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Contagion in the interbank network: An epidemiological approach

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Mervi Toivanen*

Abstract

This paper analyses the importance of individual bank-specific factors on financial stability. First, we use a novel method to model the spreading of the contagion in the interbank network by implementing an epidemiologic model. Actual data on European banks is exploited with simulated scale-free networks. The average contagion affected 70% and 40% of European banks' total assets in 2007 and in 2010, respectively. Country-level results suggest that French, British, German and Spanish banks are the most contagious ones, whereas banks from Ireland, Greece and Portugal induce only limited negative effects. Secondly, cross-sectional panel estimations are performed to disentangle the leading indicators influencing the level of contagion. Bank clustering, large in-coming interbank loans and bank reputation are more prominent explanatory variables than the size or leverage. Finally, central banks' interventions reduce contagion only slightly.

Keywords: contagion, banks, Europe, interbank, epidemiology, panel regression

JEL codes: G01, G21, C15

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Tartuntariskien leviäminen pankkien välisillä rahamarkkinoilla: Epidemiologinen sovellus

Mervi Toivanen

Tiivistelmä

Tutkimuksessa analysoidaan yksittäisten pankkitekijöiden vaikutusta rahoitusjärjestelmän vakauteen. Ensinnäkin työssä sovelletaan uutta, epidemiologiaan pohjautuvaa tutkimusmenetelmää mallintamaan pankkien välisillä rahamarkkinoilla syntyneiden häiriöiden leviämistä. Skaalavapaisiin verkostoihin sovellettua mallia simuloidaan eurooppalaisten pankkien tiedoista koostuvan todellisen aineiston avulla. Toiseksi poikkileikkausaineistoon perustuvalla paneeliestimoinnilla tutkitaan, mitkä tekijät vaikuttavat eniten tartunnan laajuuteen ja mikä on keskuspankkipolitiikan vaikutus tartuntariskiin. Tulokset osoittavat, että keskimäärin 40 prosenttia eurooppalaisista pankeista sai tartunnan vuonna 2010 ja 70 prosenttia vuonna 2007. Maakohtaiset tarkastelut puolestaan viittaavat siihen, että tartuntaa levittävät pankit ovat ranskalaisia, brittiläisiä, saksalaisia ja espanjalaisia, kun taas irlantilaiset, kreikkalaiset ja portugalilaiset pankit aiheuttavat tartuntaa vain vähän. Pankkien muodostamat ryppäät, suuret pankkien välisiltä markkinoilta otetut lainat ja pankin asema välittäjänä pankkiverkossa selittävät tartuntariskiä paremmin kuin pankin koko tai velkaantuneisuus. Keskuspankkien interventioilla on vain vähäinen vaikutus.

Avainsanat: tartuntariskit, pankit, Eurooppa, pankkien väliset rahamarkkinat, epidemiologia, paneeliestimointi

JEL-luokittelu: G01, G21, C15

1. Introduction

The early stages of the financial crisis demonstrated that financial institutions were to face substantial losses owing to sub-prime exposures and declining asset values. But due to the opaqueness of banks' balance sheets and limited knowledge of counterparty exposures, nobody really knew how heavily each institution was exposed and to what extent the losses were to materialize. At the same time, banks were tightly connected to each other via interbank lending and borrowing that form a network through which each and every bank of the network may be affected by banks in trouble. The uncertainty regarding the financial health of counterparties and a fear of contagion[1] spread like a disease through the interbank network, inducing banks to limit their interbank exposures, which explains the sudden worsening of the crisis after the Lehman bankruptcy. The highly interconnected modern financial world thus facilitated the rapid transmission of the shock. Central banks were forced to step in and provided unprecedented liquidity support for the financial system.[2]

The financial crisis clearly highlighted the importance of banks' interlinkages and the concept of "too-connected-to-fail" (TCTF) emerged alongside the "too-big-to-fail" (TBTF) paradigm.[3] This paper analyzes the importance of these notions for financial stability by assessing the impact of bank-specific characteristics, such as size, financial strength and position in the network, on interbank contagion. A cross-sectional panel model is estimated to disentangle the relationship. In contrast to previous contributions we test a large set of *individual* network-specific indicators and use real data on European banks to illustrate the spreading of the crisis. This is of importance as the previous literature gives no guidance on what specific indicators supervisors and regulators should look at in their efforts to safeguard financial stability. The analysis also sheds light on the relevance of central bank actions by assessing whether central bank interventions are helpful in containing the negative spillover effects.

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[1] Contagion refers to domino effects that spillover from one institution to another via the banks' linkages. Financial contagion arises because banks are financially exposed to one another via direct bilateral interbank exposures. Other contagion channels in the banking sector include vulnerability to common factors (such as macro shocks or credit events), information and declining asset prices forcing banks to sell (il)liquid assets (so-called "fire sales"). (Müller, 2006; Nier et al., 2007)

[2] For an overview of the crisis, see Brunnermeier (2009) and Coeuré (2012).

[3] Both concepts describe the institution's importance from the system's point of view. The bank is either too-connected with other banks or too large and that's why it cannot be allowed to go into bankruptcy as the negative effects of the failure would be too high to the whole financial system and economy.

The paper also contributes to the literature by proposing a novel approach to model the transmission and the magnitude of financial contagion with an epidemiological model. The similarities between propagation of a financial contagion and epidemics are striking, both involving the spread of negative effects that lead to increasing number of affected individuals/institutions, fear of contamination and contagion and to outright panics if things get really bad. (May et al., 2008; Haldane and May, 2011; Haldane, 2009) The starting point is the susceptible – infected – recovered (SIR) model by Kermack and McKendrick (1927) that has been widely and successfully used to explain the propagation of diseases, computer viruses, macroeconomic expectations and rumours in the population over time.[4] The model is well-suited in depicting financial contagion in interbank markets because it does not require arbitrary assumption on loss rates and balance sheets. Instead, the model captures the psychological aspects of contagion process by relating a bank's relative financial strength with the perceived counterparty risk and expectations. Despite the conceptual parallels, only Garas et al. (2010) have previously used the SIR model, in this case to investigate the transmission of a crisis between countries via international trade.

The interconnections between agents facilitate the spillovers and affect the spreading of negative effects. Many highly heterogeneous social, biological, financial and communication systems can be best described by a network model in which nodes represent individuals or organisations (here banks) and links (here interbank exposures) stand for the interactions between the units (Pastor-Satorras and Vespignani, 2001). After all, the interbank networks are social in nature as humans are responsible for the execution of deals between banks. The advantage of network modelling is that it provides valuable insights into large and complex networks by providing statistical methods to describe and quantify network properties (Newman, 2003). As previous academic studies (Boss et al., 2003; Soramäki et al., 2007) have shown that many real-world interbank banking networks have the properties of scale-free networks, a large set of networks is simulated with a model by Barabasi and Albert (1999).

The results show how contagion spreads in the European banking system, segmenting banks into two categories. On average, contagion affects negatively about 40% of the European banks in 2010, but considerable heterogeneity remains owing to the network structure and the

[4] See, for instance, Anderson and May, 1991; Bansal et al., 2010; Ebel et al., 2002; Newman et al., 2002; Carroll, 2006; Zhao et al., 2013.

characteristics of the first failing bank. The magnitude of the contagion is almost twice as large in 2007, just before the onset of the financial crisis. In terms of nationality, French, British, German and Spanish banks are able to induce widespread contagion, while banks from Ireland, Greece and Portugal have only limited negative effects on the system.

Regarding the impact of bank-specific factors on contagion, a bank's size, its central position in the network and large business volumes are important for explaining the contagion. However, high clustering of the banking system and a bank’s high connectivity and large interbank loans pose a greater systemic risk for the banking system than a bank’s size. A failure of a well-known bank is more detrimental to the banking system than is a bankruptcy of small, local bank. Weighted clustering coefficient, closeness centrality, connectivity and volume of in-coming loans are significant variables in explaining the contagion. Moreover, strong solvency position lessens contagion in 2010 but no such impact is evident in 2007. Finally, central bank liquidity operations and other central bank measures are efficient in alleviating contagion and financial crisis.

The rest of the paper is organised as follows: Section 2 overviews the previous academic literature related to interbank contagion and network analysis and section 3 describes the application of the SIR model to scale-free networks. Data, generated networks and simulation parameters are introduced in section 4 and results of the contagion analysis are presented in section 5. Section 6 contains the bank and network indicators, the panel regression analysis and its results. Section 7 concludes.

2. Previous literature

2.1. Interbank contagion

The number of studies on interbank contagion and networks has increased markedly in recent years, as the financial crisis has revealed the systemic risk aspect of interbank lending and highlighted the need to understand the functioning and vulnerabilities of the interbank markets. Both theoretical and empirical contributions examine how the transmission of contagion depends on the structure of the banking sector and the banks’ interlinkages.

Theoretical models indicate that contagion spreads in the network of banks' financial linkages and that the network's structure affects the financial stability of the banking system in a nonlinear way. (Freixas et al., 2000; Rochet and Tirole, 1996; Diamond and Rajan, 2005; Allen and Gale, 2000) A high degree of interconnectedness between banks attenuates the impact of a financial crisis while the contagion may be strong in the case of incomplete connections in interbank markets. In these models network externalities arise from poor monitoring, scarce interconnections, liquidity shortages and rapid losses of asset value (due to fire sales), which expose the interbank market to coordination failures (gridlocks) even if all banks are solvent. Moreover, Georg (2013) and Freixas et al. (2000) indicate that central bank can improve financial stability by providing liquidity to financial institutions.

Empirical studies based on granular bank-level data have analysed the negative effects of a bank failure on systemic stability of a national banking system, thus providing insight into the vulnerabilities of existing networks.[5] The domino effects in these papers arise from losses related to interbank lending to the failed bank. Results point to potentially significant contagion effects, but find that a substantial weakening of the whole banking sector is unlikely. Similar studies have also been done in connection with payment systems and have found that the risk of contagion is small (Furfine, 2003; Eisenberg and Noe, 2001). But these results are driven by the particularities of the banking system under study and do not provide general insights into the drivers of a systemic risk at the individual bank level.

2.2. Banking networks

In addition to the analyses regarding the contagion effects in the banking system, the characteristics and structure of real-world interbank networks (so-called network topology) has recently attracted considerable attention. Researchers have evaluated the structure of national interbank markets and payment systems as well as the global cross-border banking exposure network and world investment networks by applying network metrics.[6] A typical financial network is complex and is characterized by a high-level of tiering. Few banks have

[5] Upper and Worms, 2004; Sheldon and Maurer, 1998; Degryse and Nguyen, 2007; van Lelyveld and Liedorp, 2006; Wells, 2002 and 2004; Mistrulli, 2011; Toivanen, 2009; Memmel et al., 2012. In addition, Degryse et al. (2010) examine cross-border contagion between European countries, Canada, Japan and the US, while Müller (2006), Elsinger et al. (2006) and Gropp et al. (2009) have considered a wider variety of risks and factors, verifying the findings and indicating significant cross-border contagion.

[6] Boss et al., 2004; Cajueiro and Tabak, 2008; Soramäki et al., 2007; Becher et al., 2008; Müller, 2006; Craig and von Peter, 2010; Iori et al., 2008; Hattori and Suda, 2007; Minoiu and Reyes, 2011; Song et al., 2009.

large numbers of counterparties; but the majority of banks have only a few linkages. Thus, certain key players act as central hubs that connect otherwise remote parts of the interbank loan network. In technical terms, the number of banks' counterparties follows a distribution with a heavy tail and exhibits power-law properties[7]. Although the banking network has become more tightly connected over time, the number of bank linkages has decreased during the systemic banking crises.

To overcome the deficiencies of analyses based on single, one-off data observations at a given point in time, researchers have also modelled financial connections between banks as networks and have employed simulation techniques to assess the spread of a bank failure (Gai and Kapadia, 2010; Gai et al, 2011; Nier et al., 2007; Arinaminpathy et al, 2012; May and Arinaminpathy, 2010; Iori et al, 2006; Krause and Giasante, 2012). Based on a set of assumptions, accounting identities and behavioural rules, these models present a banking sector composed of individual banks with balance sheets and a transmission mechanism for shocks. The contagion arises when the losses exceed the net equity of a bank, inducing a bank failure.

To begin with, networks are shown to be "robust-yet-fragile", meaning that interconnectedness improves the ability of a banking system to absorb shocks but at the same time increases the possibility of contagion.[8] Second, the higher the capital ratios of banks and the lower the concentration of the banking sector, the more resilient the system is to large systemic risks. Third, an enlargement of interbank liabilities tends to increase the risk of knock-on defaults. Fourth, a shock to a well-connected bank is more detrimental to financial stability than a shock to other banks in the system. Fifth, a large bank is more likely to induce contagion in the system than a small bank. Finally, the structure and tiering of the network are most important for explaining the magnitude of the contagion.

The stylised models help to portray the consequences of targeted shocks on network resilience and to disentangle the relationships between banking networks and the magnitude

[7] The number of connections (i.e. degrees (x)) that a given bank (i.e. node) has with other banks in the network follows a power-law distribution, $P(x) \sim x^{-\lambda}$, with a long-tail. The power-law exponent, λ, is shown to vary from 1.76 for US FedWire system to around 2.23-3.37 for the Brazilian banking system.
[8] Using an agent-based model and simulations Acemoglu et al. (2012) report similar results.

of systemic risk. However, they are quite often based on approximations[9] and a small set of parameters, restricting models applicability to supervisory purposes. Banks' interlinkages are also often drawn from random distribution. Moreover, the previous literature gives no guidance on specific network indicators that supervisors and regulators should look at while trying to safeguard the financial stability. It is of importance to know which indicators can be used to assess whether an interbank network is capable of transmitting contagion or not.

3. SIR model in a network context

3.1. The basic SIR model

To analyse the propagation of the financial contagion a "susceptible – infected – recovered" (SIR) model by Kermack and McKendrick (1927) is applied. This general epidemic model is widely used in epidemiology and other disciplines to analyse the spreading of diseases, information, computer viruses and expectations in a host population. Owing to the similarities between contamination and contagion processes as well as the dependence on the underlying contact network, the model is also well-suited to describe the contagion in a banking network. Moreover, the model does not require arbitrary assumptions on loss rates and balance sheets. Instead, actual data can be used to depict the transmission of a contagion event. The negative effects spread if a bank's equity is seen by the markets to be too low compared to the danger of contagion originating from its counterparties. In this sense, the model captures the psychological aspects of interbank contagion as the transmission of negative effects is based on assumptions and expectations on banks' ability to wither the storm. A similar approach has already been taken by Garas et al. (2010) who analysed the transmission of economic crisis from one country to another via international trade.

The model is based on the following set of assumptions.[10] First, an individual is either susceptible (S), infected (I), or, recovered (R) at any point of time t. Only susceptible banks can get an infection and, after having been infected for some time, they recuperate for the

[9] Models use mean-field approximations that approximate a system with a high number of individual actors and interactions by replacing all individual values with an average. This reduces a multi-dimensional problem into an effective one-dimensional problem and facilitates the problem solving. The differences between banks are nevertheless demolished.

[10] See, for instance, Kermack and McKendrick, 1927; Britton, 2010; Keeling and Eames, 2005; Diekmann and Heesterbeek, 2000; Moreno et al., 2002.

remainder of the study period. In this paper, as in Garas et al. (2010), recovery means that a set of successful measures has been applied, and the bank either overcomes the crisis on its own, is rescued by the authorities or is wind up. This assumption is realistic taking into account the "zombie" banks that emerged during the latest financial crisis. The banks came under a severe stress and were bailed out by governments but continued to exist and manage their business lines. Dexia and Northern Rock are few examples of these institutions during the latest financial crisis but the history of banking crisis bears numerous other examples. In addition, many banks received capital injections during the financial crisis. Owing to recovery, the bank is no longer under market suspicion, is again eligible as a counterparty and thus no longer spreads the contagion in the banking network. Moreover, an infected bank corresponds conceptually to a contagious bank.

Secondly, the number of institutions is set at N, so that the size of the banking community does not fluctuate over time. Let the fractions of susceptibles, infected and recovered be denoted as s(t), i(t) and r(t), respectively. This assumption translates into the condition that $s(t) + i(t) + r(t) = 1$ for all $t \geq 0$. Finally, the initial number of contagious banks is assumed to be small but positive at the beginning of the period, so that $i(0)=\varepsilon$. Moreover, $r(0)=0$, indicating that the community has not previously encountered the shock. These two condition lead to the initial condition for that $s(0)=1-\varepsilon$.

The model can be defined by the following set of differential equations:

$$\frac{ds}{dt} = -\lambda s(t)i(t) \tag{1}$$

$$\frac{di}{dt} = \lambda s(t)i(t) - \gamma i(t) \tag{2}$$

$$\frac{dr}{dt} = \gamma i(t) \tag{3}$$

The equation (1) defines the number of banks that leave the susceptible category by becoming a target of market speculation. The term λs(t)i(t) portrays the fact that susceptible, s(t), must have contact with contagious banks, i(t), in order to become contaminated, and that the status is converted from contagious to susceptible at a certain transmission rate, λ. The second equation defines the number of contagious banks, by subtracting from the number of banks whose financial strength becomes questionable, (λs(t)i(t)), the number of banks recovering from the crisis ($\gamma i(t)$). Finally, equation (3) defines the total number of banks that are negatively affected by the contagion.

3.2. Extension with the individual heterogeneity and network connections

In the basic SIR model all banks are similar and the probability of a contact is uniform across the population. But in reality institutions differ, for example with respect to susceptibility, degree of activity as well as number and volume of linkages. To take into account the variation between banks and the strength of individual interbank linkages, the SIR model is applied in a network context with individual heterogeneity.

First of all, following Garas et al. (2010) and Anderson and May (1991), a single transmission rate, λ, is replaced by a set of individual transmission parameters reflecting the properties of banks. This contagion probability (p_{ij}), that a contagious bank i transmits the crisis to a previously non-affected bank j, depends on the interbank exposure between banks i and j (EXP_{ij}), the size of the overall interbank market (m), and the contagiousness of bank i (α_i) (equation 4). The interbank exposure (EXP_{ij}) is defined as the share of exposures between banks i and j (exp_{ij}) in the total amount of renewable interbank exposures of susceptible bank j (total exp_j) (equation 5). This ratio reflects the dependency of bank j on the interbank loans provided by bank i.

$$p_{ij} = EXP_{ij} \times m \times \alpha_i \quad (4)$$

$$EXP_{ij} = \frac{exp_{ij}}{total\ exp_j} \quad (5)$$

Secondly, the vulnerability of a bank (β_j) is dependent on the bank's financial strength. Arinaminpathy et al. (2011) take a similar approach by modelling the health of a financial institution as a function of the bank's capital and liquidity positions. The higher the solvency of the bank, the more resistant it is to contagion.[11]

[11] In the context of epidemiology, the heterogeneity of susceptible individuals is studied by e.g. Rodrigues et al., 2009.

Finally, banks' different network connections are modelled in the spirit of network theoretical applications (Bansal et al., 2010; Diekmann and Hesterbeek, 2000; Newman, 2003). In the current paper, nodes symbolise banks and connections between banks are represented by interbank exposures. These links act as a transmission channel for contagion between different banks. The banking network is depicted by the well-known scale-free network model by Barabasi and Albert (1999), which mimics the characteristics of real-world banking networks such as a power-law distribution for the number of interbank connections.[12]

In technical terms, the power-law properties of Barabasi-Albert network are due to the growth of the network and preferential attachment. Starting with a small number of nodes, n_0, the network is constructed by adding one nodes at a time until the network contains N nodes. At each step, a new node, n_j, enters the network and connects to the existing nodes of the network via a given number of links, k_j. The new node prefers to connect with institutions that already have a large number of contacts. This is an intuitive assumption, as trust plays an important role in money markets, and banks are more likely to establish business relationships with renowned counterparties versus less-known banks (or banks with bad reputation). Thus, the probability that a new bank j connects with an existing bank i depends on the connectivity of the bank i (k_i), i.e. $\pi = k_i / \sum_j k_j$[13] (Barabasi and Albert, 1999; Moreno et al., 2002; Keeling and Eames, 2005). It is noteworthy that although banks create equal numbers of linkages when entering the network, the final numbers of individual banks' linkages differ. Some banks will have more connections than others.

4. Data, networks and simulations

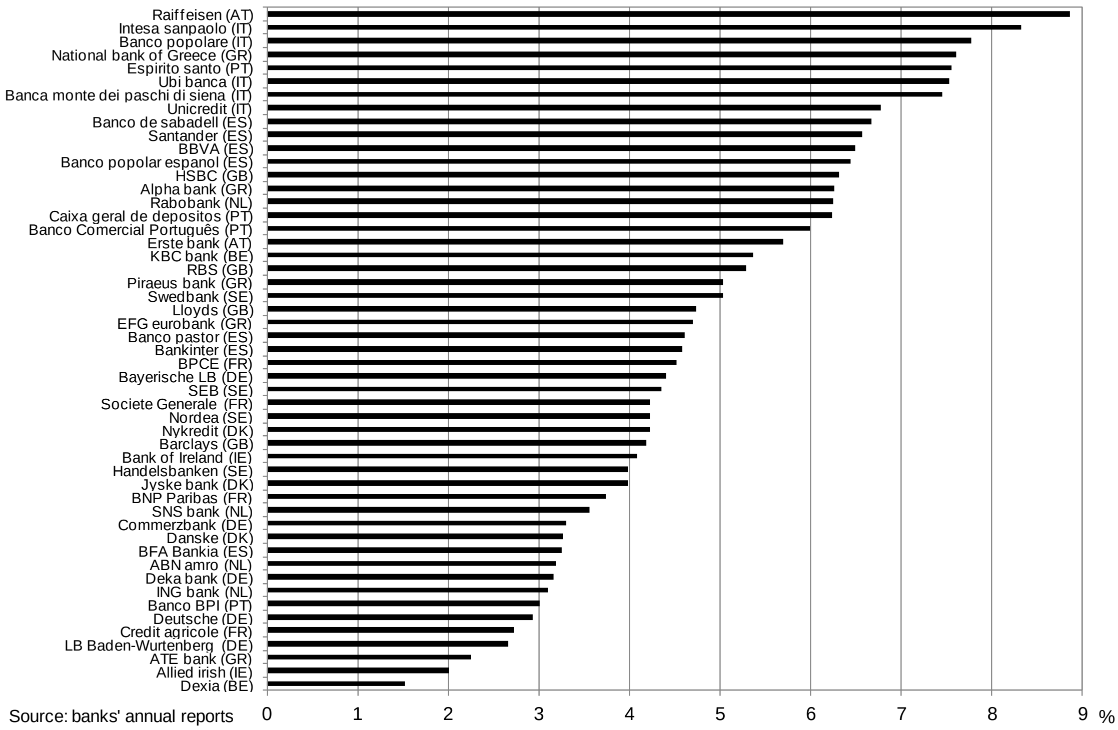
4.1. Data

The analysis is based on information from 51 major European cross-border banking groups with headquarters in Germany, France, Italy, Spain, the Netherlands, Belgium, Austria, Portugal, Greece, Ireland, the UK, Denmark and Sweden. All banks in the sample were included in the EU-wide stress-testing by the European Banking Authority (EBA). The data

[12] Boss et al., 2004; Soramäki et al., 2007; Becher et al., 2008; Cajueiro and Tabak, 2008; Bastos e Santos and Cont, 2010; Craig and von Peter, 2010; Müller, 2006; Iori et al., 2008.
[13] The probability has the following conditions: $\pi_i = [0, 1]$ and $\sum \pi_i = 1$.

are from banks' annual reports, and the dataset consists of the banks' common equity and total assets at the end of 2007 and 2010.

Figure 1. Equity ratios of large European banking groups in 2010.



The total assets of the banks in the sample amount to 26.6 trillion euro in 2010 and 25.2 trillion euro in 2007, constituting approximately 62 % of the whole European banking sector. Total assets and common equity are used to calculate bank-specific equity ratios, reflecting the bank's capital position.[14] These ratios of the banking groups differ considerably in 2010, ranging from 1.5% to 8.9% (Figure 1). The banks' financial strength has slightly declined during the financial crisis. The average equity ratios for the sample are 5.1% for 2007 and 4.9% for 2010.

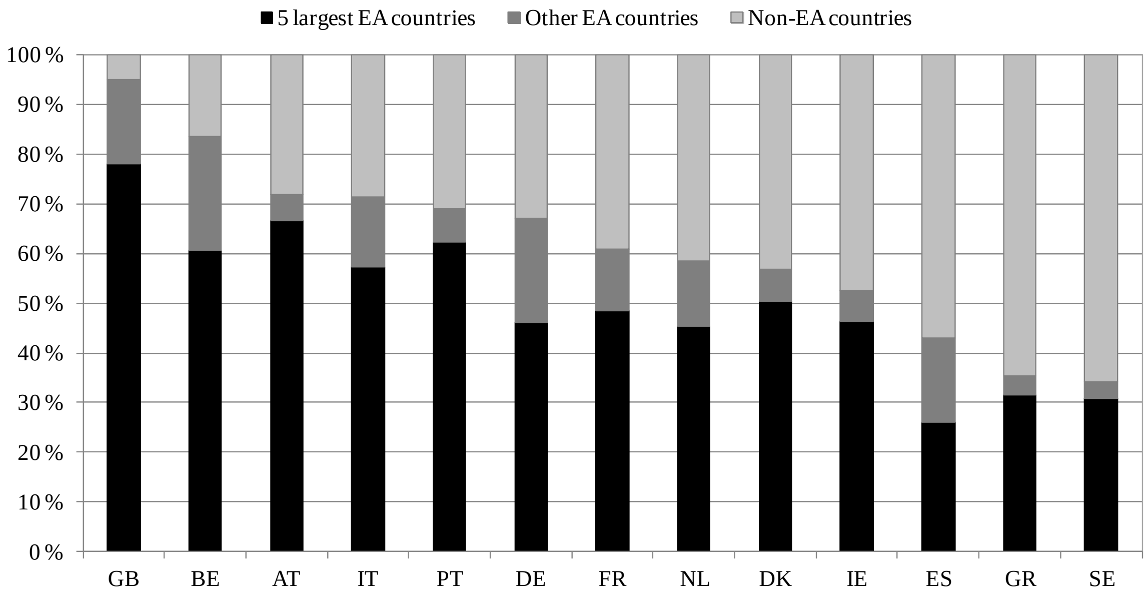
Banks' interbank exposures are approximated by using consolidated banking statistics of the Bank for International Settlements (BIS).[15] This statistical source provides information on banks' financial claims, covering the cross-border bank exposures of a country's banking

[14] An alternative measure for the financial strength of a bank is the solvency ratio, defined as regulatory capital over risk-weighted assets. However, the financial crisis has shown that this ratio may not always be representative. Tier 1 solvency ratios and core Tier 1 capital ratio are nevertheless used in robustness tests for 2007 and 2010, respectively.

[15] For more information on BIS statistics, see http://www.bis.org/statistics/consstats.htm.

sector vis-à-vis other countries. As interbank loans are allocated to the actual lender who will bear the losses in case of borrower default, the data reflect the actual financial linkages between banking sectors and can be used to evaluate banks' interlinkages within an interbank network. This data come closest to approximating the reality, as public data on actual bank-to-bank exposures are not available. In addition, data on cross-border exposures can be used to evaluate the size of the overall interbank market.

Figure 2. Share of cross-border claims on different countries, 2010



Source: BIS
Note: In calculating the total cross-border claims for each individual country (on the horizontal axis), only the banking sectors of the sample are included in the summation. The outstanding amounts of interbank lending within a country are not included in the BIS statistics. Five largest euro-area countries are Germany, France, Italy, Spain and the Netherlands; other EA countries include Belgium, Austria, Portugal, Ireland and Greece. Non-euro-area countries are Sweden, Denmark and the United Kingdom.

Figure 2 shows the cross-border claims of the sample banking sectors by nationality of counterparty in 2010. The financial claims of British banks are mainly on euro-area (EA) banks, while the counterparties of Greek and Swedish banks are mainly from countries outside the euro zone. The exposure to euro-area banks varies between 95% for the United Kingdom and 34% for Sweden. Inside the euro area, the five largest euro area countries, Germany, France, Italy, Spain and the Netherlands, account for the majority of the cross-border counterparties. Other EA countries are notable counterparties only for Belgium, Germany and Spain. Compared to 2007, the importance of the counterparties from the five largest EA countries and non-euro area countries has increased while banks' exposures from other euro area countries have diminished.

As BIS statistics do not include information on outstanding amounts of interbank lending within a country, the interbank positions of banks within the same jurisdiction are obtained from the monetary financial statistics (MFI statistics). These statistics are combined by the European Central Bank (ECB) for euro area countries and by national central banks and statistics offices of Denmark, Sweden and the UK.[16]

4.2. Interbank network

The interbank market and banks' connections in the network can be presented in an N×N matrix in which rows represent creditor banks and columns debtors. Positive values indicate a connection between two banks and the absence of a link is denoted as zero. Owing to a lack of detailed information on banks' interconnectedness, a large number of scale-free networks (SFN) are generated by using the Barabasi-Albert (1999) model to capture the wide range of plausible interbank linkages in the banking network.[17] Each realisation of the generated network is independent and has a unique structure. The network size is set at N=51, reflecting the number of the banks in the sample. Thus, each individual node in the network represents a bank and has the corresponding values for the bank's interbank exposures, solvency ratio and total assets.

Once the interbank network is in place, the weights of interbank linkages are assigned to the network based on BIS and MFI data.[18] From the BIS statistics, interbank receivables of country J's banking sector from country I (exp_{ij}) are divided by the total amount of country J's cross-border claims (total exp_j). These country level shares are subsequently taken to represent the cross-border interbank exposures of individual banks. Similarly, weights for individual banks within a country are obtained from the MFI statistics. The estimates are likely to differ somewhat from actual interbank exposures. However, data collections (and cross-border exposures) are usually governed by large, internationally active institutions similar to those included our sample. Therefore, the current weights are assessed to be

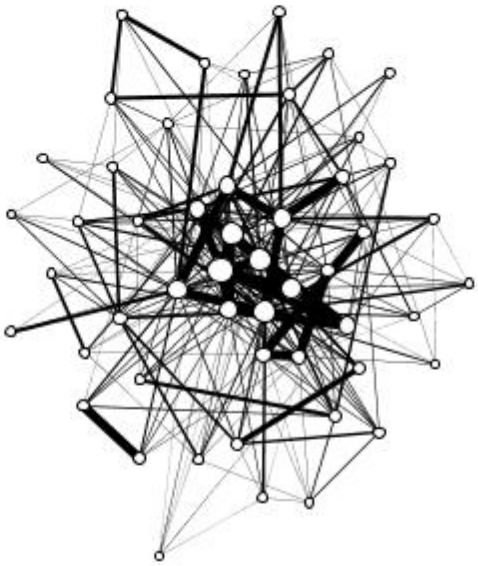
[16] For further information see, for euro area: http://www.ecb.int/stats/money/aggregates/cross/html/ index. en.html; for the UK: http://www.bankofengland.co.uk/statistics/Pages/bankstats/2012/Oct12/default.aspx; for Denmark: http://www.nationalbanken.dk/DNUK/Statistics.nsf/side/Download_statistics_-_Publications!OpenDocument; and for Sweden: http://www.riksbank.se/en/Statistics/Financial-market-statistics/Swedish-Monetary-Financial-Institutions/

[17] In the benchmark case the networks are composed by assuming that each bank creates six links ($k_j = 6$) on entering the banking network. This assumption is relaxed later on in the simulations.

[18] The underlying basic set of realisations for undirected networks remains the same for both 2007 and 2010. Only the weighting of the networks with bank and exposure-specific values differentiates the directed networks.

reasonable. Following the main stream of the literature and previous simulation exercises (Upper, 2011; Nier et al., 2007; Krause and Giasante, 2012), it is also assumed that no bank lends to itself so that the diagonal of the N×N matrix has only zeros.

Figure 3. Example of a network for European banks



Note: A realisation of the Barabasi-Albert (1999) model for the European interbank network. Each node represents a bank in the sample, and its size is scaled in proportion to the sum of interbank exposures of the given bank at the end of 2010. Similarly, the darkness of a line reflects the proportional value of a bilateral exposure.

Based on the data and scale-free network model, Figure 3 depicts a realisation of the interbank network of European banks in the sample. Banks with a large number of connections and large interbank exposures lie in the centre of the network; other banks are on the outskirts. The picture is similar to other realisations of weighted networks, but the size of exposures and the ordering of banks differ.

In order to take into account the general development of the interbank markets and the fact that interbank assets have shrunk dramatically from the onset of the financial markets, BIS data on cross-border exposures are used to determine the size of the interbank markets (m). Based on the data, the exposures of the banking sectors in the sample were 1.8 times larger in 2007 than in 2010.

4.3. Simulations and parameters

In simulations, contagion starts with an exogenous and idiosyncratic shock hitting a single bank in the system. Network-specific results are derived by letting each bank (N=1,...,51) one by one be a source of the contagion and by exposing the whole banking system to the effects of direct and indirect contagion. The probability of being contagious is thus uniform for all banks irrespective of characteristics such as size and links with other banks. The contagion process is simulated for each network realisation.

The contagiousness of a bank evolves in stages; the longer a bank has been infected, the higher the probability (α_i) that it will contaminate a susceptible bank with which it has an interbank relationship. This feature is designed to capture the heightened mistrust and uncertainty in the interbank markets as well as rising suspicions about counterparties and a reluctance to engage in business relationships with banks in trouble.[19] After the third time period, the contagious bank becomes resistant and no longer spreads the crisis any further. Each bank is removed with probability γ, which is set at unity.

Secondly, the vulnerability of a bank (β_j) is evaluated using the corresponding value of the cumulative distribution for the bank's equity ratio.[20] The ratio portrays the bank's financial strength, as it shows the share of the capital that is available to absorb losses. When the risks materialize, the equity capital acts as a first line of defense. If the equity ratio is low, the bank is likely to be more severely affected than other banks in the market.

Third, the contagion spreads in the network only if the contagion from the infected bank i is stronger than the financial standing of the susceptible bank j ($p_{ij} > \beta_j$). In this set-up it is not the direct loss caused by a bank failure per se that causes contamination of the banking system. Also playing a part is the weakness of susceptible banks to resist the power of suspicion, uncertainty, rumours and epidemic fear that spreads through the banking sector. In contrast to previous studies (Nier et al., 2007; Krause and Giasante, 2012), the SIR model does not require assumptions regarding balance sheets, amount of the losses or deductions

[19] In the baseline simulations, the incubation period is set at three, reflecting transmission probabilities of zero, 50% and 100% at the first, second and third time steps, respectively. This assumption is relaxed and tested later on.

[20] Equity ratios of the banks in the sample a follow normal distribution in 2010 with mean 4.89 and standard deviation 1.77 and in 2007 with mean 5.06 and standard deviation 2.07. Both the Jarque-Bera and Lilliefors tests confirm that the samples for both years are from normal distributions.

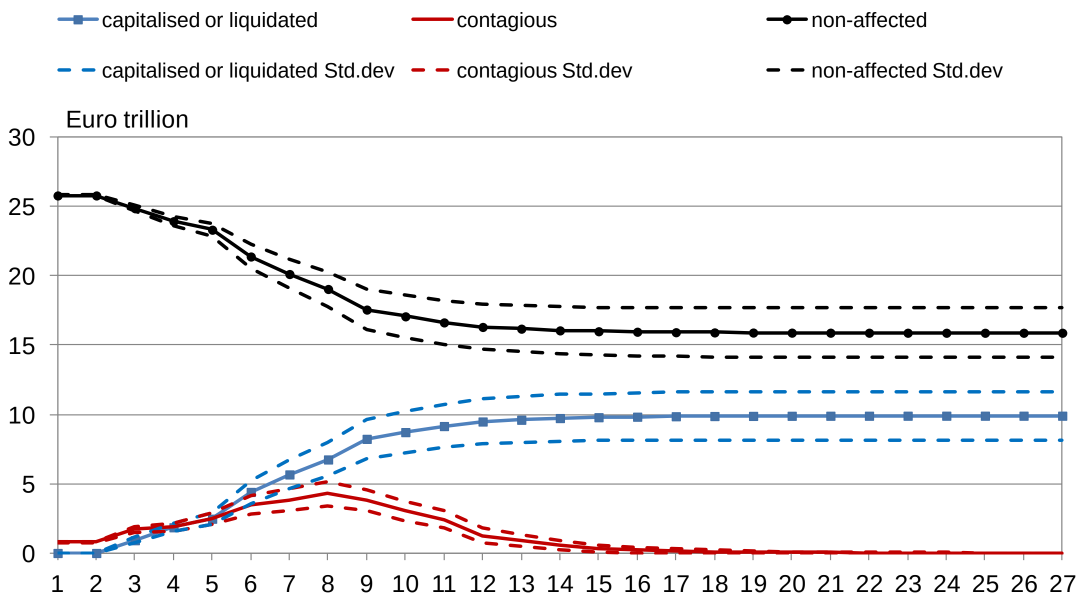
from capital in order to model the transmission of the crisis. For a failure of a bank, it is enough that the bank's financial strength is perceived as fragile in comparison to its risks in the interbank market. The benefit of this approach is that arbitrary assumptions are avoided and the model relies on the actual data. Finally, simulations stop when there are no more contagious banks or when all banks have been exposed to the crisis.

5. Propagation of the contagion

5.1. European banking sector as a whole

Simulations demonstrate how the contagion spreads in the European banking system, splitting the banking sector in two parts. A similar situation occurred during the current financial crisis when the European banking sector was divided into "good names" with an access to interbank lending and "bad names" that were excluded from money markets by means of larger haircuts and margin requirements.

Figure 4. Average crisis propagation in the European banking network in 2010



Note: Average is calculated over all banks in the sample (N=51) and all networks (SFN=10,000). Lines represent the cumulative sum of resistant and non-affected banks' total assets and the total assets of contagious banks at the given point in time. Std.dev stands for standard deviation.

Figure 4 shows that the overall results for non-affected, contagious and resistant banks in terms of total assets at a given point on the crisis' timeline. While some banks are strong enough to resist the crisis and are able to continue their business, the others fall under market suspicion, transmitting market distress further (contagious banks), and are ultimately segregated to the group of capitalised/liquidated banks. In the benchmark simulations the assets of negatively affected banks total, on average, 10 trillion euro, constituting around 40% of total assets of banks in the sample.[21] The rest of the banking system is able to avoid contagion. The standard deviation indicates that the variation between different network structures is relatively small and that the total assets of banks hit by the crisis hover around 8.2-11.7 trillion euro. However, the maximum negative impact affects 62% of the banking system in 2010, on average over all networks. And within a single network negative spillover effects can contaminate up to 82% of the banks, corresponding to 21.9 trillion euro of the total assets.

While the cumulated sum of capitalised/liquidated banks' total assets demonstrate the combined effect of the contagion on the banking system as time passes, the value of contagious banks at each point in time describes the evolution of the contagion process. The majority of transmission occurs at the beginning of the crisis, as the value of contagious banks exhibits an initial increase between the second and eight time steps. Without any further shock to the system the force of the contagion then slowly declines towards the end of the estimation period. The system stabilizes around the steady state at the 18th time step.

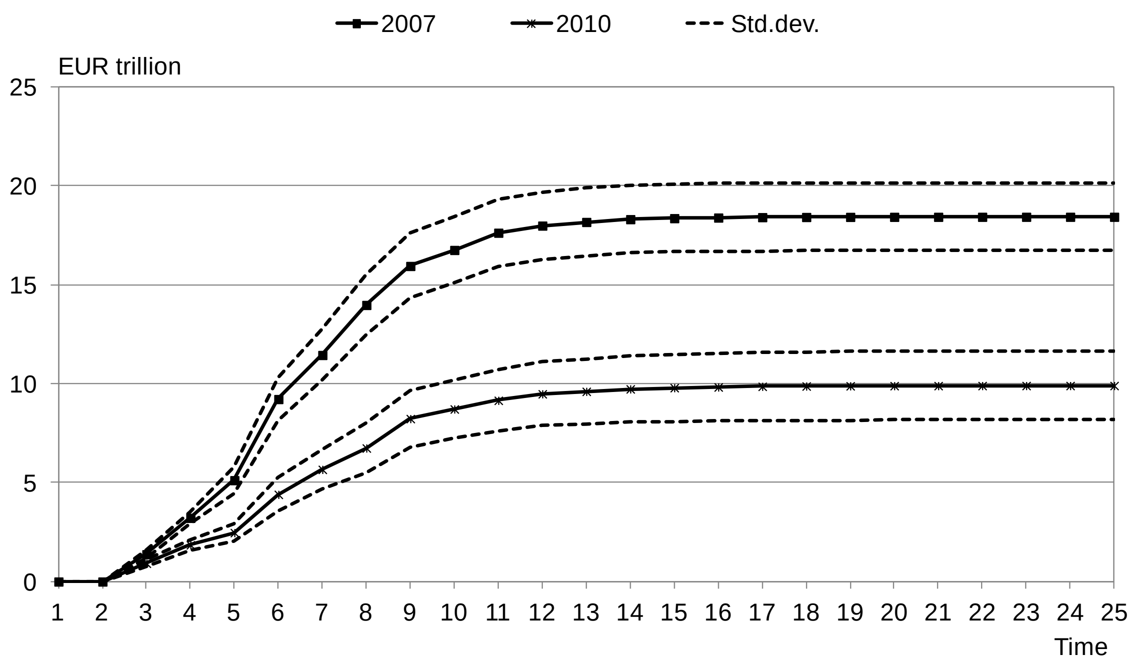
Compared to 2010, the magnitude of the contagion is almost twofold in 2007, just before the onset of the financial crisis (Figure 5). The contagion affects around 73 % of the banks, corresponding to 18.4 trillion euro of total assets. Prior to the financial crisis the European banking system was therefore much more prone to negative shocks than in 2010. The outcome reflects the increasing equity as well as banks' efforts to restrict their exposures in the midst of the financial crisis.

Robustness tests with different parameter values and solvency ratios verify the findings. Regarding the solvency ratio the results are similar both at the European level and at the country level. Increasing the size of the interbank markets (m) and exposures (EXP_{ij}) subsequently magnify the contagion, albeit in a non-linear way, as the negative effects build

[21] The overall average is obtained by first calculating the average for each individual network over all banks (N=51) and then averaging these individual network results over all simulated networks (M=10,000). The average does not include the total assets of the first failing bank.

up quickly with the initial escalation of magnitude but the impact on contagion abates later on. To reflect a prolonged financial crisis, the time period during which a bank remains contagiousness (α_i) is lengthened. Simulations show that a smoldering crisis is more detrimental to financial stability than a quickly transmitted one. The negative effect of a crisis with a long incubation period on the system's resilience is approximately 5-6 percent points larger in both years.[22]

Figure 5. Cumulative sum of contagious banks' total assets in 2007 and 2010



Note: Averages are calculated over all banks (N=51) in the sample and all networks (SFN=10,000). Lines represent averages for the cumulative sum of contagious banks' total assets at the given point in time. Std. dev. stands for standard deviation. Results do not include the total assets of the first failing bank.

5.2. Contagion at the country-level

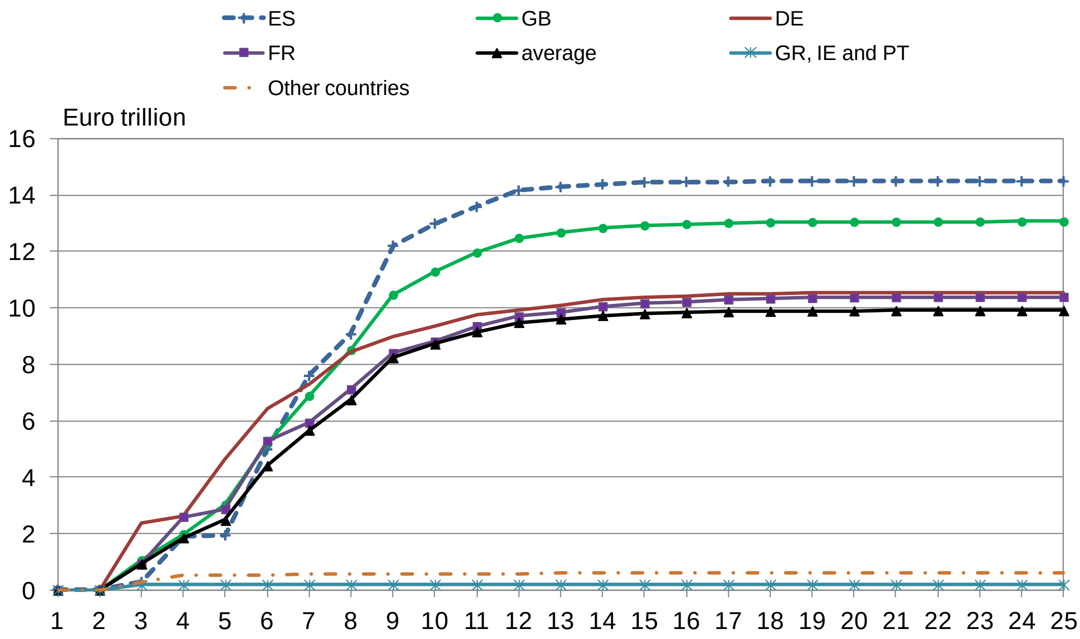
In order to shed more light on contagion in the European banking system, Figure 6 shows how the contagion depends on the nationality of the first failing bank.[23] At the end of 2010 Spanish, British, German and French banks are able to induce wide-spread contagion, while contagion from other banks is much more subtle than the average. Spanish banks are the most

[22] In addition to the parameter testing, the impact of a bank's connectivity (i.e. the number of linkages that a bank creates when entering the network) on contagion is analyzed. Increasing connectivity first increases the negative spillover effects in the banking system, but after a threshold the contagion declines and the system's resilience increases.

[23] The results are divided according to the nationality of the bank that starts the chain of the events at the beginning of the simulation. The subsequent contagion may affect any bank in the system irrespective of the home country.

detrimental to the system, as the assets of banks affected by a failure of a Spanish bank total 14.5 trillion euro, corresponding to 56% of the total assets of the system. In contrast, banks from the program countries (Ireland, Greece and Portugal) have only slightly smaller impacts on the system than banks from Belgium, the Netherlands, Austria, Sweden and Denmark.

Figure 6. Cumulative sum of contagious banks' total assets according to the nationality of the first failing bank in 2010



Note: Average is calculated over all networks (SFN=10,000) according to the nationality of the first failing bank. Other countries refer to banks from Belgium, the Netherlands, Austria, Italy, Sweden and Denmark. Results do not include the total assets of the first failing bank.

The country-level results portray the European situation at the end of 2010. Especially the Greek, Portuguese and Irish banks were facing difficulties in obtaining funding from the interbank markets and were effectively excluded from the money markets by the end of 2010. Without sufficiently large interbank positions with the rest of the European banks Greek, Portuguese and Irish banks are not able to initiate a wide-spread contagion. At the same time, the banks from relatively strong European countries such as Germany and France were still well-positioned in the interbank network, rendering them prominent sources of contagion. Throughout the sovereign debt crisis Germany has had safe-haven status, leading German banks to have strong linkages with other banks. Also, French banks were considered relatively strong counterparties in 2010. And the heightened suspicion over French banks' exposures to Greek debt came into the picture only later in 2011-2012. Meanwhile, British banks have traditionally been large institutions with multinational business models and extensive connections worldwide.

The results for Spanish and Italian banks may seem counter-intuitive at the first glance. But Spanish and Italian problems reached the limelight of the crisis only in 2011-12. Although the problems in the Spanish real estate sector were already evident in 2008, large Spanish banks still did relatively well in 2010, owing to income from Latin American countries. Spain's third largest bank, Bankia, was nationalised only in May 2012, and the country received financial support from the Eurogroup in June 2012. Despite the market volatility and uncertainty over Italy's debt servicing capacity, Italian banks were not a cause of concern in 2010.

Table 1. Average country-level contagion in 2007 and in 2010 according to the nationality of the first failing bank

	EUR trillion in 2007	EUR trillion in 2010	Change, %
ES	21.95	14.48	-34.0
DE	20.61	10.56	-48.8
IT	21.34	0.59	-97.2
FR	20.24	10.39	-48.7
NL	20.34	0.95	-95.3
PT	0.31	0.05	-84.5
AT	20.75	0.53	-97.5
BE	19.60	0.59	-97.0
GR	0.07	0.03	-50.9
IE	19.72	0.49	-97.5
GB	20.80	13.06	-37.2
DK	0.45	0.45	-0.7
SE	0.44	0.46	4.2
Average	**18.44**	**9.91**	**-46.3**

Note: Contagion is defined as the cumulative sum of contagious banks' total assets at the end of the simulation rounds. Averages are calculated over all networks (SFN=10,000) according to the first failing bank of a given country. The results do not include total assets of the first failing bank.

Comparing the country-level results in 2010 to the outcome in 2007 data, the contagion effects have decreased from all countries except for Sweden (Table 1). The results reflect banks' fear of counterparty risks and risk-aversion towards counterparties in deep trouble during the financial crisis, inducing banks to limit their exposures to weak market-players in benefit of strong banks. The danger of negative spillovers diminishes from all countries but specifically from Ireland, Belgium, the Netherlands, Italy and Austria. British, German, French and Spanish banks remain effective in transmitting the contagion in both periods.

6. Factors determining the contagion

The previous results suggest that the contagion varies depending on the banks and networks, as it is almost non-existent in some cases but in a worst-case scenario it can be widespread and detrimental to the whole banking systems. Given the outcome, it is of interest to analyse whether bank-specific characteristics such as size, solvency and bank's position in the network affect the amount of contagion. In addition, central banks worldwide have taken unprecedented actions to safeguard the liquidity and stability of banking systems. We therefore analyse what is the impact of central bank policies on contagion. The following first describes bank-specific statistical indicators investigated and the estimation methodology before turning to the results of the analysis.

6.1. Definitions and data for bank-specific indicators

To begin with, a bank's size is measured by total assets. And a bank's financial strength and riskiness are reflected in the equity ratio and leverage. The equity ratio is defined as total equity over total assets; the leverage is the reciprocal. The network related indicators describe banks' strength, importance and position in the network as well as their density and clustering in the network. These statistical network indicators are commonly used to depict the topological characteristics of the network (Song et al., 2009; Soramäki et al., 2007; Iori et al., 2008). The formulas of the network indicators are in Appendix 1.

In addition to the number of a bank's counterparties and the volume of in-coming and out-going interbank loans, the network metrics include the following indicators.[24] The average distance (average path length) indicates how quickly, on average, a bank may reach other banks in the system via the links. The maximum distance (eccentricity) illustrates how far away the most distant bank of the network is. So-called connectivity of a bank is the probability that two banks are counterparties to each other, calculated as the number of a

[24] For detailed formulas and definitions of the network indicators, see Appendix 1.

bank's existing links over all possible links of the bank. Betweenness centrality indicates how dependent other banks are on a certain bank i, and it has also been used as a proxy for a bank's reputation. Closeness centrality shows how close banks are each other in the network. Finally, the clustering coefficient depicts the probability that two counterparties of a bank are also counterparties to each other. A similar case occurs if two friends of a person have a mutual friendship. The indicator therefore measures the amount of complete triangles relative to all potential linkages. A volume-based parameter is deduced from the clustering coefficient by weighing it with the interbank payments. (Iori et al., 2008; Soramäki et al., 2007; Minoiu and Reyes, 2013; Alves et al., 2013)

In addition, central banks have taken unprecedented actions to support the ailing banking sectors during the financial crisis. For instance, the European Central Bank started to conduct its monetary policy operations with full allotment policy, providing private banks the liquidity their needed. In addition, several other liquidity-providing operations were introduced to address the tensions in financial markets. Central banks also provided emergence liquidity assistance to banks. One of the reasons given to these operations was the avoidance of negative spillover effects. Given the magnitude of the operations we disentangle their importance by including two central bank related variables in the estimations. As the interventions are first and foremost reflected in the balance sheets of central banks, we include central bank's total assets and monetary policy operations related lending to resident credit institutions as variables in the estimations. The data is collected from annual reports of central banks. In the analysis, the country-level central bank data are associated with each individual bank according to the location of the bank's headquarter.

Table 2 contains descriptive statistics for contagion and bank-specific variables at the end of 2010. Based on the data and simulated networks, the indicators are computed for each bank in the sample. In the case of network indicators, they are then averaged over all networks. Looking at the total assets, the average bank is somewhat smaller in 2007 than in 2010, but the differences in size between the largest bank and the smallest bank is more pronounced in 2007. The total capital of banks portrays a similar picture. The equity ratio and the leverage ratio indicate that some banks have a relatively good financial standing while others are highly leveraged and have a low level of capital in their balance sheets. Somewhat surprisingly the maximum leverage of banks in the sample is larger in 2010 than in 2007.

Table 2. Descriptive statistics for indicators in 2007 and 2010

Year	Variable	Mean	Std.dev.	Min	Max
2007	Contagion, EUR bn	13,182	9,442	22	22,386
	Total Assets, EUR bn	494	580	23	2,510
	Equity, EUR bn	20	24	1	125
	Leverage	23.4	9.8	10.2	47.2
	Equity ratio, %	5.1	2.1	2.1	9.8
	Change of CB's loans to banks, %	153.1	217.5	4.5	750.7
	Change of CB's total assets, %	10.3	6.7	-0.7	21.6
	Volume of in-coming interbank loans that a bank has taken, EUR bn	1.63	1.52	0.20	5.67
	Volume of out-going interbank loans that a bank has given, EUR bn	1.63	1.32	0.48	5.70
	Weighted clustering coefficient, %	3.61	1.77	1.05	7.19
2010	Contagion, EUR bn	4,892	6,149	0	15,012
	Total Assets, EUR bn	521	569	31	1,998
	Equity, EUR bn	24	27	1	116
	Leverage	23.7	10.4	11.3	65.7
	Equity ratio, %	4.9	1.8	1.5	8.9
	Change of CB's loans to banks, %	-14.3	83.0	-99.8	155.9
	Change of CB's total assets, %	10.2	33.4	-47.3	63.4
	Volume of in-coming interbank loans that a bank has taken, EUR bn	1.72	1.67	0.13	6.27
	Volume of out-going interbank loans that a bank has given, EUR bn	1.72	1.36	0.52	6.03
	Weighted clustering coefficient, %	3.66	1.87	0.86	7.42
both years	Number of counterparties	10.71	4.71	5.97	24.51
	Shortest path	1.86	0.14	1.51	2.05
	Eccentricity	2.78	0.29	2.05	3.00
	Connectivity, %	21.42	9.42	11.94	49.03
	Betweenness centrality, %	1.50	2.21	0.09	9.80
	Closeness centrality, %	1.08	0.09	0.98	1.33
	Clustering coefficient, %	31.84	1.35	27.18	33.24

Note: Indicators of banks' size and financial standing are based on the data, and network metrics are based on all simulated networks and data. Figures are calculated for each bank in the sample and in the case of network indicators averaged over the simulated networks. Std.dev. stands for standard deviation and CB signifies central bank.

Based on the network indicators banks appear to be close to each other, and the network is compact and dense, exhibiting the small-world phenomenon.[25] The simulated networks thus reflect nicely the real-world observations on the network of the large European banks. (Alves et al., 2013) Regarding the concentration and density of the network, the (weighted) clustering coefficient and betweenness centrality are relatively high, reflecting that some banks have pivotal role as hubs in the network. Although average volume of in-coming and

[25] The small-world phenomenon means that any node of the network can be reached from any other node with only a few steps (Soramäki et al., 2007).

out-going interbank loans does not differ a lot between years, the maximum volumes are higher in 2010.

Any given counterparty of a bank in the system can be reached in less than two steps while the maximum distance (eccentricity) is no more than three steps. The connectivity shows that 21% of all possible linkages are utilized on average but in some cases a bank's active links cover almost half of its potential connections. Moreover, a bank has 10.7 counterparties on average, but the most connected bank can have up to 24.5 connections.

Finally, the extension of central bank operations is more evident in loans to financial institutions than in the total assets of central banks, as can be expected. In 2007, the lending to banks increased in all countries but especially so in Portugal owing to the emergence of financial market turbulence. In 2010, the lending to financial institutions declined in many countries like for instance in Germany, Sweden and Belgium but increased heavily in so-called program countries (Portugal, Greece and Ireland) that received EU/IMF financial support during the crisis.

6.2. Estimation methodology

To determine whether the negative spillover effects are driven by bank-specific factors a cross-sectional panel model is estimated by OLS (equation 6):

$$\begin{aligned}\log\left(Cont_{i,t}\right) = \alpha_{i,t} + \delta_1 log\left(TA_{i,t}\right) + \delta_2\left(FinRatio_{i,t}\right) + \delta_3\left(NetMeasure_{i,t}\right) \\ +\delta_4(CB\_policy) + \varepsilon_{i,t}\end{aligned} \qquad (6)$$

The main variable of interest is the level of contagion, $Cont_{i,t}$, induced by bank i. We concentrate in the amounts as they depict the actual total losses of the financial system should things evolve unfavourably. The main explanatory variables consist of a bank's size ($TA_{i,t}$), financial standing ($FinRatio_{i,t}$) and network indicators ($NetMeasure_{i,t}$) as well as central bank policy of a country (CB_policy_t). Size is measured by total assets, and the bank's financial ratios, by the equity ratio and leverage. Variables regarding central bank policies refer to growth of central bank's lending to financial institutions and growth in its total assets. Network indicators consist of all indicators listed in the Appendix 1. However, as the correlations between individual network variables as well as between equity ratio and leverage are high (see Appendix 2), they are entered into the estimations one at a time. The only exception is the weighted clustering coefficient, for which the correlation coefficients with other network metrics are relatively low. Only total assets and the volumes of in-coming and out-going interbank loans are expressed in levels while other indicators are in percentages.

The regression analyses are performed in log-log form[26] for both time periods, namely for 2007 (t=1) and 2010 (t=2). And all banks in the sample (i=51) are included in the estimations. However, as three banks do not induce contagion in 2010, the sample is reduced to 48 banks in 2010 owing to log-transformation.

The coefficients for the size, leverage ratio and volume of interbank loans that a bank has taken from its counterparties are expected to have positive sign, as all of these factors contribute positively to the bank's fragility and its importance to the system. High centrality, clustering and connectivity of a bank are also assumed to impact positively on the contagion, as they reflect the bank's prominence in the network and thus its ability to transmit negative spillover effects. In contrast, high equity ratios and long distances between banks (as measured by shortest path and eccentricity) are expected to impact contagion negatively, as high solvency and sparse connections hinder the transmission process. Central bank operations are most likely to exert a negative impact on contagion.

6.3. Results

As can be expected, a failing bank's position in the network and its characteristics emerge as natural explanatory factors for the induced level of contagion (Table 3). Starting with the network-specific variables, the significant and positive coefficients of weighted clustering coefficient as well as betweenness and closeness centralities highlight the importance of a failing bank's position in the network. Weighted clustering coefficient depicts the volume of interbank loans held by two counterparties of a bank that are also linked to each other. This variable clearly highlights the importance of local clusters in the banking systems. In particular, if these clusters are composed of banks with high interbank loan volumes, a failure

[26] As a robustness test, also log-linear panel estimations are performed. They, however, produce similar results.

of one such bank can be detrimental to financial stability. In 2010 one percentage point increase in bank clustering increases contagion by 80-120%.[27] Similarly, the estimates for betweenness centrality indicate that if an important intermediary of the banking system fails, its default increases the contagion by 11%.

Table 3. Cross-section OLS estimation for explaining contagion in 2010

	Eq. 1	Eq. 2	Eq. 3	Eq. 4	Eq. 5	Eq. 6
Log (total assets)	0.25	0.14	0.28	0.28	0.27	0.27
	[0.10]**	[0.08]*	[0.14]**	[0.13]**	[0.11]**	[0.11]**
Equity over total	- 0.19	- 0.18	- 0.40	- 0.40	..	..
assets	[0.06]**	[0.05]***	[0.08]***	[0.08]***	..	..
Weighted clustering	1.19	0.82	1.18	1.16	1.18	1.18
coefficient	[0.041]***	[0.14]***	[0.12]***	[0.11]***	[0.10]***	[0.10]***
Closeness centrality	2.72	..	..	..	..	..
	[1.42]*	..	..	..	..	..
Volume of in-coming	..	0.79	..	..	..	..
interbank loans	..	[0.19]***	..	..	..	..
Betweenness centrality	..	..	0.11	..	..	..
	..	..	[0.06]*	..	..	..
Connectivity	..	..	..	3.23	..	2.83
	..	..	..	[1.44]**	..	[1.40]**
Growth in CB's	- 0.012	- 0.012	..	..	- 0.013	- 0.013
liquidity support	[0.002]***	[0.001]***	..	..	[0.001]***	[0.001]***
Growth of CB's	..	..	- 0.021	- 0.022	..	..
balance sheet	..	..	[0.004]***	[0.004]***	..	..
Number of	..	..	..	..	0.06	..
counterparties	..	..	..	..	[0.03]**	..
Total assets over	..	..	..	..	0.03	0.03
equity	..	..	..	..	[0.01]**	[0.01]**
Constant	- 7.01	- 2.83	- 2.68	- 3.16	- 6.18	- 6.18
	[1.33]***	[0.51]***	[0.48]***	[0.40]***	[0.47]***	[0.47]***
R^2	0.95	0.96	0.92	0.92	0.95	0.95
No. of observations	48	48	48	48	48	48

Notes: Heteroskedasticity-consistent standard errors of the estimates are reported under the point estimate in the brackets and are calculated according to White procedure. (*), (**), (***) indicate statistical significance at 10%, 5%, 1%, respectively.

If banks are relatively close to each other and therefore funds flow quickly across the network, the transmission of contagion is also faster that it would be in a sparse network. As closeness centrality can also been interpreted as a proxy for a bank's reputation, estimation results suggest that a failure of a bank with good reputation can almost triple the contagion in

[27] Recall that the network indicators are expressed in percentages. Thus a one-percentage-point rise in the network variable increases the level of contagion 100% times the estimated coefficient.

the banking system. This is natural as a bank with high prestige can be expected to be well-integrated in the banking network and its failure would have far reaching consequences on the system. Turning to bank-specific characteristics, a relatively high number of counterparties (i.e. connectivity) and strong capacity to borrow funds from interbank markets indicate that a bank may be hazardous to the resilience of the network. Such banks can be labelled as "super-spreaders" owing to their ability to spread contagion efficiently.

A strong solvency position lessens the transmission of negative spillover effects, whereas leverage increases contagion. According to the estimates, an increase of equity ratio reduces the contagion by 20-40% in 2010. This indicates that the implementation of new capital requirements and efforts to rein in the excess leverage of financial institution are positive developments from the financial stability point of view.

Although the size of a first failing bank affects positively the level of contagion, network indicators exhibit more prominent impacts than total assets. For instance, in 2010 one percentage point growth of a bank's total assets increases contagion only by 0.2-0.4 percentage points, while a similar increase in weighted clustering of the network approximately doubles the negative effects. The results therefore suggest that an increase in a bank's connectivity, volume of interbank business as well as in the concentration of the network poses a greater systemic risk for the banking system than an increase in a bank's size. This result supports the view that authorities should give more attention to the network topology (and to the notion of "too-connected-to-fail") rather than concentrate solely on the size and whether or not a bank is "too-big-to-fail". Large interbank market players should be closely followed and new policy instrument should be designed to take into account the network effects. In particular, local clusters that are formed of highly connected banks with large interbank positions should be monitored.

Central bank liquidity operations have a significant and negative effect on contagion, indicating that central bank policies are efficient in alleviating the crises and negative domino effects in the financial markets. However, the impact is relatively subdued. The liquidity support of central banks given in the form of loans to local financial institutions reduced contagion only by 1.2-1.3 % in 2010. Central banks may also use other non-monetary policy related measures to support national banking sectors such as emergency liquidity assistance and buying securities and bonds from markets. To take into account such measures we test the significance of growth in central bank's total assets. The impact of this variable is somewhat more pronounced as it mitigates negative spillover effects by 2.1-2.2%. The outcome might be driven by the fact that in the case of the euro area countries the total balance sheet includes also central bank's foreign-currency denominated claims on banks as well as intra-eurosystem claims that in some cases proved to be significant in amplifying the total assets. Moreover, securities market program and covered bond purchase programme were both active in 2010. Although central bank policies are useful in restraining contagion, they are not very efficient during the crisis.

Table 4. Results for cross-section OLS estimation with 2007 data

	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
Log (total assets)	0.64	0.64	0.48	0.57	0.53
	[0.17]***	[0.16]***	[0.15]***	[0.16]***	[0.15]***
Equity over total	5.63	4.99	3.36	11.46	..
assets	[12.94]	[12.76]	[12.57]	[12.89]	..
Weighted clustering	0.87	0.83	0.45	1.05	..
coefficient	[0.15]***	[0.15]***	[0.26]*	[0.14]***	..
Closeness centrality	5.22	..	..	..	..
	[2.58]**	..	..	..	..
Path	..	- 3.82	..	..	..
	..	[1.60]**	..	..	..
Volume of in-coming	..	..	1.07	..	1.72
interbank loans	..	..	[0.43]**	..	[0.16]***
Growth in CB's	- 0.002	- 0.002	- 0.001	..	..
liquidity support	[0.00]***	[0.00]***	[0.00]*	..	..
Growth of CB's	..	..	..	- 0.02	- 0.02
balance sheet	..	..	..	[0.007]***	[0.006]***
Total assets over	..	..	..	..	- 0.02
equity	..	..	..	..	[0.02]
Constant	- 6.70	6.24	0.35	- 2.03	2.89
	[2.54]**	[3.52]*	[1.13]*	[0.96]**	[0.67]***
R^2	0.72	0.73	0.73	0.72	0.74
No. of observations	51	51	51	51	51

Notes: Heteroskedasticity-consistent standard errors of the estimates are reported under the point estimate in the brackets and are calculated according to White procedure. (*), (**), (***) indicate statistical significance at 10%, 5%, 1%, respectively.

Table 4 presents the estimation results with 2007 data. Overall, the results regarding the years 2007 and 2010 are similar, confirming the positive relationship between contagion, size and network indicators. The larger and the more central the first failing bank is, the more widespread is the contagion. Also the coefficients of bank's network position related variables continue to be larger than the bank's total assets, whereas central bank policies manage to moderate contagion.

The magnitude of the coefficients nevertheless differs in 2007 and 2010. For instance, positive impact of central bank operations was almost non-existent in 2007, possibly owing to short time scale of liquidity support during the second part of 2007. On the eve of the financial crisis the failure of a big bank also induces 1.7-4.6 times larger negative effects than in 2010. In 2007 big banks were considerably larger than in 2010, indicating that the concentration of a banking system also in terms of size has negative repercussions on financial stability.

Although bank clustering continues to be significant variable, its coefficients are lower in 2007. Moreover, a bank's position as a middleman (betweenness centrality) and bank connectivity are no longer significant variables in 2007. At the same time, closeness centrality (being also used as a proxy for reputation) and the volume of in-coming interbank loans exhibit strong influence on contagion. Taken together, the results therefore seem to indicate that, although local clusters continued to play a part in the contagion process in 2007, bank reputation and the volume of its interbank business are more important factors in determining the amount of contagion in 2007 than in 2010. Finally, the resilience of the banking system declines in 2007 while the physical distance between banks (average path length) increases.

Finally, both equity and leverage ratio fail to be significant explanatory variables prior to the financial crisis. Moreover, the signs of these variables differ from the expectations. One plausible explanation for the results is that banks did not have enough good quality capital in their balance sheets to cover losses. Indeed, prior the crisis banks were often using capital-instruments that were not equity capital per se and proved to be difficult to transform into equity during the crisis. The result thus hint that the solvency of the European banking sector was not adequate for reducing the negative effects of system-wide contagion in 2007 even though the capital levels were perceived to be sufficient at the time.

7. Conclusions

The extensive interconnectedness of the modern interbank network enabled the rapid transmission of the financial crisis by creating a transmission channel for financial contagion and by exposing all banks in the network to potential losses. The limited knowledge of counterparty exposures during the crisis made it difficult to distinguish solid and well-capitalised institutions from the contagious ones. The uncertainty led banks to limit their exposures and to withdraw from money markets, bringing the market to standstill and making the crisis systemic.

This paper proposes a novel approach to describe the contagion process and applies the susceptible – infected – recovered (SIR) model by Kermack and McKendrick (1927). Using data on large cross-border banks in Europe, the SIR model is applied in the context of a theoretical network-based model by Barabasi and Albert (1999). As some banks turn out to be more hazardous to the banking system than others, it is of interest to determine whether the negative spillover effects are driven by bank-specific factors. Therefore, a cross-sectional panel model is estimated to disentangle the relationship.

The simulation results suggest that the crisis divides the banks in two categories; contagious and healthy banks. On average, approximately 40% of the European banks are affected negatively by the crisis in 2010, but the average contagion was almost twofold in 2007. In terms of nationality, French, British, German and Spanish banks are able to induce widespread contagion, while banks from Ireland, Greece and Portugal have only limited negative impacts.

The panel analysis indicates that the larger and the more central the first failing bank is, the more widespread is the contagion. However, high clustering of banking system and a bank’s high connectivity and large interbank loans pose a greater systemic risk for the banking system than a bank’s size. Especially detrimental to the financial stability would be a bankruptcy of a bank with high interbank loan volumes and numerous counterparties and positioned in a cluster of banks with similar characteristics. For instance, a failure of a bank with good reputation can almost triple the negative spillover effects, whereas one percentage point growth of a bank’s total assets increases contagion only by 0.2-0.4 percentage points.

Authorities should therefore give more attention to the "too-connected-to-fail" paradigm, to the structure of the interbank network and to the "super-spreader" banks. Moreover, as increasing density and concentration of the banking system augment systemic risks, authorities should be able to use additional macroprudential tools to mitigate the situation. According to the analysis, the following network indicators should especially be added into the toolkit of supervisors and regulators: weighted clustering coefficient, closeness centrality, connectivity and volume of in-coming loans.

Strong solvency position lessens contagion in 2010 but no such impact is evident in 2007. The outcome renders support to the view that European banks were not adequately capitalised prior to the banking crisis. Thus, new capital requirements seem to be a step in the right direction as they enhance the equity ratios of banks and limit excess leverage. Finally, central bank liquidity operations and other central bank measures are efficient in alleviating contagion and financial crisis. But as central bank policy can only limit contagion marginally during a crisis, efforts should be directed to preventive measures.

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Appendix 1: Formulas and definitions of network indicators

	Definition	Interpretation	Formula
Number of counterparties (i.e. degree), k	The number of counterparties, k, (links) of bank i (a node). k_i is set to 1 if banks are counterparties, zero otherwise.	The more the counterparties, the more the creditors/debtors of a bank.	$k = \sum_i k_i$
Strength (by in-coming links), $s_i^{w,b}$	Sum of the weights, w (volume of the interbank loan) of bank i's in-coming links.	Volume of interbank loans that bank i has taken from other banks, j=1,...,N. (bank's borrowing strength).	$s_i^{w,b} = \sum_{j=1}^{N} w_{ij}^{b}$
Strength (by out-going links), $s_i^{w,l}$	Sum of the weights, w (volume of the interbank loan) of bank i's out-going links.	Volume of interbank loans that bank i has given to other banks, j=1,...,N. (bank's lending strength).	$s_i^{w,l} = \sum_{j=1}^{N} w_{ij}^{l}$
Average shortest path length, l_i	The average shortest distance, d, from node i to other nodes, j=1,...,N, in the network.	Describes how quickly a bank may reach other banks in the system, on average.	$l_i = \frac{1}{(N-1)} \sum_{i \neq j} d_{ij}$
Eccentricity, ε_{ij}	The maximum distance, d, from node i to any other node j in the network.	Describes how far away the other banks are in the network.	$\varepsilon_i = max_j d_{ij}$
Connectivity, p_i	The number of node i's existing links, k, relative to the number of a node i's all potential links.	Unconditional probability that two banks are counterparties for each other.	$p_i = \frac{k_i}{(N-1)}$
Clustering coefficient, c_i	The connected neighbours of node i, a_i, relative to all possible connections among these three nodes. Thus, measures the number of triangles in the	Unconditional probability that bank i's counter-parties are also connected to each other. (Probability that my two friends are also likely to be friends of each other.)	$c_i = \frac{2}{k_i(k_i-1)} \times \sum_{jh} a_{ij}\, a_{ih} a_{jh}$

	network.		
Weighted clustering coefficient, c_i^w	Clustering coefficient is weighted by the volume of interbank payments.	Proportion of interbank loan volume held by two counterparties of a bank that are also linked to each other	$c_i^w = \frac{1}{s_i(k_i - 1)} \times \sum_{jh} \frac{(w_{ij} + w_{ih})}{2} a_{ij}\, a_{ih} a_{jh}$
Betweenness centrality, $C_b(i)$	Sum of fractions of shortest paths, δ, between two nodes (s,t) that pass through node i relative to total number of shortest paths between nodes s and t.	Quantifies the number of times a bank acts as a bridge along the shortest path between two other banks. Shows how dependent these banks are from bank i.	$C_b(i) = \sum_{s \neq t \neq i} \frac{\delta_{s,t}(i)}{\delta_{s,t}}$
Closeness centrality, C_i	Inverse of the sum of the average shortest distances from a node i to all other nodes, j=1,...,N, in the network.	How quickly something that is flowing through the network (f.e. contagion, liquidity) is expected to reach bank i. Also used as proxy for reputation.	$C_i = \frac{1}{\sum l_i}$

Sources: Iori et al., 2008; Soramäki et al., 2007; Minoiu and Reyes, 2013; Alves et al., 2013.
Note: N stands for the number of nodes (banks) in the network.

Appendix 2: Correlations between indicators in 2010 and 2007

In 2010	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Total Assets	1.00															
(2) Equity	0.91	1.00														
(3) Equity over Total assets	-0.17	0.11	1.00													
(4) Total Assets over Equity	0.10	-0.16	-0.88	1.00												
(5) Change of CB's loans to banks	-0.25	-0.11	0.40	-0.27	1.00											
(6) Change of CB's balance sheet	-0.21	-0.17	0.11	-0.03	0.82	1.00										
(7) Between centrality	-0.01	0.01	0.06	-0.09	-0.14	-0.18	1.00									
(8) Clustering coefficient	-0.03	-0.02	-0.01	0.04	0.13	0.14	-0.91	1.00								
(9) Closeness centrality	0.04	0.03	0.07	-0.07	-0.08	-0.09	0.90	-0.96	1.00							
(10) Connectivity	0.04	0.02	0.05	-0.06	-0.10	-0.12	0.92	-0.97	1.00	1.00						
(11) Eccentricity	-0.04	-0.03	-0.03	0.06	0.14	0.16	-0.92	0.96	-0.97	-0.98	1.00					
(12) In degree	0.04	0.02	0.05	-0.06	-0.10	-0.12	0.92	-0.97	1.00	1.00	-0.98	1.00				
(13) Strength by in-coming loans	0.31	0.30	-0.03	-0.06	-0.20	-0.20	0.87	-0.87	0.87	0.89	-0.90	0.89	1.00			
(14) Strength by out-going loans	0.01	0.02	0.09	-0.11	-0.10	-0.15	0.96	-0.96	0.97	0.98	-0.98	0.98	0.91	1.00		
(15) Shortest path	-0.05	-0.03	-0.09	0.08	0.06	0.07	-0.87	0.93	-1.00	-0.99	0.96	-0.99	-0.85	-0.96	1.00	
(16) Weighted clustering coefficient	0.43	0.46	0.07	-0.12	-0.14	-0.19	0.61	-0.53	0.62	0.61	-0.62	0.61	0.84	0.68	-0.62	1.00

In 2007	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Total Assets	1.00															
(2) Equity	0.88	1.00														
(3) Equity over Total assets	-0.42	-0.10	1.00													
(4) Total Assets over Equity	0.48	0.10	-0.93	1.00												
(5) Change of CB's loans to banks	-0.01	-0.07	-0.04	-0.02	1.00											
(6) Change of CB's balance sheet	0.08	0.15	0.23	-0.24	0.42	1.00										
(7) Between centrality	-0.04	-0.02	-0.01	0.03	0.02	-0.16	1.00									
(8) Clustering coefficient	-0.01	0.02	0.13	-0.20	0.04	0.20	-0.91	1.00								
(9) Closeness centrality	0.03	0.00	-0.06	0.16	0.05	-0.18	0.90	-0.96	1.00							
(10) Connectivity	0.02	-0.01	-0.08	0.16	0.02	-0.19	0.92	-0.97	1.00	1.00						
(11) Eccentricity	-0.01	0.00	0.08	-0.16	0.08	0.23	-0.92	0.96	-0.97	-0.98	1.00					
(12) In degree	0.02	-0.01	-0.08	0.16	0.02	-0.19	0.92	-0.97	1.00	1.00	-0.98	1.00				
(13) Strength by in-coming loans	0.27	0.23	-0.20	0.27	-0.08	-0.12	0.86	-0.89	0.89	0.90	-0.92	0.90	1.00			
(14) Strength by out-going loans	-0.03	-0.03	-0.04	0.10	-0.01	-0.19	0.95	-0.96	0.98	0.99	-0.99	0.99	0.92	1.00		
(15) Shortest path	-0.04	-0.01	0.05	-0.15	-0.08	0.17	-0.87	0.93	-1.00	-0.99	0.96	-0.99	-0.87	-0.96	1.00	
(16) Weighted clustering coefficient	0.37	0.36	-0.20	0.23	0.01	-0.08	0.66	-0.59	0.67	0.67	-0.69	0.67	0.86	0.71	-0.68	1.00

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