matrix.

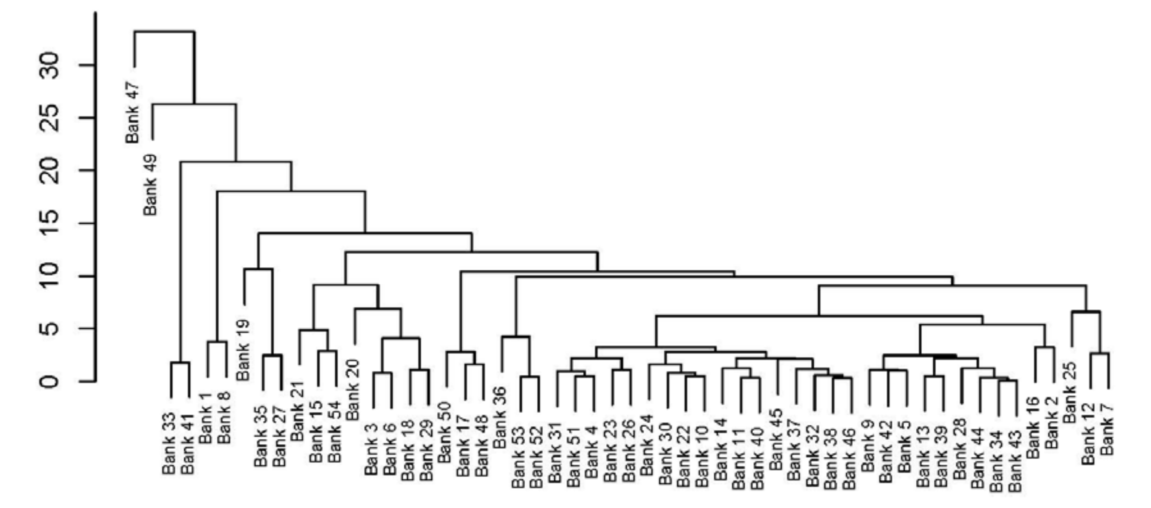
Cluster analysis can be used to summarise the key information provided by these six centrality measures. Chart 5 visually identifies systemically important banks according to the six centrality measures considered jointly.[20] However, the chart falls short of providing a numerical ranking of

[20] One could alternatively aggregate centrality measures for capturing a relative unique scaling of banks, for example, although no unique manner of aggregating the six measures (and therefore a unique ranking) exists – a problem of multidimensionality.

banks' systemic importance, for which information on the entire banking network would be a precondition.

A few distinct players in the network can be identified by their high location on the tree, which corresponds to high centrality across the six measures. In addition, banks that are 'close' in the six-dimensional space are bundled within branches. Banks 47 and 49, for example, have high overall importance in the network, whereas banks 52 and 53 show relatively low system wide importance. Banks 19 and 25 are also systemically important, but are in different branches of the tree from 47 and 49, implying that they are important in different ways, as captured by the six centrality measures.

Chart 5: Dendrogram of network centrality measures



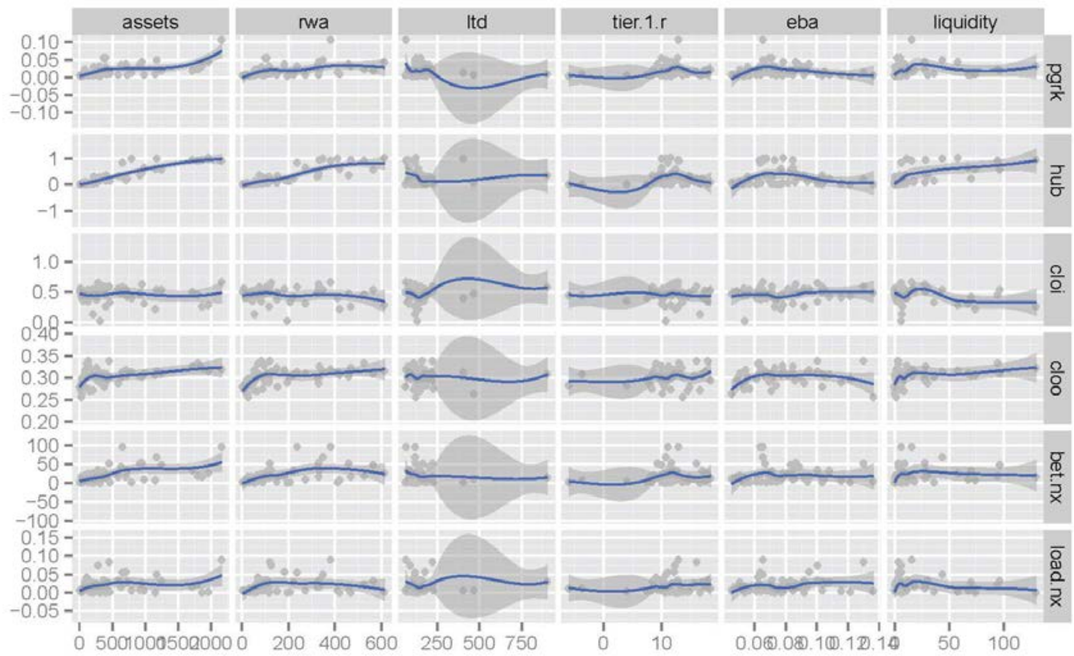
Source: ESRB, EBA and national supervisory authorities.

Note: Clusters are found over the space spanned by the six measures of centrality. The metric used is the Mahalanobis distance, which differs from the Euclidean distance in that it takes into account the correlations of the data set, is scale-invariant, and thus addresses multivariate scale size more effectively. The clustering algorithm uses the 'average' method. In addition to graphically representing the similarity of banks (captured by their location within a containing branch), the method graphically identifies banks that numerically have shown (not reported) to be important in the six-dimensional space spanned by the centrality measures.

In addition to 'pure' centrality measures, banks' individual characteristics partly determine their relative systemic importance, and therefore nuance the notion of centrality. Measures of banks' size, riskiness, business model and liquidity are expected to contribute to banks' systemic importance.

Certain bank characteristics are not perfectly correlated with network centrality measures (see Chart 6). Bank size measured by total assets (*assets*) or risk weighted assets (*rwa*) is positively correlated with centrality measures. However, no significant relationship emerges between the six centrality measures and either the loan-to-deposit ratio (*ltd*) or the EBA 2011 stressed capital ratios (*eba*). The correlation between centrality measures and robustness, as measured by the tier 1 ratio (*tier.1.r*), might be expected to be positively correlated at higher values, but no overall pattern is evident. The proportion of liquid assets (*liquidity*) also does not provide a clear relationship: liquid assets do not seem to be a factor when considering a bank's importance, although some positive relationship emerges for certain centrality measures (*pgrk* and *hits.h.nx*).

Chart 6: Centrality measures and bank characteristics



Source: ESRB, EBA and national supervisory authorities.

Note: The lines represent the generalised linear fit and the standard confidence interval is shaded in each case. The bank characteristics considered capture size (total assets, risk weighted assets), business model (loan to deposit ratio), riskiness (tier 1 ratio and EBA 2011 stressed capital ratio) and liquidity (liquid assets). The variables considered are only those made available for the exercise, and may be subject to limitations, as suggested for example for RWA by Le Leslé, V. and Avramova, S. (2012).

Banks' characteristics may explain, however, their tendency to connect with similar banks. The tendency for similar nodes to connect with each other is known as *assortativity*, and can be measured by the homophily coefficient. Table 2 shows the value of this coefficient for six bank characteristics. A more negative observation indicates a core-periphery-type structure for that variable. For example, banks' degree (a measure of connectivity) shows a negative value of homophily (-0.17). The interpretation is that more connected banks (with a higher degree) tend to be connected to less connected banks (with a lower degree). That is, banks tend to have links to and from banks that do not have the same level of relations in the network.

Similarly, large banks tend to be connected to small banks, although the strength of disassortativity is lower (shown by the homophily coefficient of -0.053). Disassortativity is even weaker for the loan-to-deposit ratio (homophily coefficient of -0.007). By contrast, homophily coefficients for all measures of bank risk (EBA 2011 stressed capital ratio, tier 1 ratio, liquidity) are positive, which indicates that robust (liquid) banks tend to connect to other robust (liquid) banks.

In all cases, the homophily coefficients generated by balance sheet variables are smaller (in absolute terms) than the homophily coefficient due to banks' degree. That is, no balance sheet variable creates a disassortative core-periphery-type structure of relations between banks more strongly than network degree. This insight suggests that network measures play a strong role in explaining network structure, beyond simple balance sheet variables. No balance sheet variable considered in Table 2 is stronger in either 'pulling' or 'repelling' similar banks than their degree.

Table 2: Indicators for the tendency of banks to associate with similar banks

Assortativity characteristic	Value (homophily coefficient)
Degree	-0.170
Total assets	-0.053
Loan to deposits ratio	-0.007
EBA 2011 stressed capital ratio	0.041
Tier 1 ratio	0.101
Liquidity	0.048

Source: ESRB, EBA and national supervisory authorities.

Note: Assortativity measures the level of homophily (or tendency of banks to associate with similar banks) in the network, based a given bank characteristic. A high positive coefficient indicates that connected banks tend to have the same characteristic, whereas a negative coefficient indicates the opposite. Homophily lies between 1 and -1; no significance level can be assigned and they support only a relative and linear comparison.

3.3. Communities in the interbank market

Assortativity captures the tendency of banks to associate with similar banks, where 'similarity' can be variously defined. Since assortativity is non-zero for all bank characteristics shown in Table 2, we may tentatively infer (albeit in the absence of time series data) that the process by which banks form links with each other is not random, but rather governed by a function which partly depends on banks' characteristics.

Given this non-random link formation process, we should expect banks to cluster in communities, according to their relative characteristics. By definition, banks in one community are more connected to each other than to other banks in other communities. Identifying these communities is thus economically meaningful, and allows policymakers to assess the impact of shocks to the interbank market with more precision. Characterisation of communities may also allow for better-targeted policy measures to increase network resilience.

The simplest set of communities in a network may be identified by clusters. More involved procedures include the edge-betweenness method; the spin glass model; label propagation; short random walks; and the info map algorithm. These methods are described in the notes of Table 3. The number of identified communities varies, depending on the method used.

Usefully for policymakers, identified communities could be analysed with respect to types of banks. For example, future work could compare communities to banks' geographic location. Such comparison would reveal the geographic areas that are more connected, and therefore the risks of cross-border contagion. This would offer better insight into potential contagion patterns resulting from shocks, since propagation is more likely to occur within bank communities than across them.

Table 3: Communities of large EU banks

Method for detecting bank types	Number of communities
Clusters (strong)[1]	2
Edge betweenness[2]	1
Spin glass[3]	6
Label propagation[4]	2
Walk trap[5]	11
Info map (total assets as bank weight)[6]	4

Source: ESRB, EBA and national supervisory authorities.

Note: The six methods for detecting bank types are defined as follows.

(1) The maximal strongly connected components of the interbank network define clusters. A component is a maximally connected sub-graph if the addition of any other bank would ruin the property of connectivity.

(2) Groups of banks densely connected themselves but sparsely connected to other groups are identified. Gradually removing edges with the highest edge betweenness scores results in a hierarchical map, a rooted tree, called a dendrogram of the graph, see Girvan and Newman (2002).

(3) A ground state of an infinite range spin glass is found, whereby community structure is interpreted as the spin configuration that minimizes the energy of the spin glass with the spin states being the community indices. The properties of such 'ground state configuration' give concise definitions of communities as cohesive sub groups, see Reichardt and Bornholdt (2006). Comparing the bank communities on a numeric basis, Rand (1971) provides some evidence that there are between two and six communities in the interbank market, and suggests that the spin-glass method may be closer in capturing these.

(4) This method works by naming banks uniquely and then updating the names by majority voting in the bank's neighbourhood. At every step banks are renamed with the name most of its neighbours have at that stage. In this iterative process densely connected groups of banks form a consensus on a unique name and thus form a community, see Raghavan, Albert, and Kumara (2007).

(5) Densely connected groups of banks (or sub-graphs) are identified via random walks, under the premise that short random walks tend to stay in the same community, see Pascal Pons and Latapy (2005).

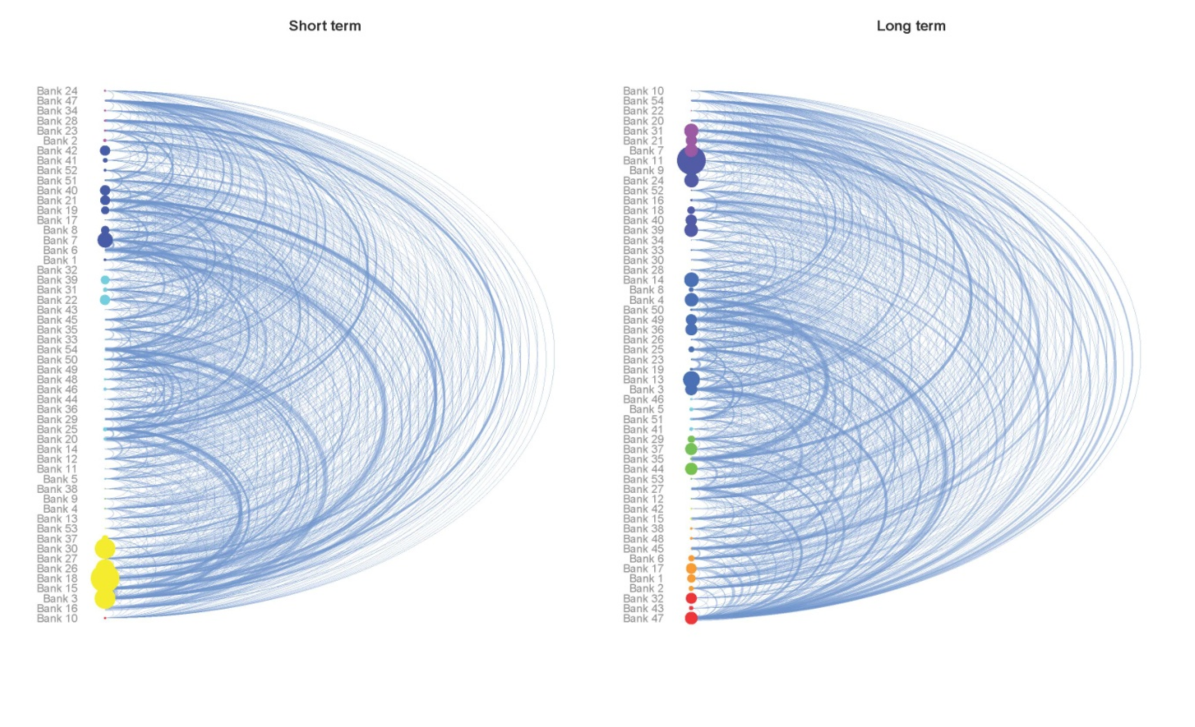
(6) The expected description length of a random walker trajectory is maximised. Links in a network induce movement across the network and result in system-wide interdependence. In doing so, it is acknowledged that most networks carry flow. A map equation is used to highlight and simplify the network structure with respect to this flow, and an algorithm efficiently decomposes large weighted and directed networks based on the map equation. See M. Rosvall, D. Axelsson, and C. T. Bergstrom (2009).

Chart 7 provides a first cut of banks' connections within and across communities. In Chart 7, the vertical axis consists of the 53 banks (represented by circles), which are ordered and colored according to communities of banks identified by the spin-glass method.[21] Table 3 shows that the spin-glass method identifies six communities in the full network of interbank exposures. Chart 7 splits this full network into sub-networks of short-term exposures (in which there are six communities) and long-term exposures (in which there are 10 communities). This suggests that different communities of banks exist for different types of funding activities. The size of the circle representing each bank is proportional to the bank's betweenness centrality (see section 2.2), showing that different banks are

[21] The spin-glass method is chosen for illustrative purposes even though any method identifying different communities would be sufficient to illustrate differences of communities depending on the functionality of the network analysed.

central within each network. Arc network representations of short- vis-à-vis long-term interbank exposures highlight the different structure of the two networks.

Chart 7: Interbank exposures shorter and longer than one year



Source: ESRB, EBA and national supervisory authorities.

Note: The arc representation displays the distinct nature of short- versus long-term exposure. This is evident in the different communities (identified by bubbles' colour). Moreover, within communities different banks are in the core and the periphery (in terms of the betweenness centrality measure, which fixes the size of the bubble).

3.4. Conclusions on network fragility measures

This section has established four principal results, which are summarised here.

First, the network depicts a very high level of activity among large EU banks operating across national borders, in contrast to studies based on national markets alone. In particular, the tiered structure typically found in national interbank markets does not exist to the same extent internationally. This result is a consequence of the high importance of all 53 banks in the sample, which would probably be in the first tier (core) of their respective national interbank markets.

Second, and partially qualifying the first point, a few banks stand out with regard to their systemic importance, in terms of their activity, control and independence. While the particular form of centrality that these institutions exhibit varies, these banks play a particularly important role in this market and their activity is likely to be difficult to substitute.

Third, the centrality of the banks in the system does not appear to be strongly related to banks' overall soundness, liquidity or size, which suggests that unique network characteristics exist. This notwithstanding, connected banks weakly tend to be of a different size and exhibit similar robustness.

Fourth, no unique structure explains banks' interconnections in the sample, as identifiable bank communities vary depending on the method used. That being said, it is likely that about six communities exist. Identifying communities may be useful for future work to characterise the resilience of both the sub-networks and the network as a whole to shocks affecting some of the communities.

Notwithstanding these important results, the systemic fragility of the interbank market ultimately depends on the nature of the shocks affecting it. Evidence presented in this section on whether systemically important banks act as shock absorbers or shock propagators is not conclusive. Banks' robustness in terms of capital, and their potential role as shock propagators, is analysed in more depth in the next section.

Section 4: Default and liquidity simulation[22]

This section assesses the potential consequences of solvency and liquidity contagion in the European banking system. Consistent with the literature (see Box 1 in Section 1), the analysis consists of several scenarios: first modelling solvency problems only as triggers of contagion; and second considering solvency and liquidity problems jointly.

4.1. Definition of the scenario and methodology

Default simulation within financial networks consists of two distinct components: an initial shock and a contagion mechanism. The initial shock is the trigger. The contagion mechanism is the means by which losses propagate from the initial shock. Different scenarios can be assumed, focusing on different contagion mechanisms (such as interbank exposures, equity cross-holdings or fire sales of common exposures) and making different assumptions (for example, on the rate of loss given default).

Initial shock

First, we define the initial shock, which incorporates both idiosyncratic and common components. A tractable idiosyncratic shock consists of the failure of one (and only one) of the banks in the sample; with 53 banks, there are 53 such scenarios. Each bank fails due to a loss on its non-interbank assets, the magnitude of which depends on an exogenous recovery rate. This begs a parameter choice with respect to the recovery rate. However, the extant literature highlights the difficulty of reaching consensus on a reasonable value for the recovery rate. James (1991) and Furfine (2003), for instance, propose LGD rates of 30% and 5% respectively; ranges of 15%-45% are found in the 2011 EBA stress test. In order to maintain agnosticism with respect to this parameter choice, we compute results with LGDs from 0-100%. Nevertheless, LGD rates above approximately 45% in the interbank market may be considered extreme.

This idiosyncratic shock is complemented by an exogenous common shock to the value of non-interbank assets. The intuition behind imposing a common shock is that lower real economic activity lowers the value of all banks' claims, thereby weakening all banks' capital positions, potentially triggering contagion within the banking system. Given that no granular information is readily available on banks' non-interbank assets, it is difficult to incorporate a sophisticated common shock. As a tractable solution, we model a common shock to all non-interbank assets in equal proportion (and therefore implicitly assuming perfect correlation across asset classes). For the purposes of retaining some agnosticism over the level of this common shock, results for losses of between 0% and 4% on non-interbank assets are shown.

As a benchmark, in the 2011 EBA stress test, the most affected bank's change in its core tier 1 capital ratio over 2010-12 was -18%.[23] If this single worst movement were applied to the whole banking system, it would correspond to an aggregate loss of 0.8% on total assets. Consequently, a common loss of approximately 1% on the value of non-interbank assets may be considered as a relatively severe shock.

[22] The main contributors to this chapter were Jean-Cyprien Heam, Franka Liedorp and Santiago Tavolaro.

[23] European Banking Authority 2011 EU-wide stress test aggregate report (July 15 2011), page 11 chart 8.

Solvency contagion mechanism

Second, we define the solvency contagion mechanism. The literature on solvency contagion takes two distinct approaches: the iterative default cascade approach and the clearing payment vector approach (see Upper (2011) for a survey):

- The *iterative default cascade* approach is based on two rules (Furfine, 2003). First, a bank defaults when its capital falls below a given threshold. Second, when a bank defaults, all its counterparties suffer a loss on their direct exposures. The algorithm derives counterparty losses, round by round, until no further bank defaults.
- The *clearing payment vector* approach is based on the insight that repayments are complementary goods (Eisenberg and Noe, 2001). In the event of default, increasing the repayment of one bank helps its counterparties to repay their own debts. This approach, which relies on Merton's model of firm value, endogenously generates recovery rates on interbank exposures (see Gourieroux et al. (2012); Gourieroux et al. (2013); Demange (2012)).

The clearing payment vector approach is adopted here. This approach is most suitable: solvency contagion is a purely mechanical exercise, based on balance sheet structures, where a bank's behaviour does not play a role. Given values of non-interbank assets and bilateral interbank exposures, banks' capital and debt values are endogenously computed for each scenario of hypothetical bank default. The solvency contagion mechanism is then applied. Some banks may incur losses that exceed their capital. A creditor sustains a loss only if its debtor's capital is insufficient. Low capital levels indicate a fragile balance sheet, but do not imply losses for banks' creditors. The magnitude of the loss incurred by a failing bank's creditors depends on the debtor's loss. Box 2 provides an illustrative example of this solvency contagion model.

Box 2: Solvency contagion mechanism

If bank A defaults and is liquidated, all creditors of bank A recover a payment based on bank A's remaining assets, in proportion to the size of their nominal claims (assuming equal ranking between creditors). Banks that are exposed to bank A will be impacted; others will not be directly affected. If a new bank defaults due to these losses, a new wave of losses will spread through the system (and so on).

Table 4 illustrates an example with two banks (A and B). The balance sheet representation of bank A (under the heading 'Before shock' in Table 4) is simplified for the exercise. The interbank liabilities of bank A are supposed to be held entirely by bank B. Bank B and external (non-bank) creditors, exposed to the defaulting bank A, will incur a loss on their claims on bank A. Depending on bank B's balance sheet, this loss may cause bank B to default. External creditors' effects on the financial system are not taken into account here, given that no particular information is available beyond banks A and B.

Consider that bank A incurs an initial loss rate of 20% on its non-interbank claims. In the first instance, this loss is absorbed by bank A's capital (5), which is entirely eroded. This leaves a loss of 15 (= 20% x (100-5)) which cannot be absorbed by bank A's capital holders, and must therefore be distributed among bank A's creditors. Bank A's creditors (including bank B and non-bank creditors) recover a payment from bank A's remaining assets in proportion to the size of their claims on bank A (see 'After shock' in Table 4).

Table 4: Bank A's balance sheet

Before shock				After shock			
Assets		**Capital and Liabilities**		**Assets**		**Capital and Liabilities**	
		Capital	5			Capital	0
External Assets	100	External Liabilities	85	External Assets	80	External Liabilities	72.9
Interbank Assets	10	Interbank Liabilities	20	Interbank Assets	10	Interbank Liabilities	17.1
	110		110		90		90

In this numerical example, bank A's loss of 20 on external assets implies recovery of 110 – 20 = 90 for the remaining creditors. Compared with the value of their initial claim (105), bank A's creditors therefore suffer a loss of 105 – 90 = 15, which translates into a loss rate of 15 / 105 ≈ 14%.

With the *pari passu* assumption, this loss rate of 14% applies equally to bank A's creditors (including other banks and 'external' non-bank creditors). Thus the value of other banks' claims on bank A decrease by 20 * 0.14 ≈ 2.9 to 17.1, and that of non-banks' claims by 85 * 0.14 ≈ 12.1 to 72.9.

The loss (recovery) rate is thus endogenous to the change in the value of assets. If this loss, at any step, is fully offset by a bank's capital buffer, then under this framework the bank is not in default. The capital level simply decreases by the amount of the loss, while other liabilities remain unchanged.

Liquidity contagion mechanism

Large capital losses have direct and immediate consequences for banks' liquidity positions. To capture this mechanism, a liquidity contagion channel is also modelled. Liquidity risk can be analysed from two perspectives: fire sales on the asset side; and reduced wholesale funding on the liability side. The analysis in this paper focuses on the wholesale funding channel.

The wholesale funding channel is modelled by adding a behavioural heuristic to the solvency contagion process, whereby banks that have a low solvency ratio (but are nevertheless still solvent) face a shortage of short-term interbank loans, since other banks perceive that counterparty risk has increased. This perception induces other banks to reduce their exposure to the deteriorating bank. Weak banks are thus able to rollover only some of their short-term interbank liabilities.

In order to meet this funding shortfall, weak banks could sell liquid assets outright. However, we assume that banks respond to shocks by trying to preserve their business model, which would be violated if asset composition were to substantially change. The alternative strategy is for banks to engage in repurchase agreements, in which they receive cash in exchange for liquid securities. By assumption, the supply of reverse repos is relatively stable, since repos tend to be overcollateralized and therefore somewhat insulated from counterparty credit risk (Gorton and Metrick, 2010a).

Weak banks' ability to respond to a funding shortfall by engaging in repurchase agreements depends on their holdings of liquid assets relative to their funding shortfall. If liquid assets are inadequate, the bank defaults due to the funding shortfall. Where such defaults occur, the solvency contagion mechanism is applied (see box 2), which might then lead to further solvency and liquidity contagion.[24]

The liquidity contagion mechanism depends on four parameters:

1. The event which might trigger funding withdrawal is bank-specific. Unfortunately, there is no strong empirical evidence that points to a level of solvency below which funding problems arise. Nevertheless, an intuitive threshold under which all banks would be perceived as weak might be the regulatory minimum capital ratio. Two potential thresholds are considered: core tier 1 capital ratios of 5% and 7%.
2. A conservative assumption (with respect to the 2011 EBA stress test exercise) is that the weakened bank is able to roll-over some quantity (less than one but greater than zero) of its short-term interbank funding. This also implies that other bank counterparties decrease their short-term exposure by the amount which is not rolled over.
3. The short-term funding shortfall needs to be filled by repurchase agreements. Since repos tend to be overcollateralized, we impose a conservative haircut of 20% on the transfer of securities (see, for example, Gorton and Metrick (2010b) and Dang et al. (2011)).
4. If a bank does not have enough liquid assets, that bank defaults with an exogenous loss for its creditors. In the algorithm, this loss given default is applied to solvent banks (whose assets are higher than their non-capital liabilities) that only suffer from liquidity problems. We assume a conservative liquidity-based LGD of 20% (see James (1991) for evidence from US banks).

Box 3: Liquidity contagion mechanism

Recall bank A's balance sheet from Box 2 (reproduced in Table 5, 'Before shock'). In addition, consider that holdings of liquid assets are 30. Assume that the default of another bank reduces the value of bank A's interbank claims from 10 to 7. This loss of 3 is absorbed by bank A's capital, which reduces to 5 – 3 = 2. Bank A's leverage ratio would therefore fall from 5/110 = 4.5% to 3/107=2.8%. For illustration, consider that bank A's risk-weighted assets to total assets is 50%. In this case, bank A's risk-weighted solvency ratio would fall from 9% to 5.6%.

Under the assumptions of the liquidity contagion mechanism, bank A's weak solvency ratio of 5.6%, which is below the upper threshold of 7%, prompts other banks to reduce their lending to bank A. In this numerical example, bank A's short-term interbank funding therefore falls from 15 to 3.75, which corresponds to a 75% decrease. The resulting funding gap of 15 – 3.75 = 11.25 must be filled by new repurchase agreements. Here, we assume a 25% haircut, such that EUR1 of cash must be exchanged for EUR1.25 of liquid securities. The bank therefore needs 11.25 / (1 – 0.25) = 15 of liquid assets in order to obtain 11.25 of cash.

In this case, bank A holds 30 of liquid assets: sufficient to cover its requirement (15). Bank A successfully enters into repo contracts to fill its funding gap. In Table 5, bank A's balance sheet is shown according to IFRS accounting standards (in the simplified case of a zero repo rate). After the shock, external liabilities increase by 11.25 from 85 to 96.25 due to the repurchase agreement. Liquid assets remain at 30, although 15 of these

[24] A sequential approach is used: after the initial solvency mechanism, the liquidity channel is at work. If the liquidity channel results in further defaults, the solvency mechanism is run again, followed by the liquidity channel, and so on, until no further defaults occur.

liquid assets have temporarily been transferred to the counterparty on the other leg of the repo.

However, if bank A held less than 15 of liquid assets, the bank would not be able to obtain sufficient cash from repurchase agreements to fill its funding gap. The bank would be unable to fund its assets and would default. This case is shown in Table 6, with an example in which liquid assets before shock are 5.

Table 5: Bank A's balance sheet – high level of liquid assets

Before shock				After shock			
Assets		**Capital and Liabilities**		**Assets**		**Capital and Liabilities**	
		Capital	5			Capital	2
External Assets	100	External Liabilities	85	External Assets	100	External Liabilities	96.25
Of which Liquid	*30*	Interbank Liabilities	20	*Of which Liquid*	*30*	Interbank Liabilities	8.75
Interbank Assets	10	*Of which Short Term*	*15*	Interbank Assets	7	*Of which Short Term*	*3.75*
	110		110		107		107

In Table 6, the initial default of another bank causes a loss of 3 for bank A, as in Table 5. Consequently, 75% of bank A's short-term interbank creditors do not roll-over their funding, reducing bank A's short-term liabilities from 15 to 3.75. Unlike in Table 5, bank A's liquid external assets of 5 in Table 6 are inadequate to fund the necessary quantity of repos (i.e. 15). As a result, bank A defaults, triggering the solvency contagion mechanism (Box 2), with an assumed exogenous LGD of 20% on external assets.

The loss of 100 * 0.2 = 20 on external assets leads to a liquidation process, based on an asset value of 87 (80 of external assets and 7 of interbank assets). Outstanding liabilities total 93.75, which implies a recovery rate of 87/93.75=92.8%. External creditors therefore recover 85*92.8%=78.9 and interbank creditors recover 8.75*92.8%=8.1 (see "After shock" in Table 6).

Table 6: Bank A's balance sheet – low level of liquid assets

Before shock				After shock			
Assets		**Capital and Liabilities**		**Assets**		**Capital and Liabilities**	
		Capital	5			Capital	0
External Assets	100	External Liabilities	85	External Assets	80	External Liabilities	78.9
Of which Liquid	*5*	Interbank Liabilities	20	*Of which Liquid*	*5*	Interbank Liabilities	8.1
Interbank Assets	10	*Of which Short Term*	*15*	Interbank Assets	7	*Of which Short Term*	*3.5*
	110		110		87		87

Application of the methodology to interbank exposures data

We apply this methodology for solvency and liquidity contagion (boxes 2 and 3) to the dataset on interbank exposures (see Section 2). Exposures are defined as the total of credit claims, debt securities, other assets, derivatives and off-balance-sheet items. This set of instruments is larger than usual in most of the extant literature, given that it also includes off-balance-sheet exposures. Moreover, exposures are overestimated since the data do not include collateralization. The exercise therefore corresponds to a conservative stress test.

The methodology requires us to distinguish interbank assets from external assets. External assets are calculated as the difference between total assets and reported interbank exposures. Moreover, the methodology for the liquidity contagion mechanism requires distinction between interbank exposures with residual maturity of less than one year (short-term) and more than one year (long-term). Finally, nominal debt is defined as the difference between total assets and tier 1 capital.

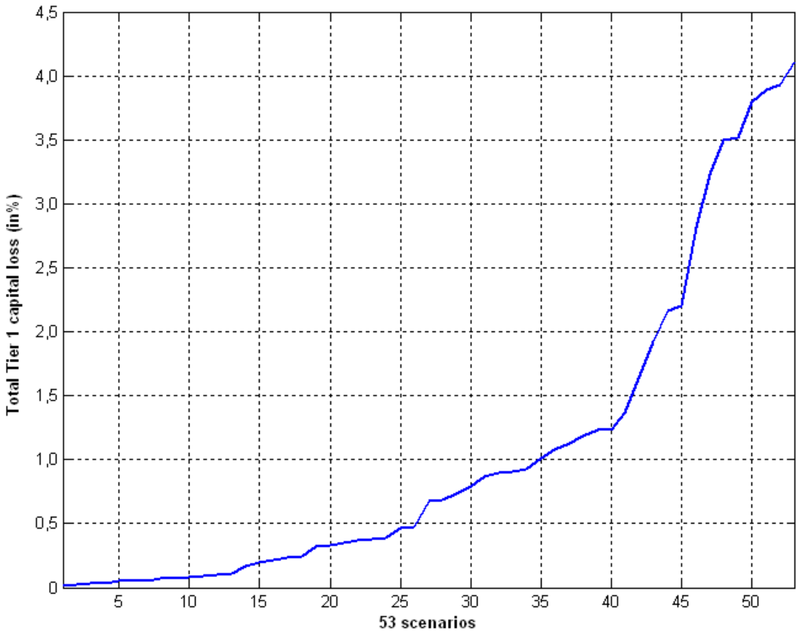
4.2. Results

We first present results of simulations using only the solvency contagion mechanism, distinguishing between scenarios with and without a common shock. Results point to two aspects of systemicity (importance and fragility) that appear to be correlated with credit ratings. Second, the liquidity component is added in order to integrate banks' behaviour into the framework.

Solvency contagion and idiosyncratic shock

In the first instance, the common shock is set at 0%, such that the scenarios are based only on idiosyncratic shocks. Chart 8 shows the results. The vertical axis shows the total (system-wide) tier 1 capital loss as a percentage of total tier 1 capital, given default of one of the 53 banks. The horizontal axis shows the 53 scenarios (53 bank defaults), in ascending order of the severity of the resulting system-wide capital loss. For example, the 25th scenario with the lowest impact generates losses that are slightly less than 0.5% of total banking system tier 1 capital. A loss lower than 1.5% occurs in 40 scenarios; the highest loss is just above 4.0%. Interestingly, the system-wide capital loss rises nonlinearly after the 40th scenario. This suggests that approximately 13 banks stand out as systemically more important, in the sense that their default would trigger disproportionately large losses for other banks in the system.

Chart 8: Total Tier 1 capital loss over initial Tier 1 capital (%) (no common shock; idiosyncratic shock with LGD = 100%)



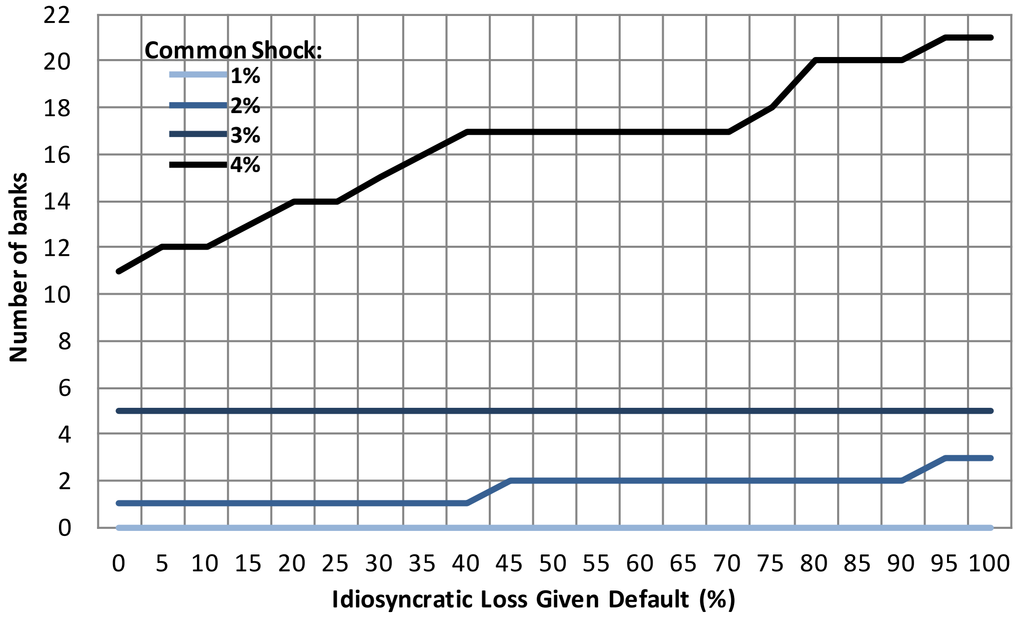
Solvency contagion and common shock

The idiosyncratic shock scenarios are very informative about the effect of hypothetical individual defaults, but give few clues as to the effects of such defaults during a crisis.

To capture the effect of a crisis, we impose a common shock across all banks' external assets in addition to an idiosyncratic default. Chart 9 presents the evolution of the number of banks that would default under at least one scenario according to two dimensions: the magnitude of the idiosyncratic loss given default (0-100%) and the magnitude of the common shock (1-4%). When the idiosyncratic LGD is 0%, the results correspond to the number of banks that would default under at least one scenario due to the effect of the common shock only. For example, a common shock of 4% on all banks' external assets would cause 11 banks to default before any contagion phenomenon is considered.

In this set-up, contagion is triggered only when the common shock is at least 2%. With the exception of the largest common shock, the number of defaulting banks is quite stable with respect to the idiosyncratic LGD. For the common shock of 4%, the number of banks which default under at least one scenario moves from 11 to 21 with the idiosyncratic LGD level.[25]

Chart 9: Number of banks in default (under at least one shock scenario) for various idiosyncratic LGDs and common shock magnitudes



Explanation: With an idiosyncratic LGD of 40%, the number of banks in default under at least one shock scenario is one (respectively 17) when the common shock is a loss of 2% (respectively 4%) on external assets.

[25] In addition to the number of banks which default due to contagion, we should be interested in the types of banks which default. For example, it is important to consider the total value of assets of banks which default. This extension is left for future research.

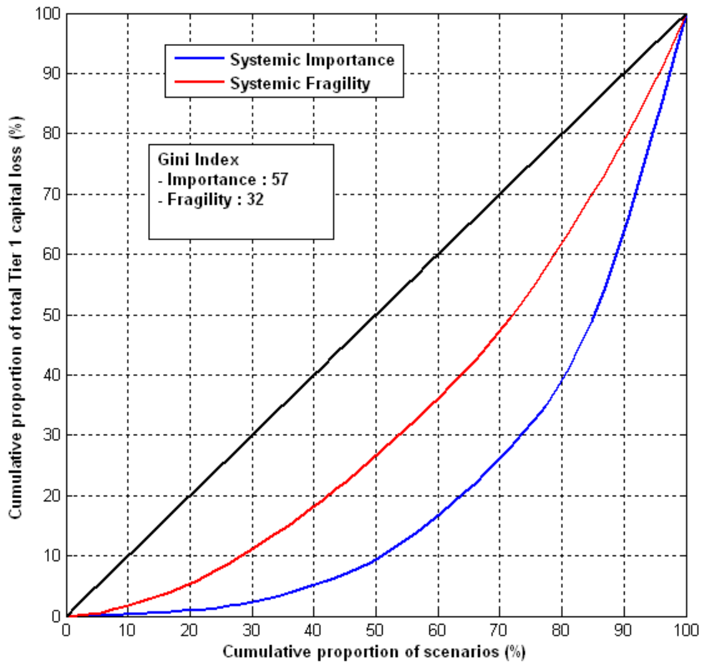
Systemic importance and fragility

Systemicity has two dimensions. First, a bank can be systemic in the sense that its default causes substantial system-wide losses ('systemic importance'). Second, a bank can be systemic in the sense that it is particularly vulnerable to the defaults of other banks ('systemic fragility'). These two concepts can be clearly identified and analysed within the approach adopted here.

Chart 10 presents the cumulative distribution of total loss (expressed as a percentage of total Tier 1 capital) in the 53 scenarios, based on a statistical measure of dispersion related to the Gini index. The shape of the curve indicates the heterogeneity of banks' relative systemicity: a curve closer to the 45-degree black line indicates less heterogeneity.

In terms of systemic importance (blue line), banks in the top 20% of systemic importance generate 60% of total losses (over the 53 scenarios). This can be inferred from the blue line's intersection with the point (80%, 40%). In terms of systemic fragility, the most fragile 20% of banks sustain 40% of total system-wide losses (from the intersection of the red line with the point (80%, 60%)). Dispersion of systemic importance is double that of systemic fragility (according to the two Gini indices). This result suggests that contagion originates from a relatively small number of systemically important banks, but propagates somewhat more homogenously throughout the banking system.

Chart 10: Dispersion: Total Tier 1 capital loss over initial Tier 1 capital (%) (no common shock; idiosyncratic shock with LGD = 60%)



Explanation: The cumulative frequency of systemic importance (blue line) and systemic fragility (red line) indicate the dispersion of these two measures relative to the 45-degree benchmark (black line). For example, the blue line intersects 10% cumulative proportion of total tier 1 capital loss at the 50th percentile of scenarios. Thus 50% of the scenarios with the smallest systemic impact generate 10% of total losses over the 53 scenarios.

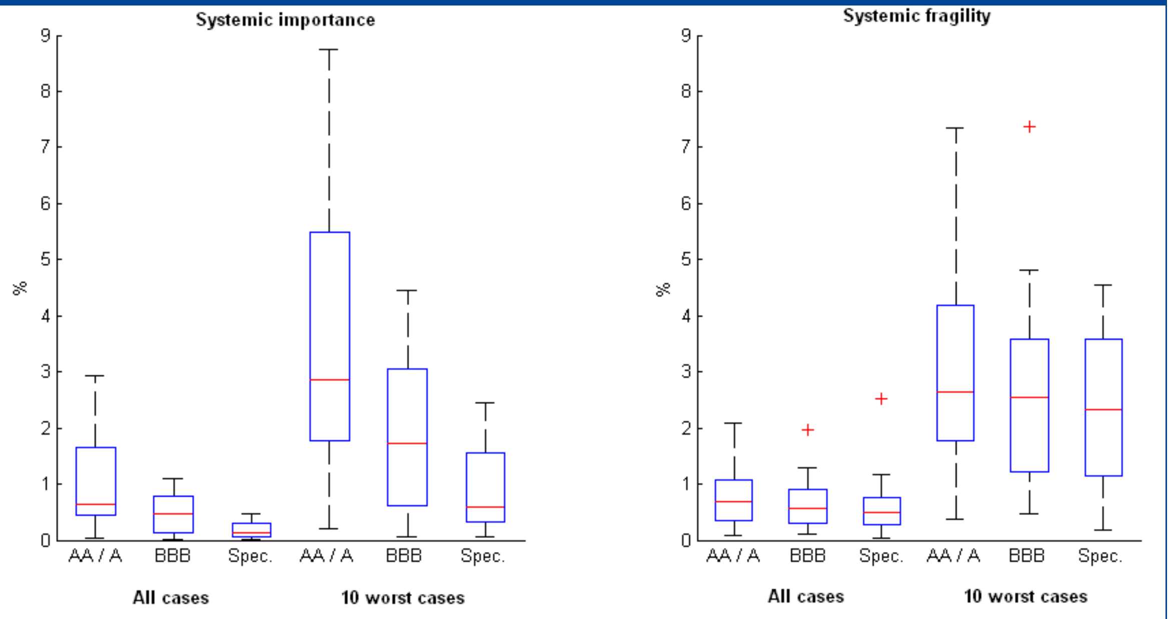
Systemicity and rating

Chart 11 reports systemic importance and systemic fragility with respect to three classes of rating (AA/A, BBB and Speculative). Matching the two dimensions of systemicity with banks' ratings provides two important insights:

1. First, more systemically important banks tend to have higher ratings, particularly in the 10 worst cases of total Tier 1 capital loss. This finding implies that scenarios in which the most systemically important banks default are less likely to occur, since these systemically important banks have higher ratings, and are therefore less likely to default.
2. Second, banks' systemic fragility is less sensitive to banks' ratings, even if worst case scenarios are considered. Thus while the probability of large system-wide losses occurring is relatively low, the system-wide impact of losses if they materialise is nevertheless relatively high. This mimics the 'robust yet fragile' property of financial systems which has been observed in the extant literature (Gai and Kapadia (2010)).

Notwithstanding these two important insights, Chart 11 presents aggregated results, and may therefore hide information contained at the bank-level. To remedy this, Chart 12 zooms in on individual banks. In the benchmark scenario, the 53 banks fall into four distinct groups in terms of whether they contribute or are exposed to system-wide losses.

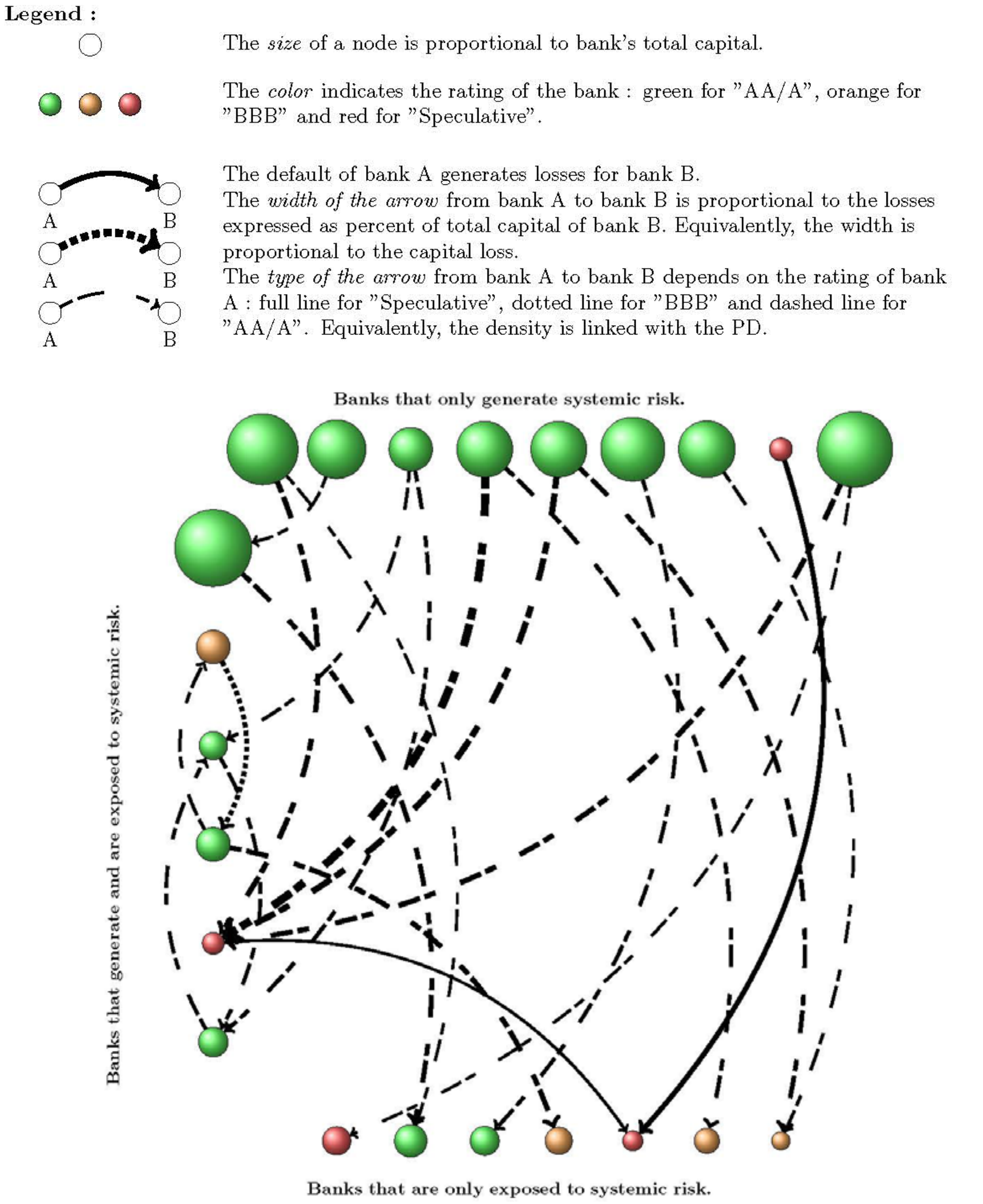
Chart 11: Total Tier 1 capital loss over initial Tier 1 capital as a percentage per rating (Common shock LGD at 0% and idiosyncratic shock LGD at 60%)



Explanation: In the worst 10% of cases, the highest rated banks generate losses with a median value slightly below 3% of total Tier 1 capital (right-hand box plot).

Box plot: the blue rectangle represents the 25% and 75% percentiles, the red line the median and the dashed line the 5% and 95% percentiles. The red crosses are outliers.

Chart 12: Sub-network of capital losses in the 53 scenarios (Loss above 10% of individual Tier 1 capital, common shock LGD = 0%; idiosyncratic shock LGD = 60%)



Notes: The size of a node is proportional to the Tier 1 capital. The rating of a node determines its colour (green for AA/A, orange for BBB and red for Speculative) and the type of arrows stemming from the nodes (a dashed line for AA/A, dotted for BBB and solid for Speculative). The width of an arrow is proportionate to the loss incurred by the target node, expressed as a proportion of its capital, from the default of the origin node (with an initial LGD of 60%). The banks that do not appear do not suffer losses over 10% of their capital, nor do they trigger a loss above this threshold.

The first group (at the top of Chart 12) represents banks that generate losses without being exposed to contagion ('systemic importance'). The second group (at the bottom of Chart 12) is formed of banks that suffer from contagion without generating it ('systemic fragility'). The third group (on the left-hand side of the figure) represents banks that are both exposed to contagion (systemic fragility) and generate losses (systemic importance). The fourth group is independent from solvency contagion.

Banks' ratings (illustrated with green, orange and red colours) provide an indication of the likelihood of financial distress at a given bank. If we focus only on those banks with speculative-grade ratings (red nodes), contagion risk is particularly pronounced from the small red banks at the top and to the left of the chart to the small red bank at the bottom of the chart. Exposures between these banks are illustrated by a solid line to show this elevated contagion risk.

Solvency and liquidity contagion

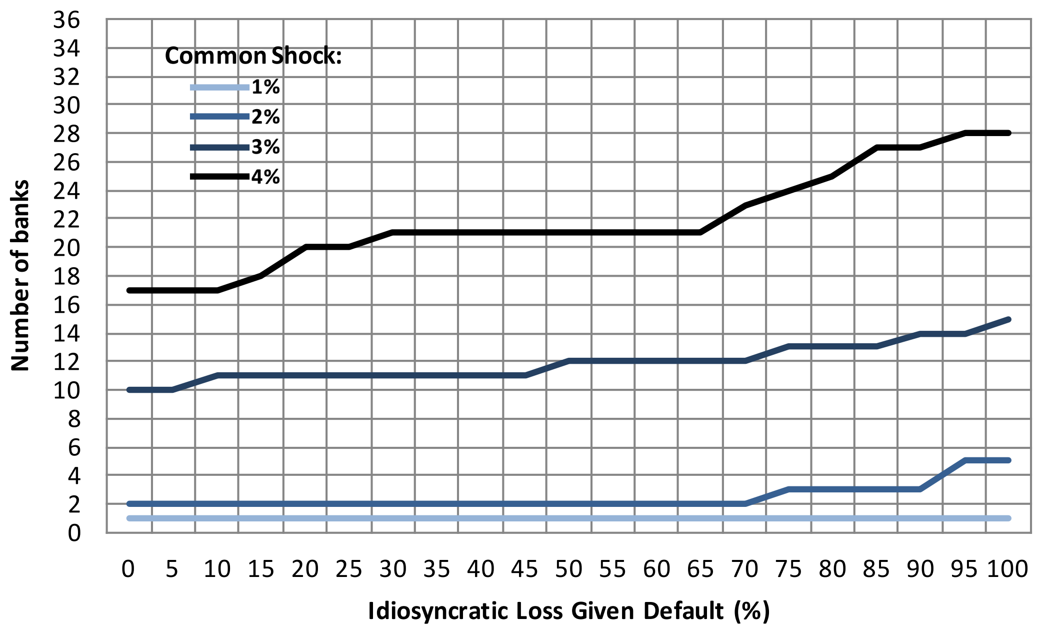
This section presents the results of the liquidity contagion mechanism in combination with the solvency contagion mechanism (see Box 3). Chart 13 illustrates the number of banks in default in at least one shock scenario. Panels A and B show the results under two critical thresholds (5% and 7% respectively) for the Tier 1 capital ratio. Below these thresholds, distressed banks are unable to roll-over some of their short-term interbank funding.

To analyse the marginal impact of the liquidity contagion mechanism, one may compare the number of banks in default owing to both solvency and liquidity contagion (shown in Chart 13) with results from pure solvency contagion (shown in Chart 9). Four findings emerge:

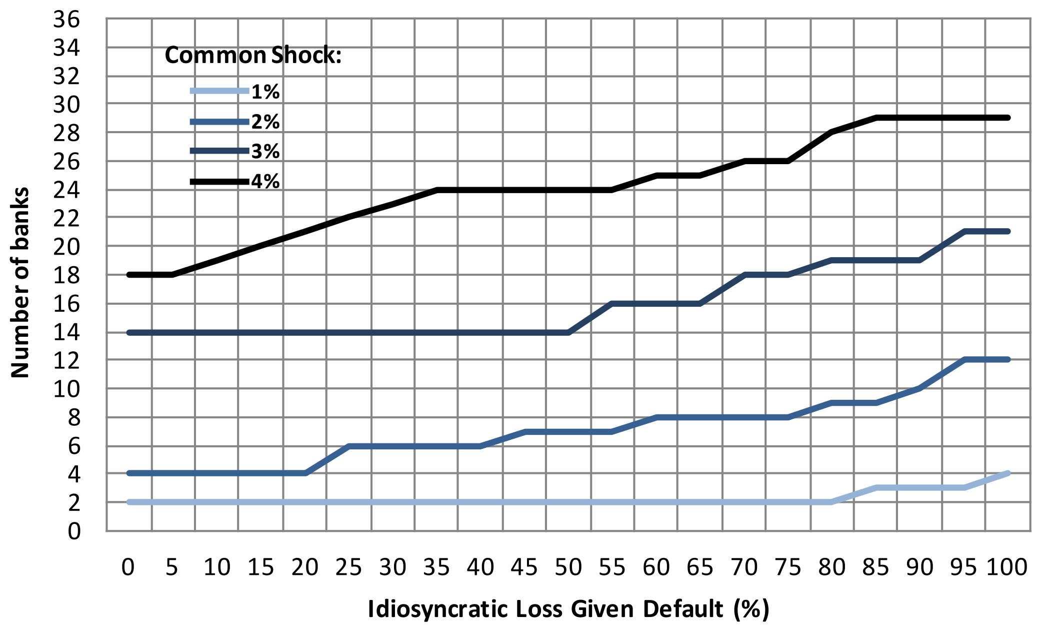
1. When the idiosyncratic LGD is 0% (such that there is no loss for the creditors of the defaulting bank), the number of banks in default under at least one scenario is substantially higher with liquidity contagion than without. For example, when the idiosyncratic LGD is set to 0% and the common shock is 4% of banks' non-interbank assets, 17 banks default under at least one scenario with liquidity contagion (based on the 5% T1/RWA threshold shown in Chart 13, Panel A), compared to 11 without (Chart 9). This result arises due to banks' pre-existing balance sheet composition: some banks are inherently fragile with respect to liquidity (for instance if their leverage ratio is high or they hold few liquid assets).
2. Sensitivity to the idiosyncratic LGD of the number of banks which default under at least one scenario is higher with inclusion of the liquidity contagion mechanism. For example, under the 7% T1/RWA threshold (Chart 13, Panel B), the number of banks which default under at least one scenario increases from four to 10 as the idiosyncratic LGD increases from 20% to 90%. The comparable increase under the pure solvency contagion mechanism (Chart 9) is from one to two defaulting banks.
3. Points 1 and 2 highlight that the marginal impact of the liquidity contagion mechanism on the magnitude of contagion is substantial. Nevertheless, the most important source of loss remains the common shock to non-interbank assets.
4. In the benchmark stress scenario (defined as a common shock of 1% and idiosyncratic LGD of 45%), no bank defaults in any scenario due to contagion, even with a Tier 1 capital ratio threshold for funding shortages set at 7%. Contagious defaults occur only for common shocks higher than 1% of banks' non-interbank assets.

Chart 13: The number of banks in default in at least one shock scenario
(with respect to the idiosyncratic LGD and common shock magnitudes)

Panel A: Funding shortage under 5% Tier 1 capital ratio threshold



Panel B: Funding shortage under 7% Tier 1 capital ratio threshold



Explanation: For a funding shortage with a Tier 1 capital threshold of 7%, with an idiosyncratic LGD of 25%, there are six (respectively 14) banks in default, in at least one scenario, when the common shock is a loss of 2% (respectively 3%) on the external assets.

4.3. Conclusions on default and liquidity simulation

This section has undertaken dynamic network analysis of the system of claims between large EU banks. The analysis is 'dynamic' in the sense that it studies the mechanisms by which contagion is transmitted throughout the network. Transmission mechanisms are defined by the simulation of default and liquidity contagion.

In order to trigger these transmission mechanisms, the model defines a stress scenario comprising initial shocks, both common and idiosyncratic. To generate a common adverse shock, all banks' claims on non-interbank entities are subjected to a loss of between 1% and 4% of their original book value. The idiosyncratic shock consists in an individual bank's default, with varying recovery rates for that bank's creditors. One and only one bank defaults in each scenario; with 53 banks in the sample, this amounts to 53 distinct stress scenarios. Both the common and idiosyncratic shocks are exogenous: the origin of these shocks is not modelled, although the magnitude of the shocks is within the range of plausible adverse shocks observed historically.

These initial common and idiosyncratic shocks are transmitted through the system of interbank claims by two mechanisms:

- *The solvency contagion mechanism*. When an individual bank defaults, that bank's creditors receive a haircut. The size of that haircut depends on the shock to the defaulting bank's asset value minus the equity value. Some of the defaulting bank's creditors are other banks; these counterparties incur the loss caused by the defaulting bank, in addition to losses caused by the initial common exogenous shocks. If any further bank defaults due to these losses, the consequences for the second bank's creditors are computed, and so on, until the system is solved. If no further bank defaults, the simulation stops.
- *The liquidity contagion mechanism*. The underlying behavioural assumption is that banks will withdraw their supply of short-term funding to other banks whose capital ratio falls below a critical threshold. These distressed banks try to replace this funding shortfall by entering new repurchase agreements. Success therefore depends on the distressed bank's holdings of liquid assets. If liquid assets are inadequate to fund sufficient repurchase agreements, the bank defaults due to lack of liquidity, thereby triggering a new round of solvency contagion. If liquid assets are adequate, the simulation stops.

Application of this model to the interbank exposures data suggests that the risk of default due to contagion is low in most scenarios. Numerous contagious defaults only begin to occur under large common shocks (2% of non-interbank assets and above), for high values of loss given default (greater than 45%) and particularly under the most conservative calibration of the liquidity contagion mechanism (in which the critical threshold is set at a 7% core tier 1 capital ratio).

However, sensitivity of the number of contagious defaults to the value of the idiosyncratic loss given default increases substantially beyond a given level of stress. Under the most conservative calibration of the liquidity contagion mechanism (Chart 13, Panel B) and a 2% common shock, the number of contagious defaults increases from zero to two as the idiosyncratic LGD increases from 0% to 40%. In contrast, under a 4% common shock, the number of contagious defaults increases to six for the same increase in idiosyncratic LGD.

These changes in sensitivity suggest that the interbank system has a 'tipping point' property. The system appears robust to shocks until a critical magnitude. In this study, that magnitude appears to be high: very unlikely shocks are required to trigger numerous contagious defaults. But beyond this magnitude of shock, the system's fragility increases nonlinearly, with numerous banks defaulting due to small increases in relevant parameter values.

These results may be sensitive both to new realisations of the data generation process and to methodological choices:

- On data, exposures between large EU banks amounted to 6.4% of their total assets at the end of 2011. If and when the interbank market becomes more liquid, counterparty exposures will increase, along with the susceptibility of the system to contagion.
- On methodology, this analysis was restricted to modelling the solvency contagion mechanism in conjunction with the liquidity contagion mechanism. No attempt was made to model other mechanisms of contagion, such as heterogeneous common exposures or confidence effects. Nor does the methodology capture the many variations of assumptions which are made when modelling the contagion channel. Such variations include different thresholds for 'default' or the impact of supervisory mechanisms on losses. In this sense, results presented here should be seen as a lower bound on the true potential for contagion in the interbank system.

Overall, the analysis presented in this section, along with analysis on measures of network fragility presented in section three, supports the general proposition that interconnectedness is a core component of systemic risk. It is therefore imperative to continue to closely monitor the system of claims between large EU banks. Crucially, ongoing monitoring of the interbank system requires that exposures are observed at sufficiently high frequency and with a sufficiently granular set of instruments.

Annex: List of Members of Team on Interconnectedness

This paper has benefited from the input of the entire team listed below, with the authors being marked with an asterisk.

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