Cross-border interbank contagion in the European banking sector*

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[PRELIMINARY AND INCOMPLETE DRAFT. PLEASE DO NOT QUOTE OR DISTRIBUTE.]

Abstract

This paper studies the scope for cross-border contagion in the European banking sector using true exposure data at a bank-to-bank level. Using a model of sequential solvency and liquidity cascades in a network setting we analyze geographical patterns of loss propagation from 2008 until 2012, and study the distributions of contagion outcomes after a common shock and an exogenous bank default over 100 couples of simulated networks of long- and short-term claims. To obtain a realistic representation of interbank exposures, we exploit for the first time a unique dataset of money market transactions estimated from TARGET2 payments data. Our results document the critical impact of the underlying network structure on the propagation of financial losses and point to the importance of considering the evolving nature of interbank claims when running realistic contagion simulations. An econometric analysis of the determinants of contagion shows that bank exposures to the riskiest counterparties in the system and bank position in the network before the shock are significant explanatory variables of default outcomes, behind banks' own financial ratios.

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Keywords : Contagion, Interbank market, Stress Testing, Liquidity Hoarding, Counterparty Risk.

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1 Introduction

The 2007-2008 financial crisis revealed the fragility of financial institutions worldwide. More importantly, it disclosed the major role of interconnectedness among banks in the propagation of financial distress. Interconnections, due to bilateral contractual obligations but also to exposure to common risk factors and sudden collapses in market confidence, have grown dramatically in the run-up to the crisis. [1] While higher interconnectedness is a crucial means of efficient risk transfer, it may also lead to contagious *default cascades* : an initial shock may propagate throughout the entire banking system via chains of defaults and liquidity shortages that follow highly dynamic patterns.

Direct and indirect linkages among banks arose as a key component of financial contagion in the European Union, as revealed first by the default of Lehman Brothers in September 2008, and then by the euro area sovereign debt crisis. Especially after the European Banking Authority's disclosure of the extent of European banks' common exposures to stressed sovereigns in 2011[EBA, 2011a], the potential for contagion effects through interbank transactions has taken a peculiar - geographical - dimension in the euro area, with banks reducing their exposure particularly to banks headquartered in the periphery of the euro area (see, e.g., Abascal et al. [2013] who measure fragmentation in interbank market and three other financial markets (sovereign debt, equity and the CDS market for financial institutions).

This paper is the first to investigate the scope for cross-border contagion in Europe using true exposure data at a bank-to-bank level. We analyze geographical patterns of shock propagation between 73 European banking groups from end-2008 until end-2012. Cross-border interbank exposures are generally hard to obtain. National supervisors can have at best a partial view of the largest long-term credit claims of supervised banks via credit registers. [2] To circumvent the unavailability of accurate information on domestic and cross-border interbank exposures, and obtain a realistic representation of how European banks are connected through their long- and short-term claims, we exploit for the first time a unique dataset of interbank money market transactions, with various maturities, estimated from TARGET2 payment data (see Arciero et al. [2013]). More specifically, we employ money market loans with maturities up to one month to reconstruct the network of short-term interbank linkages and a realistic probability map of short-term loans among banks ; at the same time, we use information on the size and frequency of money market loans with longer maturities to construct a realistic probability map of long-term bank-to-bank exposures. These maps, together with the amount of individual banks' aggregate loans to other banks, are used to simulate a large number of long-term exposure matrices through a novel methodology proposed by Halaj and Kok [2013].

The extent of interbank contagion is assessed relying on Fourel et al. [2013] model of sequential

1. Total cross-border banking flows rose several-fold from 1978 to 2007 compared to their long-term average, see Minoiu and Reyes [2011].

2. For instance, the German credit register contains quarterly data on large bilateral exposures - derivative, on- and off-balance sheet positions - above a threshold of EUR 1.5 m. The French "grands risques" data include individual banks' quarterly bilateral exposures that represent an amount higher than 10% of their capital or above EUR 300 m. Italian banks submit to the Banca d'Italia their end-of-month bilateral exposures to all other banks.

solvency and liquidity cascades in a network setting. More specifically, we look at the distribution of simulation outcomes resulting from a common market shock on (listed) banks' capital, coupled with an exogenous bank default ; the distributions are obtained over 100 different simulated networks of long- and short-term exposures. We observe the total number of defaulted banks after several rounds of solvency and liquidity contagion, and the total capital loss experienced by a certain country's banking sector when contagion is triggered by a default of a foreign or domestic bank. Heat maps are used to assess, on the one hand, which banking sectors are the most "systemic" in terms of the losses that the failure of one of their banks can impose to foreign countries' banks and, on the other, to identify which banking sectors are the most prone to cross-border contagion from European counterparties.

Simulation of multiple realistic short- and long-term networks allows us to analyze the determinants of contagion using an econometric approach. Relying on five years of data and 100 pairs of simulated networks we are able to identify both bank and network characteristics that make a bank/system more fragile/resilient to contagion.

We find that both solvency and liquidity contagion are tail risks : losses averaged over stress-scenario, initial bank defaults or simulated networks are rather limited ; however, averaging conceals rare extreme events. We document that losses at the tail of the distribution can reach one third of the system capital in 2008, and that the resilience of the system improves significantly over time. Under severe equity market stress and following an exogenous default of one bank, cross-border contagion can materialize in the European banking system. The overall average losses caused by a foreign bank default, however, vary remarkably over time and over different banking sectors. A foreign default has on average a small impact on most banking sectors and even less over time. However, for some banking systems, a default by a foreign bank may cause a loss as large as 15% of the capital of the impacted banking sector. Overall, tour results document that the European banking system has substantially increased its capacity to withstand the same kind of adverse financial conditions that it had to face after the default of Lehman Brothers. The heat maps allow us to discern specific geographical patterns of cross-border contagion in the European Union, which vary significantly over the years. In general, the maps for 2009, 2010 and 2012 show that the potential for cross-border contagion has constantly decreased over time. This is related to a generalized reduction in the share of long-term interbank loans in bank balance sheets, on the one hand, and to an increase in banks' capitalization during those years compared to 2008.

Finally, our results show the strong impact on the domestic and cross-border propagation of losses of heterogeneity and concentration in the structure of interbank exposures. The number of defaults resulting from extreme market stress coupled with one bank's default can be five or six times larger depending on the underlying structure of interbank linkages. This is consistent with recent models of contagion in financial networks relying on simulated networks of exposures (see, Georg [2013] and Gai and Kapadia [2010]), and points to the need to account for the evolving nature of the web of interbank linkages when running contagion analysis. This is the first paper, to our knowledge, to document this feature simulating probabilistic interbank exposures based on actual bank-to-bank level data.

A large literature exists that relies on counterfactual simulations based on a network setting to estimate the potential for interbank contagion (see Upper [2011] for a comprehensive survey). Notwithstanding the increasingly international dimension of contagion, however, these simulations have so far focused essentially on national banking sectors, estimating their frailty/resilience only at one specific point in time. Moreover, only very recently have economists started to integrate behavioral foundations into their modelling frameworks, hence providing different contagion channels, and to consider the impact of common shocks on the network of interbank loan exposures, possibly resulting in concurrent losses for banks.

Our study contributes to this literature by analyzing cross-border contagion at a bank-to-bank level using realistically simulated networks from true exposure data. Up to now, a handful of papers have analyzed cross-border contagion using price data such as equity or credit default swaps, therefore relying on some form of market efficiency and not being able to identify the structural channels driving the co-movement of prices (see, Gropp et al. [2009]). Other papers focused their attention on BIS country statistics to study cross-border contagion ; but this has the strong drawback that authors have to assume that the whole or a part of a country's banking system defaults and that losses propagate to other country's banking sectors (see, Degryse et al. [2009] and Espinosa-Vega and Sole [2010]).

We exploit the idea of probabilistic networks to study propagation of contagion : multiple simulated networks, drawn from real data probability maps (thanks to TARGET2 data), differ from the real existing network and, moreover, demonstrate significant heterogeneity. This allows us to analyze not only the vulnerability of one particular network realization retrieved from the real data, but plenty of potential realistic networks. All the simulated networks display well-documented properties such as a low density and a highly skewed (weighted and unweighted) degree distribution. Furthermore, we pursue the analysis one step further and econometrically identify balance sheet and network properties which drive the contagion outcome.

We perform an econometric exercise on three different levels. First, we investigate bank-level contagion and explain the determinants of bank fragility or systemicity with both banks' balance sheet and exposure characteristics. Then we consider the system as a whole and analyze the determinants of system-wide contagion by exploiting within-year across-networks heterogeneity. And lastly, we refine the analysis at a more granular level by scrutinizing what drives cross-border contagion at the country-level.

The remainder of this article is structured as follows. In section 2, we present the theoretical model for the imputation of losses and the liquidity hoarding mechanism. In section 3, we describe the banks' sample, the interbank exposures data and the algorithm used to generate interbank networks. We provide descriptive evidence on both the European banking system in the period 2008-2012 and the structural properties of generated long- and short-term networks. The results of our simulations are presented and commented on in section 4. Section 5 introduces the econometric analysis of the determinants of contagion outcomes. Section 6 discusses robustness checks, section 7 concludes.

2 The model

Our model builds on the work by Fourel et al. [2013]. In the following we expose its main theoretical blocks as well as some extensions we implement, while we refer the reader to Fourel et al. [2013] for more details.

Let us consider a system of N financial institutions indexed by i. Each of them is characterized by a stylized balance sheet presented in **Table 1**. The asset side of bank i is decomposed into several items : long- and short-term interbank exposures ($E^{LT}(i,j)$ and $E^{ST}(i,j)$ for $j \in [1;N]$), cash and liquid assets (cash from now on) $Ca(i)$ and other assets $OA(i)$. We denote the total assets by $TA(i)$. The liability side of bank i consists of equity $C(i)$ (hereafter capital), long- and short-term interbank exposures ($E^{LT}(j,i)$ and $E^{ST}(j,i)$ for $j \in [1;N]$) and all other liabilities gathered in $OL(i)$.

	Assets	**Liabilities**	
Long Term	$E_t^{LT}(i,1)$	$E_t^{LT}(1,i)$	Long Term
Interbank	$\vdots$	$\vdots$	Interbank
Assets	$E_t^{LT}(i,N)$	$E_t^{LT}(N,i)$	Liabilities
Short Term	$E_t^{ST}(i,1)$	$E_t^{ST}(1,i)$	Short Term
Interbank	$\vdots$	$\vdots$	Interbank
Assets	$E_t^{ST}(i,N)$	$E_t^{ST}(N,i)$	Liabilities
Cash	$Ca_t(i)$	$OL_t(i)$	Others
Others	$OA_t(i)$	$Ca_t(i)$	Capital
Total assets	$TA_t(i)$	$TL_t(i)$	Total liabilities

Table 1: Bank i's stylized balance sheet at date t

Banks are connected by two types of links : short-term and long-term commitments. The distinction between these links is essential within the present model as it enables defining two channels of contagion (liquidity vs. solvency contagion). Short-term exposures are represented mainly by short-term loans, e.g. with overnight or one-week maturity, and a link can be easily cut from a certain day/week to the subsequent one. This property of the link allows banks to hoard liquidity, that is, to reduce or to cut their exposures to a counterparty when needed. As explained below, liquidity contagion here propagates through the network of short-term exposures. On the contrary, long-term exposures represent a more stable source of funding and can not be cut before maturity. Therefore, only if a bank defaults do its counterparties lose all their long-term exposures to it (taking a recovery rate into account). A network of long-term exposures is the main channel for the propagation of solvency contagion.

The model consists of three parts : a common market shock, solvency contagion propagation and liquidity hoarding behavior. This section provides the main intuitions and describes the building blocks, while additional technical details can be found in Appendix A.1.

Common market shock

The way a market shock is simulated is essential. The latter weakens the resilience of the system, thus revealing more plainly the potential for contagion (see Upper [2011]). In the absence of national supervisory data allowing to shock various asset classes in bank balance-sheets (as in Elsinger et al. [2006a], Elsinger et al. [2006b], or in Fourel et al. [2013]), we implement a common shock directly on all listed banks' capital using a one-factor model for equity returns (see details in Appendix A.1). The same shock is consistently applied over the whole time period, 2008-2012, which allows us to make sure that contagion in the system is driven purely by the change in the network structure and banks' capitalization and liquidity levels. As depicted in figure 2, the shocks represent on average 5% of bank capital among scenarios but can reach up to 25% in extreme cases ; such orders of magnitude are absolutely in line with bank capital losses observed during the recent crisis (see, e.g., on Banking Supervision [October, 2010] and Strah et al. [2013]).

After the system is hit by a market shock, one bank at a time is exogenously pushed to default. Losses through solvency and liquidity contagion channels are then computed. The fact that only one banks fails at a time allows us to estimate losses due to the default of each bank and to rank the banks as more or less systemic.

Solvency contagion

Following Fourel et al. [2013], we define solvency contagion as follows. Let bank i default, then its counterparts lose all their exposures to this bank. If another bank or some of the banks are highly exposed to the defaulted bank, they might default as well. A general condition for a bank to default due to default contagion is as follows :

$$\underbrace{[C(j) - \epsilon(j)]}_{\text{Capital after initial shock}} \quad - \quad \underbrace{\sum_i R^S(i)E(j,i)}_{\text{non-recovered exposures}} \quad < 0 \tag{2.1}$$

where $(1 - R^S(i))$ is a recovery rate. To account for all the losses due to solvency contagion, the Furfine algorithm of iterative default cascade (Furfine [2003]) is used. This algorithm allows incorporating liquidity hoarding behavior of banks in the same framework with solvency contagion.

Liquidity hoarding

Banks regularly perform liquidity management, estimating their liquidity stock, outflows and inflows for the next period. In normal times, they can foresee with some certainty how much liquidity they will need to satisfy reserve requirements or other commitments ; to this end they can borrow from other banks in the interbank market as well as from the central bank (e.g. through weekly main refinancing operations). In a well functioning interbank market banks with excess liquidity can lend it to those who lack short-term funding. This situation can however radically change during times of increased uncertainty. On one hand, banks' assets become much more volatile creating liquidity outflows in terms of margin calls, higher haircuts and requirements for collateral, which are difficult to foresee. On the other hand, confidence in the market evaporates quickly, counterparty risk rises, and banks fear both their inability to get liquidity when needed as well as counterparty risk. All this can lead banks to a precautionary demand for liquidity hence to *hoarding* behavior, by which they

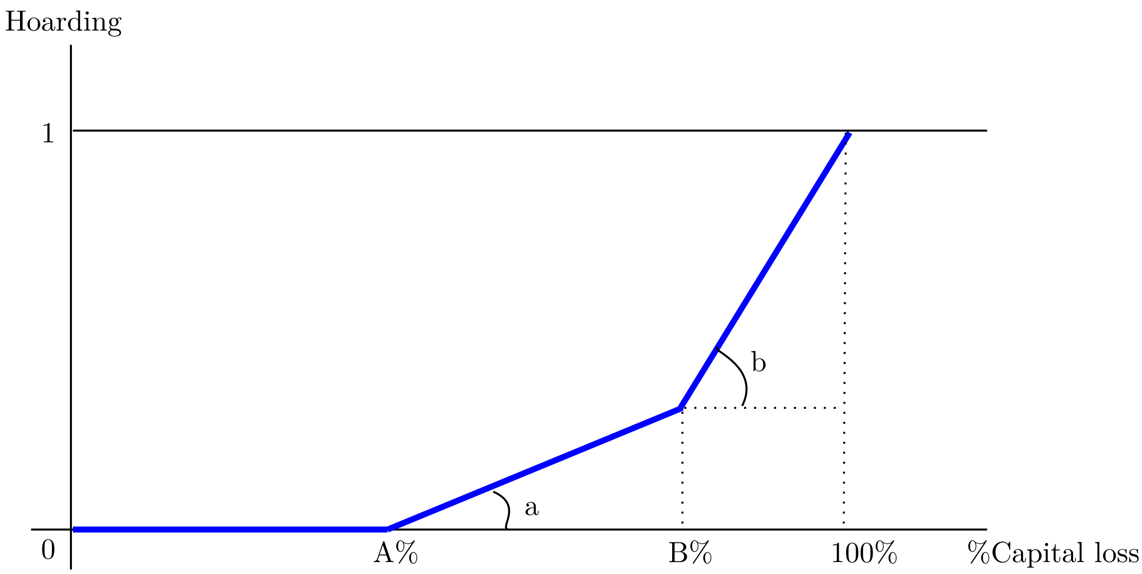

Figure 1: Liquidity hoarding behaviour.

reduce lending to each other in order to secure their own liquidity needs and to reduce exposure to counterparty risk. [3]

Banks start hoarding liquidity when there is a signal of market malfunctioning or they start experiencing problems themselves. For instance, a signal can be a drop in asset prices, high volatility or unexpectedly large losses. In our simulations we assume that a shock-related capital loss above a certain threshold represents such a signal. Therefore, banks that were impacted by a market shock and/or by solvency contagion will start hoarding liquidity, and the higher loss they experience, the more they hoard. We assume a function for liquidity hoarding depends linearly on the capital loss, $\lambda(Loss)$. The function, **Figure 1**, has 4 intervals : banks do not hoard liquidity in intervals 1 and 4, that is, when capital loss is below some threshold $A\%$ (no signal of crisis) or more than 100% (bank is insolvent). Banks hoard less ($a\%$) in interval 2 when the shock is moderate and more ($b\%$) in interval 3 when the shock is more adverse.

Banks will decide how much to hoard based on their own perception of market uncertainty. But they also have to decide how much and from which counterparty they will hoard. A straightforward assumption is that the riskier the counterparty is, the more a bank hoards liquidity. Provided banks have no private information about the riskiness of other banks' portfolios, they can rely on leverage μ as a proxy for the riskiness of a counterparty (Das and Sy [2012], Lautenschlager [2013]). The easiest way for a bank to hoard liquidity is to stop rolling over short-term loans. After all the banks decide how much to hoard and make claims, the following condition has to be satisfied for a bank to be liquid :

$$[Cash] + [To\,Be\,Recieved] - [To\,Be\,Paid] > 0 \tag{2.2}$$

3. For the UK sterling market, Acharya and Merrouche [2013] document that riskier UK settlement banks held more reserves relative to expected payment value in the immediate aftermath of 9 August 2007, thus igniting the rise in interbank rates and the decline in traded volumes. Berrospide [2013] documents evidence for the precautionary motive of liquidity hoarding for U.S. commercial banks during the recent financial crisis.

3 Interbank exposures and network simulation

This section presents the numerical algorithm used to generate a large number of networks of long- and short-term interbank exposures, as well as the data used to calibrate and run it. Additional balance sheet items used for the simulations and the econometric analysis are also presented. The last subsection provides descriptive evidence on the structure of simulated networks and on the domestic versus cross-border nature of the simulated national banking sectors.

3.1 The algorithm

We apply the algorithm proposed by Halaj and Kok [2013] to simulate a large number of interbank networks that are used to run the stress scenarios. In the absence of interbank lending and borrowing data, one common method in the literature relies on their estimation through entropy maximization (see Sheldon and Maurer [1998], Wells [2004] and Mistrulli [2011] for a comparison of this methodology with actual exposure data). We adopt an alternative methodology proposed by Halaj and Kok [2013] for different reasons. First, one essential drawback of the entropy maximization method is that the obtained matrix of bilateral exposures is such that strictly positive links are estimated between any two banks which have a strictly positive aggregate interbank exposure, i.e. the obtained network is not sparse and does not display the empirically documented core-periphery structure (averaging bias). When national banking systems are considered, such an undesirable feature may be neglected, as domestic banks within a country are typically densely interconnected. On the contrary, applying the same methodology when cross-border exposures are considered would amount to neglect either a possible home-bias in interbank exposures or the fact that financial interconnections are evenly spread nor among banks within a national banking sector neither among different countries' banking sectors. In other words, preferential banking relationships do exist, as well as strong geographical patterns. Second, the entropy maximization method yields a unique solution for the bilateral exposures matrix, and may therefore badly account for the fact that interbank exposures are likely to change quickly. In addition, performing stress scenarios on a unique exposures matrix typically fails to obtain a probability distribution over the simulation outcomes. By contrast, the methodology introduced by Halaj and Kok [2013] addresses these two issues by enabling the construction of a large number of sparse and concentrated networks that all match the aggregate exposure levels. Third, this methodology enables us to make use of additional information on actual interbank links obtained from TARGET2 payment data. [4]

The algorithm to simulate bilateral exposure matrices relies on two inputs : *(i)* a probability map and *(ii)* aggregate interbank exposures data at a bank level (i.e. the sum of the exposures of any bank i to all other banks in the system). Denote Π_t a $N \times N$ probability map at date t whose each element (i, j) is $\pi_{ij} \in [0; 1]$ with $\pi_{ii} = 0$ and $\sum_j \pi_{ij} = 1$ for all i. π_{ij} is the share of funds lent by any bank i to any bank j and is later used as the probability structure of interbank linkages.

4. In 2012 TARGET2 settled 92% of the total large value payments traffic in euro.

The construction of a large number of exposure matrices at date t relies on the Π_t matrix and on the total interbank loans granted by any bank i to all its counterparties within the network, denoted L_i^t. The construction of one particular exposure matrix, i.e. of all bilateral elements L_{ij}^t, uses an "Accept-Reject" scheme. A pair (i, j) of banks is randomly drawn, with all pairs having equal probability. This link in the interbank network is kept with a probability π_{ij} and, if so, the absolute value of this exposure, denoted $\tilde{L}_{ij}$, equals L_i multiplied by a random number drawn from a uniform distribution with support $[0; 1]$. The amount of exposures left to be allocated is thus reduced. The procedure is repeated until the difference $\left(L_i - \sum_j \tilde{L}_{ij}\right)$ is below some threshold κ.

3.2 Data and calibration

3.2.1 Banks' sample

We run our contagion analysis using a sample of 73 European banking groups, whose list is provided in Table 4. Given our focus on the resilience of the European banking system, we select a subset of the banks that underwent the 2011 stress tests carried out by the European Banking Authority (EBA). In particular, our sample includes all the banking groups headquartered in Europe that are part of the list of Global Systemically Important Banks (G-SIBs), while it excludes some Spanish "cajas" to avoid an over-representation of the Spanish banking sector. [5] It is worth noting that our sample also includes savings and cooperative banks, hence non-listed European institutions : differently from the extant empirical literature on contagion that relies on market data, this allows us to assess also the impact of a shock hitting relatively smaller market players.

3.2.2 Simulating European interbank exposures : TARGET2 data and the probability maps

Long-term interbank exposures. Information on the total interbank loans L_i granted by any bank i to all its counterparties within the network is retrieved via the balance sheet item named "Net loans to banks" available in *SNL Financials*. [6]

The probability map Π_t is obtained based on term interbank money market loans settled in TARGET2 during each year t. The money market dataset we use is the output of the Eurosystem's implementation of the Furfine [1999] methodology to TARGET2 payment data (see Arciero et al. [2013] for more details on the identification methodology). More specifically, we use loans with

5. See EBA [2011b]. The latest list of G-SIBs has been published by the Financial Stability Board in November 2012 and is available at http://www.financialstabilityboard.org/publications/r_111104bb.pdf.

6. Net loans to banks are defined as *Net loans and advances made to banks after deducting any allowance for impairment*. The main difference between this item and "Loans and advances to banks" or "Deposits from banks" available e.g. in Bankscope, is that the latter also include loans to or from central banks (see Upper [2011]), which would be a major drawback for our analysis.

maturities ranging from one month and up to six months to compute shares of preferential lending. These percentages are then imputed in the simulation algorithm as *prior* probabilities about the existence and size of an interbank linkage.

For the last quarter of each year, for each lender, we bundle all term loans and compute the average amount lent to each borrower ; hence based on such average amounts we look at how total credit was allocated among counterparties. Three details are worth noting in the assumptions we make to build the probability structure of interbank exposures. First, our computation includes all the banking groups participating in the interbank euro money market, i.e. not only the 73 banks belonging to our sample. Subsequently, to form the 'true' as well as the simulated networks of exposures, the shares are normalized to consider only the 73 sample banks. [7] Second, we use only the term market segments in the calculations because it is for unsecured lending at such longer maturities that preferential interbank lending relationships are more likely to exist and relatively stronger geographical patterns emerge. This is especially so in periods of heightened uncertainty about counterparties' solvency. [8] Third, we consider the average size of a long-term loan traded between a lender-borrower couple independently of the frequency at which the two banks interact in the market over the quarter. An undesirable aspect of this choice is that we may turn up assigning a very high link probability to a lender-borrower couple even if they have interacted only rarely in the market. Nonetheless, we deem this choice to be the most appropriate in the context of assessing interbank contagion, since it is the actual size of exposures/links that matters for the propagation of distress (see Cont et al. [2010]), independently of whether that link was set up every month rather than just once in the whole quarter. [9]

Short-term interbank exposures. In the context of our model, liquidity contagion occurs through liquidity hoarding in the unsecured interbank money market. We take actual interbank loans, with maturities from overnight to one month, among the 73 sample banks from the dataset of Arciero et al. [2013]. Notwithstanding the availability of five real networks of short-term interbank exposures from end-2008 to end-2012, we decided to simulate for each year 100 short-term interbank networks using the Halaj and Kok algorithm. This allows us to duly capture the evolving nature of short-term funding linkages and its impact on contagious losses. Moreover, we will use the large number of simulated long- and short-term networks to analyze the effect of their structural

7. This enables us to avoid any bias in the results related to the assignment of too large shares of interbank credit to banks that are in our sample but may represent only a small fraction of the amounts lent by a certain bank to European counterparties. Note that the 73 sample banks represent on average more than 90% of the overall euro money market turnover in the various maturity segments.

8. See Cocco et al. [2009] and Brauning and Fecht [2012] for evidence of interbank lending relationships in the Portuguese and German money market, respectively. The second paper finds that during the 2007-08 crisis German borrowers paid on average lower interest rates to their relationship-lenders than to spot-lenders. The ECB euro money market study ECB, 2010 reports increasing market fragmentation in the euro money market in relation to the euro area sovereign debt crisis.

9. Alternative calibrations, e.g. in which prior probabilities are based on the daily average amount lent to counterparties (thus also taking into account the frequency of bank interactions over the quarter), have been used as a robustness check. Also, note that, as reported in Arciero et al. [2013], the algorithm underestimates longer term loans at the beginning and at the end of the sample. This possibly affects our construction of the probability map for 2012 as this relies on loans traded in the last quarter of the year. We will be able to account for the underestimation as soon as new estimates of the loans are available that include TARGET2 transactions in the first months of 2013.

properties on the propagation of both solvency and liquidity contagion.

3.2.3 Additional balance sheet data

Additional year-end balance sheet information (Cash and cash equivalents, Total assets, Common equity) is retrieved from SNL Financials. [10] Table 5 reports, for each year, a set of summary statistics of banks' balance sheet ratios that are relevant for our analysis. On average, interbank exposures represent about 8% of total assets over the sample period. In 2009 banks display a reduced aggregate amount of interbank exposures (in percentage of total assets) than in 2008. The variation in the cross-section is also lower, while the ratio of common equity to total assets is on average higher, which could possibly result from the recapitalization imposed by banking supervisors after the EBA stress tests in 2009. In 2010 interbank loans continue decreasing, whereas bank liquidity deteriorates slightly and bank equity to assets ratio remains constant. In 2011 and 2012 liquidity improves, on average, while the level of common equity to total assets reduces. In fact, this is related to the negative common equity reported by various Greek and one Spanish bank for the last two years. Excluding from the sample banks with negative common equity, we can observe an increase in the average equity to assets ratio from 4.20% to 4.43% in 2011 and from 4.42% to 5% in 2012. [11]

3.2.4 Simulation dates

We repeat our counterfactual simulations at year-end for five dates, $t = 2008, 2009, 2010, 2011, 2012$. [12] Repeating the same stress scenario at multiple points in time allows tracking the evolution both of the financial system resilience to extreme financial distress and of the relative influence of the different contagion channels over time.

3.3 Descriptive evidence on simulated interbank networks

Table 6 reports summary statistics about the structure of the 100 long-term interbank networks simulated using the Halaj and Kok's algorithm and the TARGET2-based probability map. The topological properties of the average simulated network are similar across the years and consistent

10. Data are exceptionally retrieved from Bankscope when not available in SNL. Consistency between the two databases has been carefully cross-checked.

11. In 2011 and 2012 balance sheet data are not available for two Greek banks (Agricultural Bank of Greece, or ATE Bank, recapitalized in July 2011 after having failed EBA stress tests and subsequently sold to Piraeus Bank in 2012, and TT Hellenic Postbank, liquidated in August 2012), nor for Bank of Cyprus and Cyprus Popular Bank in 2012. Additionally, Eurobank Ergasias and Piraeus Bank report negative common equity in 2011 and 2012, while Alpha Bank, National Bank of Greece, and Bankia have negative common equity in 2012.

12. Given that the TARGET2 database for unsecured interbank loans starts as of June 2008, it is not possible to run the simulation for earlier years.

with those observed for real interbank structures. [13] For instance, each bank is connected only with a small subset of other banks in the market (five on average across the years), so that the degree of connectivity or *density* of the networks is very small. This notwithstanding, the average length of intermediation chains is very short, i.e. banks are generally close to each other, and losses can spread from the bank in difficulty to its direct and indirect counterparties via less than three exposures, on average, and at most via four. While most of the banks have very few counterparties, there are some banks who lend to many others. The ratio between the maximum and the median number of counterparties (the *degree*), is high and increases over time : in 2012, on average across 100 networks, the most interconnected bank was about five times more connected than half of the others ; for one network the ratio between maximum and median degree was as high as seven. This points to an increasing concentration of exposures over the years and to a core-periphery market structure. Table 7 reports summary statistics for the structure of the 100 short-term interbank networks obtained using the Halaj and Kok algorithm and actual short-term money market exposures. The topological properties of the average short-term simulated network are similar to those of the long-term one across the years.

Table 8 reports summary statistics of cross-country long-term exposures over 100 simulated interbank networks. The numbers displayed are the average ratios of domestic and cross-border country-level exposures in percentage of the total capital of the country. In the upper part of the table, we notice that on average during the five years banks of one country are at least 2 times more exposed to their home counterparties, with domestic exposures reaching 19% of a country's capital and foreign exposures being around 4-7%. These average figures conceal a high heterogeneity across the simulated banking sectors, which shows up clearly looking at the *maximum* ratios of domestic and foreign exposures to aggregate capital. The maximum ratios are of similar order but follow different trends over the years. Domestic interbank exposures steadily decrease from 1.89 times the country's capital in 2008 to 0.76 in 2011, with a jump to 1.48 in 2012 ; whereas maximum foreign exposures increase from 1.10 times the country's capital in 2008 to 2.04 in 2011, and decline slightly to 1.94 in 2012. However, it is important to keep in mind that such big ratios of domestic and cross-border interbank exposures relative to a banking sector's total capital are very rare events. The median domestic and foreign exposures ratios range between 1 to 6% of countries' capital.

All in all, this evidence supports our claim about the realism of the exposure networks over which contagion simulations are run. The methodology we adopt is realistic in terms of the structural properties verified, but also because it allows capturing an evolving nature of bank interconnections. The simulated networks can be considered as probabilistic networks ; networks that could be possibly formed in other realizations, however a specific simulated exposure can differ remarkably from one network to another, as well as from the actual short-term funding loan observed in the unsecured euro money market via TARGET2.

13. See for instance Soramaki et al. [2007] and Iori et al. [2008].

4 Simulation results

In this section we look at simulation outcomes resulting from several rounds of solvency and liquidity contagion triggered by 500 different realizations of the 5% worse equity market shocks, and an exogenous bank default. As widely used in the literature we impose idiosyncratic bank defaults one by one. For each year, for each shock scenario, simulation results are computed over 100 pairs of simulated networks of long-term and short-term interbank exposures. The parameters used to calibrate the common market shock and the model are given in Table 3 in Appendix 1. It is important to keep in mind that the results are three-dimensional : we compute the distributions of number of bank failures/losses in the European banking system due to an initial default of one of the 73 banks, over 500 market shock scenarios and 100 network pairs. Thus, in order to describe the results we aggregate contagion outcomes at the level of market and idiosyncratic shocks (initial bank defaults).

We start our analysis by looking at the distribution of average and maximum losses caused by the default of one bank over a set of shock scenarios. Then we compute a Value at Risk-like indicator of losses in the system, thereby synthesizing tail risks in our three-dimensional simulation framework. Thereafter, we study the extent of cross-border contagion in the European banking system and use heatmaps to visualize the more systemic or more fragile national banking sectors. Similarly, we try to exploit contagion outcomes to rank European banks as most systemic or most fragile. We conclude by describing changes in simulation results over the years, trying to identify patterns of increasing or decreasing system resilience.

4.1 Contagion as a tail risk

Table 10 depicts the distribution of losses in the system averaged over the shock scenarios and over the defaults of an initial bank. The part '...before liquidity hoarding' accounts for losses due to both the common market shock and solvency contagion (excluding the capital loss of the bank exogenously set into default) ; the part '...after liquidity hoarding & further rounds of contagion' displays total losses due to all contagion channels. The difference between the two can therefore be attributed to mere liquidity contagion. We can see that average losses are rather limited in terms of number of defaulted banks as well as in size of depleted capital (less than 2 and 5% of system capital, respectively), and that the common shock and the solvency contagion channel account for most of them. In fact, the summary statistics in table 10 show that the distributions of losses due to the shock and to solvency contagion are relatively thin-tailed across the 100 network pairs, suggesting that the underlying long-term interbank networks display only a mild variation. On the contrary, short-term interbank exposures seem to be more volatile : while in half of the network pairs average system losses (5% of overall system capital) can be explained by the initial shocks and by solvency contagion, the heavy tail of the distribution of total losses captures the variability of liquidity contagion results, with the share of depleted capital after all contagion channels reaching a maximum value of 13% in 2008 and of 10% in 2012 (corresponding to more than 4 bank failures in 2008 and more than 3 in 2012).

The relatively low dispersion of these results is easily explained : by averaging over the initial bank default, we average away the high heterogeneity of a realistic banking system. On the contrary, European interbank networks are highly heterogenous, with a handful of very large banks and numerous small ones whose default impact on the system can be markedly different. This can easily be seen by analyzing the *maximum* number of bank failures and the *maximum* share of depleted capital upon an initial bank default. Table 11 shows that the exogenous default of one bank (always coupled with a common market shock) can lead to the default of other 14 banks in 2008 and to a capital loss as large as one third of total system capital. Also in this table the common shock and solvency contagion account for most of the failures/losses. Notice that upon the default of the same bank, the maximum amount of losses is significantly larger in 2008 than afterwards.

Figures 3, 4 and 5, 6 and 7 allow us to have a more detailed view of how maximum losses (in terms of capital and number of bank failures) can vary from one network to another. Figure 3 depicts the share of depleted capital in the system over networks ordered by total losses. We can observe that losses merely due to liquidity contagion (the difference between the green and blue dots) as well as total losses (the green dots) indeed vary among the networks. Total losses (due to the market shock and both contagion channels) can represent from about 10% to 35% of total system capital in 2008, and from about 7% to 22% in other years. Interestingly, liquidity hoarding plays a very different role from one year to another, and seems to be more important in 2008 and 2010 : for some networks, losses due to liquidity contagion can represent up to half of the total. The same findings are observed by comparing figures 4 and 5 with maximum losses in capital and figures 6 and 7 with maximum number of bank failures, where we present distributions in the form of box plots. In these figures, we exclude losses due to the market shock. Both distributions in terms of capital losses or number of failures have in general higher median and heavier tails after accounting for the impact of liquidity contagion, particularly in 2008 and 2010. The number of defaults resulting from the market stress coupled with one bank's default can vary significantly depending on the underlying structure of interbank linkages : from 7.5% of system's capital (or 4 banks) in one network to 30% of capital (or 14 banks) in another. Thus, consistently with recent models of contagion in financial networks relying on simulated networks of exposures (see, Georg [2013] and Arinaminpathy et al. [2012]), our results reveal the critical impact of the underlying network structure on the propagation of financial losses. Importantly, it points to the need to account for the evolving nature of the web of interbank linkages when running contagion simulations.

So far, we have averaged contagion outcomes over the market shocks and looked at how different the impact of contagion is with respect to the initial default bank and the underlying network. We have seen that maximum losses can be sizeable, whereas average losses are limited. To better investigate the likelihood of such tail risks, we analyze for each year the distribution of the Value at Risk (VaR) or $VaR(5\%)$ of our banking system. This is defined as the 95th left percentile of the distribution of losses (as a percentage of system capital) over both idiosyncratic and market shock scenarios. Figure 9 plots the distribution of $VaR(5\%)$ of losses due to contagion over 100 network pairs. We can see that the 5% worst capital loss stands on average at 8% and 5% over the networks in 2008 and all other years correspondingly, and that the loss distribution in 2008 has heavier tail. By comparing figure 9 and 5, we observe that losses in the 5% worst cases are almost half smaller than in the worst case, demonstrating the tail nature of contagion.

4.2 Cross-border contagion

Table 12 allows us to glance at the extent of domestic *versus* cross-border contagion in the European banking sector. It summarizes the results provided in the heat maps (figures from 10 to 14) : panel A. presents the distribution of the losses on the main diagonal for each of the heat map figures, that is total losses imposed by an average bank in a banking system on its domestic counterparties ; panel B. shows the distribution of the off-diagonal losses, in other words, losses imposed by an average bank in a banking system on its foreign countparties. We can immediately observe that, on average, a national banking sector imposes larger losses domestically than across the borders. However, maximum losses imposed domestically are usually smaller than losses imposed across the borders, except in years 2010 and 2012, when they are almost equal.

We plot heat maps in order to analyze the potential for cross-border contagion in the European banking sector. The cells $(A; B)$ of the map represent with colors the strength of the total capital loss experienced by country A's banking sector (as a fraction of its aggregate initial capital) given a common market shock and the default of a bank in the foreign banking system B. Examining heat maps in figures from 10 to 14, we can easily identify the most 'systemic' banking sectors, on the one hand (i.e. those resulting in a *vertical* line in which warmer-colors prevail), and the systems which are the most 'fragile', on the other (i.e. those resulting in a *horizontal* line in which warmer colors dominate). Note that a black in the color-scale of the map corresponds to a maximum country loss ranging between 7% and 14%, respectively in 2010 and in 2008, of the country's aggregate initial capital, while white cells correspond to no loss at all. [14]

In 2008 the banking sectors of countries E, H and K appear to be more systemic in terms of the total capital loss that a default of an average bank in these countries can impose on foreign banking sectors. The systems B and J follow, but the aggregate losses that the default of an average bank from these countries imposes on foreign banking sectors are much lower. The default of a bank headquartered in D, F, G or I does not have a sizeable impact on other European banks. With regard to the banking sectors that are the most exposed to cross-border contagion, banks from A, B and J generally seem to experience the highest loss following a foreign default (more numerous red and/or orange cells).

The 2009 and 2010 maps show that the potential for cross-border contagion has constantly

14. Total country capital losses following the market shock and an idyosincratic foreign bank default are computed on average over 500 realizations of the market shock ; over 100 different pairs of long- and short-term exposure networks ; over the initially defaulting foreign banks. They have been normalized to account for the different number of banks (and hence of simulations) considered for the various national banking sectors. Heat maps have been anonymized for data confidentiality reasons, and countries for which less than 3 banks are available in the sample have been removed. Countries are ordered randomly, with the same order over time.

decreased over time, and that the overall potential capital loss through contagion was twice lower in 2010 than it was back to the end of 2008. More specifically, table 12 shows that the maximum loss caused by a foreign bank's default reduced from a value of 14% of foreign countries' total banking capital in 2008 to an overall loss of 10% in 2009 and of 7% in 2010. This is possibly related to a generalized reduction of long-term interbank loans and to an increase in banks' capitalization during those years (see section 3.2). In 2009 and 2010 we observe the geographical patterns identified persisting : E remains the most systemic banking sector ; A and B the most fragile with respect to cross-border contagion stemming from a number of other European banking sectors ; C and G appear vulnerable only to a few banking systems. Banks in I are relatively isolated in 2008 but become progressively more exposed to cross-border contagion in 2009 and even more in 2010. The level of vulnerability observed for most other countries changes across the years, although, as already mentioned, a generalized increase in the resilience of the system can be observed.

In 2011 and 2012 the light colors in the maps reveal a European banking system overall less vulnerable to cross-border contagion. However, the lower extent of contagion in these two years, and especially in 2012, compared to 2008 conceals important differences among national banking sectors.

All in all, we find that, under extreme equity market stress and following the exogenous default of one bank, cross-border contagion can materialize in the European banking system. The average and maximum loss caused by a foreign bank's default, however, varies remarkably over time. In particular, in 2009 and 2010 the European banking system seems to have significantly increased its capacity to withstand the same kind of adverse financial conditions that it had to face after the default of Lehman Brothers. In 2011 and 2012, banks reduce their interbank exposures (see table 5), and most notably so cross-country (see table 8), possibly as a consequence of continued sovereign-bank financial tensions in Europe. This leads to lower contagion losses overall concealing, however, a high heterogeneity across countries.

4.3 Systemic and fragile banks

Figure 15 depicts the systemic importance of all banks in each year from 2008 to 2012. We define a bank as 'systemic' when its default imposes more than the 85th percentile of the loss distribution over a given network pair. On the vertical axis we see the number of networks in which each bank appears to be systemic. Most of the banks are systemic in none or very few networks, however some banks turn out to be systemic in more than 60% and even 90% of the networks. Interestingly, this chart points to the same subset of banks as 'usual suspects' across the years, however there is also some variability : the subset is not identical from one year to another, only 60% of the banks appear systemic in more than 3 years.

Similarly, we try to rank banks according to the capital loss that they experience following the default of all other banks. In particular, we define a bank as 'fragile' if it suffers losses above the 85th percentile of the loss distribution over the set of shock scenarios. Figure 16 points in all the years from 2008 to 2010 some of the banks that did experience severe difficulties in 2011-2012.

4.4 Focusing on system resilience over time

As already highlighted, the system vulnerability to contagion differs from one year to another. The evidence presented so far points to a pattern of increasing (although not uniform) resilience to contagion from 2008 to 2012. For instance, we have seen in Table 10 and Table 11 that upon the default of the same bank, the average and maximum amount of losses are significantly larger in 2008 than in the subsequent years. The larger maximum shares of depleted capital in 2011 and 2012 are possibly related to the disappearance of 4 and 9 banks, respectively, from the sample in these years due to actual defaults. This determines both a lower total system capital and a lower diversification of interbank assets, thus resulting in a higher contagion outcome.

Figures 8 and 9 demonstrate the evolution of the system resilience to contagion over time. The year when the system was the most fragile is 2008, both with respect to solvency and liquidity contagion. In fact, in both graphs the 2008 loss distributions are characterized by a higher median and a heavier tail than those in the other years. The overall resilience of the system with respect to solvency contagion gradually improved over time, except for a small deterioration in 2011. By comparing the distributions in both figures, we can deduce that losses due to liquidity contagion do not follow the same pattern : the system seemed to be again more fragile in 2010. To statistically test this hypothesis, we perform the two-sample Kolmogorov-Smirnov test which allows us to compare the distributions of losses due solely to solvency contagion *versus* losses due to both contagion channels. This test shows that at 5% confidence level we can reject the null hypothesis of the two data sets being drawn from the same distribution for years 2008 and 2010, which means that liquidity hoarding behaviour was more of an issue in those years.

Resilience to solvency contagion. The reasons behind increasing system resilience to solvency contagion are threefold. First, banks became better capitalized : average (max) common equity to total assets ratio increased from 4.18% (11.13%) in 2008 to 5% (14.82%) in 2012 with a decrease to 4.43% in 2011 (table 5). Second, the average fraction of 'Net loans to banks' to total assets gradually fell from 8.31% in 2008 to 6.81% in 2012 (table 5), and 'Net loans to banks' is the item used to reconstruct the long-term exposure networks on which solvency contagion takes place. Third, the network characteristics also changed. Namely, the network became less connected over the years (the ratio of actual to possible links reduced from 8% in 2008 to 5% in 2012) ; more skewed (the ratio of max to average degree jumped from 3.35 in 2008 to 4.6 in 2012) ; with increasing average shortest path length (in 2008, the median distance separating any two banks was of only 2.64 other institutions, whereas it reached 3.14 in 2012, and 2.77 in 2011) (table 6).

The intuition for the relationships between network measures and the results of contagion propagation goes as follows. First, less connected networks are less fragile because there are less links through which contagion may propagate. Second, more skewed networks may be more resilient to contagion, on average, since most of the banks have only few exposures, so that their default has little impact on the system. However, in those rare scenarios when a highly connected bank defaults, losses can be sizeable. This is consistent with the observation that although the system is on overage safer in 2012 than in 2008, in some extreme cases losses can reach 22% of the total system capital. Third, a higher average shortest path length has a direct explanation for the ease of losses propagation : the lower the average length of intermediation chains, the more easily losses may reach any other bank.

Resilience to liquidity contagion. As already mentioned, the system is most vulnerable to liquidity hoarding in 2008 and 2010. Given that in the algorithm liquidity contagion comes after solvency domino effects, one could expect to observe the following relationship : higher losses due to solvency contagion → weaker system → more banks hoard liquidity → higher losses due to liquidity contagion. Indeed, this mechanism does in part explain the impact of liquidity hoarding on the system, most notably in 2008 ; but it is not the only reason. An explanation why the system appears to be so vulnerable in 2010, for instance, comes from balance sheet statistics : banks held less cash in 2010, only 8.68% of total assets while more than 9.5% in all the other years (see table 5).

Short-term network characteristics do play a role too : banks were on average at a shorter distance from each other exactly in 2008 and 2010, and the logic behind the ease of propagation of interbank losses is the same as for solvency contagion. Moreover, the ratio of max to mean degree for short-term networks was lower in 2008 and 2010, which suggests that the relationship between the skewness of the degree distribution in short-term networks and system resilience is opposite to the one discussed above for long-term networks and solvency contagion. The intuition between the lower max to mean degree ratio figures and system stability goes as follows : the less skewed the distribution of the number of counterparties, the higher the number of banks that could hoard liquidity from many of their borrowers, thus increasing the potential for liquidity contagion. Finally, it is interesting to note that the short-term networks in 2009 and 2012 (the years displaying lower contagion) look very similar : they are the least connected (on average only 6% of all possible exposures do actually exist, against 8-9% in other years) ; have the longest intermediation chains (3.11 and 2.97 links separate any two banks in 2009 and 2012, respectively, against 2.55 in other years) ; are the most skewed (the most connected bank is exposed to a number of counterparties about 4 times larger than the average bank in 2009 and 2012, against only about 3 in other years).

5 Econometric analysis

In order to shed light on the relationship between simulation results, banks' financial ratios and network characteristics, we conduct an econometric analysis of the determinants of contagion. First, we analyze the determinants of bank-level contagion. In later subsections, we study contagion outcomes at a system level and at a country level.

5.1 Econometric specification

As explained below, all our dependent variables are bounded below (by zero) and above (by the number of banks in the system, or by the capital in the system) and both boundary values are likely to be observed in the data. The estimation of such a model cannot rely on OLS. A convenient way of overcoming this difficulty is by normalizing the dependent variables so that they take values on $[0; 1]$. For instance, rather than using the average number of times that a bank defaults following a set of shock scenarios, we focus on the average frequency with which it defaults ; rather than using the loss amount suffered by a bank, we use the average proportion of its capital that gets depleted following the shock scenarios. The estimation of models with fractional response variables relies on the methodology proposed by Papke and Woolridge [1996]. It uses the generalized linear model (GLM) developed by Nelder and Wedderburn [1972] and McCullagh and Nelder [1989].

Let Y be the dependent variable. It is assumed to be generated from a distribution in the exponential family, whose mean μ depends on the independent variables X through :

$$\mathbb{E}[Y] = \mu = \Gamma^{-1}(X\beta) \tag{5.3}$$

where β is a vector of unknown parameters and Γ the p.d.f. of the link function. Furthermore, the variance of Y is a function of the mean, so that :

$$\mathrm{Var}[Y] = \mathrm{Var}\left[\Gamma^{-1}(X\beta)\right] \tag{5.4}$$

In order to model proportions, a convenient specification is that by Papke and Woolridge [1996] who assume that the dependent variable can be modeled by a binomial distribution, in combination with a logit link function Γ. The vector of parameters β is estimated by maximum likelihood.

5.2 Bank-level determinants of contagion

This section explains the determinants of bank fragility or vulnerability with both balance sheet and exposure characteristics.

5.2.1 Default outcomes

This section estimates the determinants of both bank *fragility* (i.e. average number of defaults and average amount of losses suffered following a set of shock scenarios) and bank *systemicity* (i.e. the average number of defaults and average amount of losses caused by the initial default of a bank, over a set of shock scenarios). Thus, dependent variables in the various specifications of the default model are related to default outcomes, whereas independent variables are network, exposure and balance sheet characteristics.

More specifically, for each year of results we estimate the following specification :

$$Y(i, n, t) = g^{-1}(\beta_0 + \beta_1 * X(i, n, t)) + \epsilon(i, n, t), \tag{5.5}$$

where $Y(i, n, t)$ denotes the various fragility or systemicity default outcomes for simulated (pair of) network n in year t. The vector of regressors $X(i, n, t)$ is composed of variables related to financial ratios, network position pre-shock, exposures to the weakest banks and control variables described below.

5.2.2 Explanatory variables and expected effects

The following regressors have been used to estimate equation 5.5 :

Financial ratios. Solvency ratio : $Common\ equity\ /\ Total\ assets$; Liquidity ratio : $Short-term\ funding\ /\ Total\ assets$.[15] Everything else equal, we expect banks that are more capitalised and more liquid to be less vulnerable to contagion due to their long and short term interbank exposures. The effect of higher financial ratios on bank systemicity is less obvious. Nonetheless, the mechanics of the model suggests that removing well capitalised and liquid banks from the system would result in a more fragile banking sector overall. Therefore, we can expect that being more leveraged and illiquid results in higher bank systemicity.

(Long-term) Network position pre-shock. Closeness, betweenness or eigenvector centrality in the network of long-term interbank exposures have been alternatively tested as explanatory variables.[16] Recent literature has shown that the position occupied by a financial institution in the network of interbank connections can explain e.g. its capacity to access interbank liquidity after a shock (see Abbassi et al. [2013]), the price at which it can fund itself in the money market (see Gabrieli [2012]), or its daily liquidity holdings as a participant in a large value payment system (see Bech et al. [2010]). Based on this evidence, we expect *(i)* banks occupying a more central position in the interbank network in terms of being directly exposed to many counterparties (i.e. banks that are *closer* to all banks), *(ii)* banks that are more central in that they interpose themselves on many intermediation chains in the interbank network (i.e. banks with higher *betweenness*), *(iii)* banks occupying a central position because of their exposures to highly central counterparties (i.e. banks with higher *eigenvector* centrality) to be more systemic. The effect of higher centrality on bank fragility is less clear cut. On the one hand, one could expect more central banks (in terms of the three measures described) to be more exposed, hence more vulnerable, to contagion. On the other, banks that are direct lenders to many counterparties are also more diverisified in the asset side of their balance sheet, hence potentially more resilient to the propagation of interbank losses.

15. The ratio of long term exposures to common equity has also been tested as proxy for bank solvability. The ratio of short term to long term funding and the so called "interbank ratio" (interbank assets divided by interbank liabilities) have been tested as proxies for bank liquidity.

16. Refer to Abbassi et al. [2013] for a description of network centrality indicators and their economic interpretation.

Exposures to weakest banks. For each bank and year, we construct the share of bank i long-term interbank lending directed to the three "riskiest" banks in the system. The latter are identified as the three *(i)* most leveraged, *(ii)* least liquid, *(iii)* most interconnected, *(iv)* most indebted European banks at the end of year t. Beyond the importance of a bank's own financial ratios, exposures to risky counterparties can have a negative effect on banks' resilience to adverse shocks. In general, we expect a bank's fragility to be higher the higher the share of its interbank loans granted to risky (more leveraged, less liquid, more indebted) counterparties. The effect of being largely exposed to very interconnected banks, however, is less straightforward. As in the case of banks with high eigenvector centrality, being exposed to banks with many counterparties in the long-term exposures network might actually lower bank fragility, because of the higher resilience of very connected (hence more diversified) counterparties. At the same time, however, exposures to banks that are highly interconnected in the short term (liquidity) networks could increase bank frailty, because a very connected counterparty could be subject to more contemporaneous liquidity withdrawals.

Control variables. To clearly identify the effect of the regressors of interest on the contagion-dependent variables, we control for the structural features of the simulated long- and short- term networks. These are notably : network *clustering*, reflecting the extent to which banks lending to each other tend to have a third common counterparty ; *average shortest path length*, reflecting the length of intermediation chains ; the ratio of maximum to mean degree, indicating to what extent the distribution of the number of bank counterparties is heavy tailed, with few (core) banks that are very highly interconnected, and most (peripheral) banks that have links only to few counterparties.

5.2.3 Results

Bank fragility. Table 13 shows the results for $Y(i, n, t)$ being successively the average number of defaults and average amount of losses suffered by bank i in network (pair) n in $t = 2008$ over a set of 500 shock scenarios. The results show that balance sheet ratios (for both solvency and liquidity) are key determinants of banks' vulnerability to contagion, especially in terms of the number of times that a bank defaults. The coefficient capturing the role of a bank position in the network before the shock is also significant. Interestingly, it reveals that banks that are highly interconnected are less likely to default following a shock scenario, but more likely to suffer larger losses. This result is consistent with our expectations : on the one hand, a higher degree of interconnectedness reflects a higher degree of diversification of interbank assets, thus reducing the frequency of bank defaults across scenarios ; on the other, being directly exposed to a high number of counterparties can induce larger losses. The coefficients of the shares of interbank lending directed to the riskiest banks in the system confirm our intuition that being exposed to the most leveraged and least liquid banks increases both the likelihood of bank failure and the amount of losses experienced. These "exposure metrics" are however less important than network centrality and banks' own financial ratios in economic terms. Finally, it is interesting to note that structural network characteristics do not explain different degrees of bank vulnerability. The only exception is the extent to which the

interbank network tends toward a core-periphery structure. More specifically, a system where few banks have several times the number of counterparties of the average institution seems to be more resilient to the propagation of interbank losses.
We obtain similar evidence for 2009, although the network variable that turns out to better explain bank fragility is eigenvector and not closeness centrality. For this year, longer intermediation chains can explain both a lower fragility and a lower systemicity of the average bank. Results are consistent across years with minor differences.

Bank systemicity. Table 14 shows the results for $Y(i,n,t)$ being successively the average number of defaults and average amount of losses caused by the failure of bank i in network (pair) n in $t = 2008$ over a set of 500 shock scenarios. Similarly to the results for bank fragility, a bank's own financial ratios appear to be the most important determinants of its contagious impact. The magnitude of estimated coefficients is, however, lower than in the previous tables both for the average proportion of bank defaults and the average amount of losses. Closeness centrality turns out to increase a bank systemicity : the closer a bank is to a higher number of counterparties because of its numerous direct lending exposures, the higher the proportion of banks failing and the proportion of capital lost in the banking network following the propagation of a shock. Differently from the fragility regressions, these tables show that being exposed to the riskiest counterparties does not influence a bank's systemic importance. However, being largely exposed to the most indebted banks increases both the likelihood of causing other failures and the proportion of losses following a shock.

5.3 System-wide determinants of contagion

In this section, we analyze the determinants of system-wide contagion by exploiting within-year heterogeneity. Thus the European banking sector is tentatively treated as a unique system. The methodology described in 5.1 will be used to study the determinants of system fragility measured by both aggregate number of defaults and aggregate losses in each network (pair) n in each year t ($t = 2008, 2009, ..., 2012$) over a set of 500 shock scenarios. More specifically, we estimate the following regression :

$$Y(n,t) = g^{-1}(\beta_0 + \beta_1 * X(n,t)) + \epsilon(n,t), \tag{5.6}$$

where $Y(n,t)$ denotes the contagion output variables for simulated (pair of) network n in year t. As in the bank level specification, we transform the dependent variables so as to obtain fractional responses taking values on $[0;1]$. For instance, rather than using the aggregate number of bank defaults following a set of shock scenarios, we focus on the average proportion of bank defaults; rather than using the absolute loss suffered by the banking system as a whole, we focus on the proportion of system capital that is lost following shock scenarios. The regressors are the aggregate version of those described for the bank-level specification.

5.3.1 Results

[TO COMPLETE]

5.4 Country-level determinants of cross-border contagion

In this section, we refine the analysis at a more granular level by investigating the country-level determinants of cross-border contagion.

5.4.1 Results

[TO COMPLETE]

6 Ongoing work

We are currently completing the analysis presented in the paper. In particular :

- The money market dataset that we rely upon to build the probability maps matches potential loan payments between direct TARGET2 participants (i.e. settler banks). However, a new dataset with originators and beneficiaries of TARGET2 transactions (i.e. indirect TARGET2 participants) has been recently made available. Such a dataset will allow us to obtain a more reliable representation of the universe of interbank money market loans, and potentially affect the construction of the probability maps that we use to simulate probabilistic networks of interbank exposures. In particular, the identified geographical patterns of cross-border contagion may differ from those obtained using the dataset with settler banks. The difference may reveal substantial for specific network realizations ; on the other hand, the impact on average results - i.e., those we present in the paper, for instance through heat maps - is less clear cut.
- We are running several robustness checks to test the stability of simulation results after changes to model parameters.
- Finally, we plan to complete the results section with system-level and country-level regressions.

7 Conclusions

This paper investigates the scope for cross-border contagion in Europe based on true exposure data at a bank-to-bank level in a joint framework of solvency and liquidity contagion. We analyze geographical patterns of shock propagation between 73 European banking groups from end-2008 until end-2012.

We exploit for the first time a unique dataset of interbank money market transactions, with various maturities, estimated from TARGET2 payment data (see Arciero et al. [2013]) to obtain a realistic representation of how European banks are connected through their long- and short-term claims. We rely on the money market database to construct realistic probability maps of interbank exposures. This maps, together with the amount of individual banks' aggregate loans to other banks, are used to simulate a large number of long- and short-term exposure matrices through a novel methodology proposed by Halaj and Kok [2013].

Simulation of multiple networks from real data probability maps with significant heterogeneity among them allows us to analyze not only the vulnerability of one particular network realization retrieved from the real data, but of plenty of potential realistic networks. We find that both solvency and liquidity contagion are tail risks : losses averaged over stress-scenarios, initial bank defaults or simulated networks are rather limited ; however, averaging conceals rare extreme events. We document that losses at the tail of the distributions can reach one third of the system capital in 2008, and that the resilience of the system improves significantly over time.

We find that, under extreme equity market stress and following the exogenous default of one bank, cross-border contagion can materialize in the European banking system. The average and maximum losses caused by a foreign bank's default, however, varies remarkably over time. In particular, in 2009 and 2010 the European banking system seems to have significantly increased its capacity to withstand the same kind of adverse financial conditions that it had to face after the default of Lehman Brothers. In 2011-2012, banks reduce their interbank positions, and most notably so cross-country, possibly as a consequence of continued sovereign-bank financial tensions in Europe. This leads to lower contagion losses overall, concealing however a high heterogeneity across-countries.

Finally, we document a strong impact on the cross-border propagation of losses of heterogeneity and concentration in the structure of interbank exposures. Moreover, the number of defaults resulting from extreme market stress coupled with one bank's default can be more than three times larger depending on the underlying structure of interbank linkages. This is consistent with recent models of contagion in financial networks relying on simulated networks of exposures (see, Georg [2013] and Arinaminpathy et al. [2012]), and points to the need to account for the evolving nature of the web of interbank linkages when running contagion analysis. Furthermore, we exploit this heterogeneity in order to investigate the determinants of bank fragility or systemicity that drive contagion outcomes with both banks' balance sheet and exposure characteristics. As well, we analyze the determinants of system-wide and country-level contagion by exploiting within-year across-networks heterogeneity.

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A Appendix

A.1 The model

A.1.1 Common market shock

We model a shock with both a common component and an idiosyncratic component. First, a market shock hits all listed banks' capital. As mentioned by Upper [2011], contagion is more likely with such a shock. Second, a bank is exogenously assumed to fail.

The market shock is modeled using a one-factor model for equity returns. The principal factor and loading coefficients for all listed banks [17] in our sample (42 institutions) are computed using daily equity returns over a period spanning from January 1999 to December 2008. The first factor is fitted to a Student t distribution, from which 100,000 simulations are drawn. The 500 left-tail realizations of the first principal component are kept, corresponding to approximatively 5% tail shocks. The impact on each bank's capital is recovered through the factor loadings.

We keep the same market shock for each year in order to make sure about the change in fragility of the system to contagion during these five years.

Simultaneously, one bank is forced to default. One advantage of such a shock is that it enables analyzing the systemic importance of each institution, even though it abstracts from actual bank probabilities of default. Losses through solvency and liquidity channels are then computed.

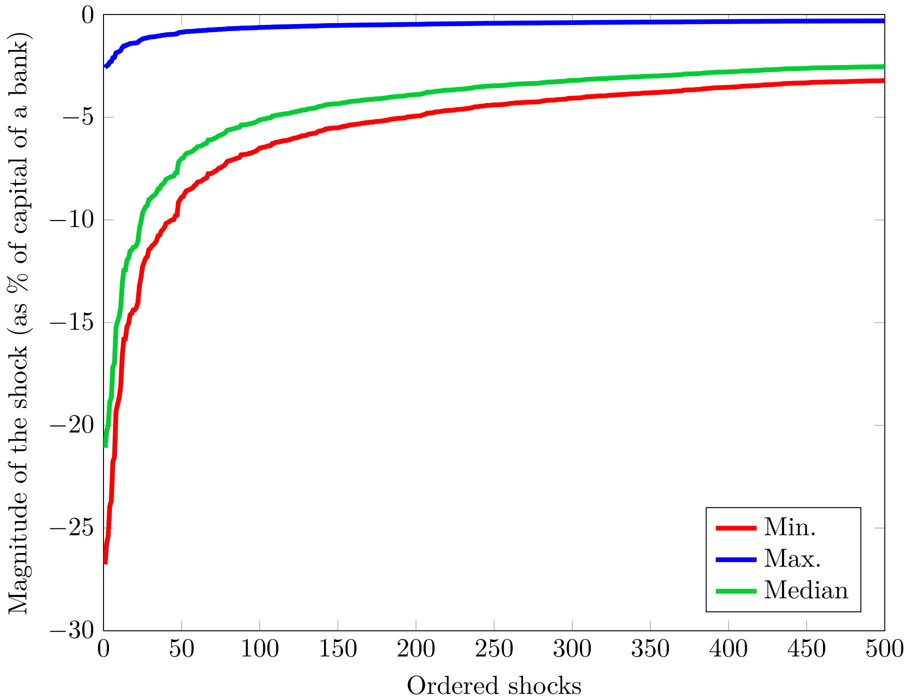

Figure 2: Distribution of the shocks to individual banks over 500 shock scenarios, measured as percentage of banks' capital

17. Non-listed banks are assumed to face no market shock, as their equity value is assumed not to be correlated with market prices.

Table 2: Distribution of the idiosyncratic and market shocks to the whole system measured as percentage of total system capital

	Min	**Mean**	**Median**	**Max**
Idiosyncratic shock	0,04%	1,37%	0,70%	6,64%
Market shock	1,94%	3,38%	2,66%	16,17%

A.1.2 Solvency contagion

We closely follow the model by Fourel et al. [2013]. At time $t = 1$, banks are hit by a shock ϵ according to the methodology previously described. If the initial losses are higher than the capital of a bank, the latter goes into bankruptcy. We can therefore define the set of all banks defaulting due to a market shock, named "fundamental defaults", as

$$\begin{aligned} \mathbf{FD(C)} &= \left\{ i \in \mathbf{N} : C_0(i) + \underbrace{\epsilon(i)}_{\text{initial shock}} \leq 0 \right\} \\ &= \{ i \in \mathbf{N} : C_1(i) = 0 \}\,, \end{aligned} \tag{A.7}$$

where $C_1(i) = (C_0(i) + \epsilon(i))^+$ is the capital of bank i just after the initial shock.

From this situation, we can define a *solvency default cascade* (in Amini *et al.*'s terminology) as a sequence of capital levels $(C_2^k(i),\, i \in \mathbf{N})_{k \geq 0}$ (where k represents the algorithmic step) occurring at time $t = 2$ and corresponding to the defaults due to insolvency :

$$\begin{cases} C_2^0(i) = C_1(i) \\ C_2^k(i) = \max(C_2^0(i) - \sum_{\{j,\, C_2^{k-1}(j)=0\}} (1 - R^S) \times E_0(i,j); 0), \text{ for } k \geq 1, \end{cases} \tag{A.8}$$

where R_S is an exogenous recovery rate for solvency contagion.

The sequence is converging (in at most n steps) since $(C_2^k)_k$ is a component-wise decreasing sequence of positive real numbers. Note that subscripts are used for periods of time and superscripts for rounds of cascades. By "period", we mean the sequential spread of losses through different channels. This should not be interpreted *stricto sensu* : we rather consider a sequence of events that can concomitantly occur in a short period of time, e.g. within one week.

Comparison of the banks initially in default (that is $\mathbf{FD(C)}$) and the banks in default at the end of $t = 2$ corresponds to the set of institutions that defaulted only due to solvency default contagion. We label this set S_2.

A.1.3 Liquidity hoarding

In the liquidly hoarding section of our contagion simulations we employ a different functional form than in Fourel et al. [2013]. We closely follow their model in the remaining sections.

Decision on how much to hoard

To know how much liquidity a bank hoards in total, and how much it hoards from each counterparty, we make some assumptions. First of all, the total amount of liquidity withdrawn depends on the size of the shock to the bank's capital : the bigger the losses due to the market shock, the more the bank hoards liquidity. The proportion of liquidity to be hoarded by bank i is $\lambda(i) \in [0;1]$. It is assumed to depend on the capital loss $Loss(i)$: at time t, we denote $\lambda_t(i) = a\,Loss(i)\,\mathbf{1}_{[A;B]} + b\,Loss(i)\,\mathbf{1}_{[B;100]}$, where $\mathbf{1}$ is an indicator function [18]. We assume that bank i curtails its positions in the short-term interbank money market by stopping rolling over debt for a total amount $\lambda_t(i)E_t^{ST}(i)$ where $E_t^{ST}(i) = \sum_{j \in S_{t-1}} E_{t-1}^{ST}(i,j)$ and S_{t-1} is the set of non-defaulted banks at the end of period $t-1$.

How much to hoard from each counterparty

Second, the amount of liquidity the bank hoards from each counterparty depends on the generalized market perception of its credit risk, for which the leverage ratio can be used as a proxy. The higher the leverage, the riskier a bank is perceived, the more its counterparties will hoard from it. Defining $\mu_t(j)$ as $\mu_t(j) = 1 - C_t(j)/TA_t(j)$, we can decompose the total amount of liquidity hoarded by bank i from its counterparties as follows :

$$\lambda_t(i)E_t^{ST,k-1}(i) = \lambda_t(i)E_t^{ST,k-1}(i) \underbrace{\sum_{j,C_t^{k-1}(j)\geq 0} \frac{\mu_t(j)E_t^{ST,k-1}(i,j)}{\Sigma_h \mu_t(k)E_t^{ST,k-1}(i,h)}}_{=1}. \tag{A.9}$$

Liquidity condition

When a bank hoards liquidity, it improves its short-term funding position, whereas liquidity withdrawals by its counterparties deteriorate it. The following liquidity condition must hold :

$$\underbrace{Ca_t(i)}_{\text{cash}} + \underbrace{\lambda_t(i)E_t^{ST,k-1}(i)}_{\text{hoarding inflows}} - \underbrace{\sum_{j,C_t^{k-1}(j)\geq 0} \lambda_t(j)E_t^{ST,k-1}(j)\frac{\mu_t(i)E_t^{ST,k-1}(j,i)}{\Sigma_l \mu_t(l)E_t^{ST,k-1}(j,l)}}_{\text{hoarding outflows}} > 0. \tag{A.10}$$

That is, bank i needs to have enough liquid assets, either interbank or non-interbank, to pay its short-term debt.

In line with the solvency contagion algorithm, we state that a bank is in default when its capital has been fully wiped out (solvency condition) or when it can not satisfy its short-term commitments (liquidity condition).

Update of the algorithm to account for the losses due to solvency and liquidity contagion

18. We test a range of parameters value in order to check the robustness of our results.

$$
\begin{cases}
C_t^0(i) = C_{t-1}(i) \\
\text{ for } k \geq 1, \\
\textbf{Solvency condition :} \\
C_t'^k(i) = C_t^0(i) - \sum_{\{j,\, C_t^{k-1}(j)=0\}} (1-R^L) E_t^{ST}(i,j) \\
\textbf{Liquidity condition :} \\
C_t''^k(i) = \begin{cases} 0 & \text{if } Ca_t(i) + \lambda_t(i) E_t^{ST,k-1}(i) - \\ & \sum_{h, C_t^{k-1}(h) \geq 0} \lambda_t(h) E_t^{ST,k-1}(h) \frac{\mu_t(i) E_t^{ST,k-1}(h,i)}{\Sigma_l \mu_t(l) E_t^{ST,k-1}(h,l)} < 0 \\ C_t'^j(i) & \text{otherwise} \end{cases} \\
\textbf{Updating equation :} \\
C_t^k(i) = max(C_t'^k(i); C_t''^k(i); 0)
\end{cases}
\tag{A.11}
$$

At the end of period t, the algorithm provides the status of each bank (alive or in default), its capital level and short-term exposures. Some banks may have defaulted during period t, thus some non-defaulted banks have recorded losses on their capital level. If the capital is then lower than their economic one, another round of liquidity hoarding treated in period $t+1$ will take place.

A.1.4 Model calibration

The following exogenous values are used to calibrate the model.

Table 3: Parameters used to calibrate the model

	Values of exogenous parameters
Recovery rate (R^S)	0,4
First hoarding threshold (A)	0
Amount hoarding (a)	0,1
Second hoarding threshold (B)	0,3
Amount hoarding (b)	0,5
Proportion of free cash	0,4

A.2 The sample

Table 4: The sample

Country	Bank Name	Country	Bank Name
AT	Erste Group Bank	GR	Alpha Bank**
AT	Raiffeisen Bank International	GR	ATE Bank*
AT	Oesterreichische Volksbanken	GR	Eurobank Ergasias*
BE	Dexia	GR	National Bank of Greece**
BE	KBC Groep	GR	Piraeus Bank*
CH	Credit Suisse Group	GR	TT Hellenic Postbank*
CH	UBS	HU	OTP Bank Nyrt
CY	Bank of Cyprus Public**	IE	Allied Irish Banks
CY	Cyprus Popular Bank Public**	IE	Bank of Ireland
DE	Bayerische Landesbank	IT	Banca Monte dei Paschi di Siena
DE	Commerzbank	IT	Banca Popolare dell'Emilia Romagna
DE	DekaBank	IT	Banco Popolare Società Cooperativa
DE	Deutsche Bank	IT	Intesa SanPaolo
DE	HSH Nordbank	IT	Unicredit
DE	Hypo Real Estate Holding	IT	Unione di Banche Italiane
DE	Landesbank Baden-Württemberg	MT	Bank of Valletta
DE	Landesbank Berlin Holding	NL	ABN AMRO Group
DE	Landesbank Hessen-Thueringen	NL	ING Bank
DE	Norddeutsche Landesbank	NL	Rabobank Group
DE	Westdeutsche Genossenschafts-Zentralbank	NL	SNS Bank
DK	Danske Bank	NO	DnB ASA
DK	Jyske Bank	PL	Powszechna Kasa Oszczednosci
DK	Nykredit Realkredit	PT	Banco BPI
DK	Sydbank	PT	Banco Comercial Português
ES	Banco Bilbao Vizcaya Argentaria	PT	Caixa Geral de Depositos
ES	Banco de Sabadell	PT	Espirito Santo Financial Group
ES	Banco Popular Espanol	SE	Nordea Bank
ES	Banco Santander	SE	Skandinavinska Enskilda Banken
ES	Bankinter	SE	Svenska Handelsbanken
ES	Caja de Ahorros y Monte de Piedad de Madrid**	SE	Swedbank
ES	Caja de Ahorros y Pensiones de Barcelona	SI	Nova Ljubljanska Banka
FI	Op-Pohjola Group	UK	Barclays
FR	BNP Paribas	UK	Lloyds Banking Group
FR	BPCE	UK	HSBC Holdings
FR	Crédit Agricole	UK	Royal Bank of Scotland
FR	Crédit Mutuel	UK	Standard Chartered
FR	Société Générale		

This table provides the sample of 73 banks used for the default simulations and the econometric analysis, as well as their domestic country. It is a subset of the list of banks that underwent the 2011 stress tests carried out by the European Banking Authority (EBA [2011b]). The * and ** indicate banks which are not included in the 2011 and 2012 sample, respectively, due either to failures or to unavailable data. The country abbreviations are as follows : AT = Austria, BE = Belgium, CH = Switzerland, CY = Cyprus, DE = Germany, DK = Denmark, ES = Spain, FI = Finland, FR = France, GR = Greece, HU = Hungary, IE = Ireland, IT = Italy, MT = Malta, NL = Netherlands, NO = Norway, PL = Poland, PT = Portugal, SE = Sweden, SI = Slovenia, UK = United Kingdom.

A.3 Descriptive statistics

Table 5: Descriptive statistics of sample banks' balance sheet ratios

	Year				
	2008	**2009**	**2010**	**2011**	**2012**
Cash and cash Equivalents / Total Assets					
Average	9.96%	9.54%	8.68%	9.64%	9.68%
Minimum	1.44%	1.45%	1.03%	1.09%	0.99%
Median	8.70%	8.49%	7.71%	8.38%	8.34%
Maximum	32.78%	29.35%	30.64%	29.88%	27.53%
Standard deviation	5.94%	5.19%	5.20%	5.48%	5.10%
Common Equity / Total Assets					
Average	4.18%	4.73%	4.73%	4.20%*	4.42%*
Minimum	0.62%	1.05%	0.08%	-5.72%	-4.54%
Median	3.90%	4.40%	4.55%	3.76%	4.33%
Maximum	11.13%	13.06%	13.32%	13.85%	14.92%
Standard deviation	2.25%	2.35%	2.42%	2.76%	2.99%
Net Loans to Banks / Total Assets					
Average	8.31%	7.93%	7.19%	7.24%	6.81%
Minimum	0.88%	0.88%	0.68%	0.64%	0.54%
Median	7.09%	6.61%	5.60%	5.49%	4.70%
Maximum	31.73%	29.14%	30.17%	29.61%	26.28%
Standard deviation	6.01%	5.55%	5.50%	5.65%	5.73%

* Excluding from the sample banks with negative common equity, we can observe an increase in the average leverage ratio from 4.20% to 4.43% in 2011 and from 4.42% to 5% in 2012. Source : SNL Financials and own calculations.

Table 6: Descriptive statistics of the 100 networks of long-term interbank exposures.
Networks have been simulated using the methodology developed by Halaj and Kok [2013]. The probability map has been obtained from data on actual euro money market loans with maturities from one to six months.

	Year				
	2008	2009	2010	2011	2012
Number of links					
Minimum	298.00	316.00	295.00	291.00	205.00
Median	398.50	405.50	378.50	365.50	272.00
Maximum	622.00	624.00	609.00	580.00	438.00
Standard deviation	37.40	38.92	35.32	32.38	25.97
Density					
Minimum	0.06	0.06	0.06	0.06	0.04
Median	0.08	0.08	0.07	0.07	0.05
Maximum	0.12	0.12	0.12	0.11	0.08
Standard deviation	0.01	0.01	0.01	0.01	0.00
Average shortest path					
Minimum	2.29	2.30	2.29	2.43	2.64
Median	2.64	2.80	2.80	2.77	3.14
Maximum	3.07	3.60	3.42	3.19	4.09
Standard deviation	0.15	0.15	0.17	0.14	0.22
Max / Median degree					
Minimum	2.20	2.17	2.40	2.55	3.00
Median	3.35	3.00	3.68	3.89	4.60
Maximum	5.88	4.67	7.00	6.29	7.80
Standard deviation	0.62	0.52	0.81	0.74	0.86

Table 7: Descriptive statistics of the 100 networks of short-term interbank exposures.
Networks have been simulated using the methodology developed by Halaj and Kok [2013]. The probability map has been obtained from data on actual euro money market loans with maturities up to one month.

	2008	2009	2010	2011	2012
Number of links					
Average	468,43	289,43	437,30	439,47	319,97
Minimum	423,00	205,00	403,00	403,00	284,00
Median	467,50	272,00	435,00	439,50	321,00
Maximum	500,00	480,00	474,00	476,00	349,00
Standard deviation	15,29	64,71	14,36	17,82	11,68
Density					
Average	0,09	0,06	0,08	0,08	0,06
Minimum	0,08	0,04	0,08	0,08	0,05
Median	0,09	0,05	0,08	0,08	0,06
Maximum	0,10	0,09	0,09	0,09	0,07
Standard deviation	0,00	0,01	0,00	0,00	0,00
Average shortest path					
Average	2,44	3,11	2,58	2,63	2,97
Minimum	2,22	2,45	2,40	2,29	2,67
Median	2,42	3,12	2,58	2,62	2,94
Maximum	3,09	3,88	2,91	2,96	3,49
Standard deviation	0,11	0,29	0,09	0,13	0,15
Max. / Median degree					
Average	2,78	4,38	2,93	3,30	3,66
Minimum	2,14	2,00	2,00	2,50	2,88
Median	2,76	4,33	2,91	3,27	3,63
Maximum	3,80	7,17	3,91	4,50	4,86
Standard deviation	0,28	1,01	0,39	0,39	0,42

Table 8: Descriptive statistics of domestic and cross-country exposures in the 100 long-term interbank networks.

The probability map has been obtained from data on actual euro money market loans with maturities from one to six months. Table A. shows statistics of total exposures of banks to their domestic counterparties over the total capital of the system. Table B. shows statistics of exposures of banks to their foreign counterparties (by country) divided by the total capital of the system.

	Year				
	2008	2009	2010	2011	2012
A. Domestic interbank exposures (country level, % of country's capital)					
Mean	15%	19%	12%	12%	19%
Min	0%	0%	0%	0%	0%
Median	1%	6%	6%	5%	3%
Max	184%	189%	112%	76%	148%
Std dev	40%	41%	24%	19%	36%
B. Cross-border interbank exposures (country level, % of country's capital)					
Mean	6%	5%	5%	7%	4%
Min	0%	0%	0%	0%	0%
Median	1%	2%	1%	2%	0%
Max	110%	116%	116%	204%	194%
Std dev	13%	11%	11%	20%	14%

Table 9: Explanatory variables for the system-wide determinants of cross-border contagion

Variable	Comment
Network characteristics	
Density	Number of actual links over the number of possible links. It provides information about the level of interconnectedness within a network, for a given level of bank total exposures.
Average shortest path	Average number of links along the shortest paths for all possible pairs of network nodes. The average shortest path proxies for the closeness of banks within the network.
Weighted Max/Median degree	Ratio of the weighted maximum node degree over the median node degree. This ratio provides information about the tail of the weighted degree distribution.
Unweighted Max/Median degree	Ratio of the unweighted maximum node degree over the median node degree. This ratio provides information about the tail of the unweighted degree distribution.
Balance sheet characteristics	
σ long-term exposures to low-liquid banks	Standard deviation of the share of banks' long-term exposures to the 10% banks with the lowest ratio of cash over interbank borrowing.
σ long-term exposures to low-capitalized banks	Standard deviation of the share of banks' long-term exposures to the 10% banks with the lowest ratio of capital over total assets.
σ long-term exposures to high-beta banks	Standard deviation of the share of banks' long-term exposures to the 10% banks with the highest correlation with the market shock.
σ long-term exposures to large banks	Standard deviation of the share of banks' long-term exposures to the 10% largest banks (by total assets).
σ long-term exposures to highly connected banks	Standard deviation of the share of banks' long-term exposures to the 10% banks with the largest number of counterparties.
σ long-term exposures to low connected banks	Standard deviation of the share of banks' long-term exposures to the 10% banks with the lowest number of counterparties.
σ long-term exposures to highly exposed banks	Standard deviation of the share of banks' long-term exposures to the 10% banks with the ratio of long-term exposures to capital.

This table describes the explanatory variables used to analyse the determinants of system-wide contagion (section X). All of these variables exploit within-year heterogeneity at a European level.
σ stands for the standard deviation.

A.4 Simulation results

Table 10: Summary statistics of simulation results averaged over 500 shock scenarios and the defaults of an initial bank.

Distribution of default outcomes over 100 pairs of networks. Default outcomes are averaged over the shock scenarios and over the defaults of an initial bank. Default outcomes are reported in terms of number of bank failures triggered by the default of an initial bank and of losses as a proportion of total system capital (i.e. of depleted capital). All the losses due to the common market shock and to solvency contagion are accounted for in '... before hoarding', whereas total losses are accounted for in '... after hoarding'. Thus the difference between the two is attributed to liquidity contagion

	2008	2009	2010	2011	2012
A. Number of defaults before hoarding					
Min	1,27	1,19	1,18	1,22	1,08
5th percentile	1,33	1,23	1,20	1,24	1,12
Mean	1,49	1,34	1,28	1,33	1,19
95th percentile	1,73	1,54	1,41	1,44	1,30
Max	1,97	1,68	1,51	1,58	1,45
Std dev	0,13	0,10	0,06	0,07	0,06
B. Percentage of depleted capital before hoarding					
Min	4,61%	4,41%	4,38%	4,46%	4,40%
5th percentile	4,67%	4,45%	4,39%	4,47%	4,43%
Mean	4,95%	4,61%	4,51%	4,58%	4,55%
95th percentile	5,45%	4,82%	4,69%	4,72%	4,77%
Max	6,38%	5,05%	5,01%	5,14%	4,95%
Std dev	0,26%	0,12%	0,10%	0,09%	0,11%
C. Number of defaults after hoarding					
Min	1,29	1,22	1,18	1,25	1,09
5th percentile	1,35	1,25	1,23	1,26	1,12
Mean	1,74	1,44	1,61	1,47	1,25
95th percentile	3,13	2,07	2,88	2,34	1,41
Max	4,55	2,49	5,21	3,25	3,11
Std dev	0,58	0,25	0,74	0,37	0,26
D. Percentage of depleted capital after hoarding					
Min	4,65%	4,45%	4,40%	4,46%	4,40%
5th percentile	4,76%	4,48%	4,41%	4,50%	4,43%
Mean	5,37%	4,71%	4,87%	4,70%	4,65%
95th percentile	7,43%	5,22%	6,74%	5,27%	4,94%
Max	13,41%	5,92%	8,65%	6,86%	10,22%
Std dev	1,29%	0,27%	0,81%	0,35%	0,61%

Table 11: Summary statistics of simulation results : maximum losses over 500 shock scenarios and the defaults of an initial bank.

Distribution of maximum default outcomes over 100 pairs of networks. Maximum default outcomes are measured in terms of maximum number of bank failures triggered by the default of an initial bank and of losses as a proportion of total system capital (i.e. of depleted capital). All the losses due to the common market shock and to solvency contagion are accounted for in '... before hoarding', whereas total losses are accounted for in '... after hoarding'. Thus the difference between the two is attributed to liquidity contagion

	2008	2009	2010	2011	2012
A. Number of defaults before hoarding					
Min	4,00	3,00	3,00	3,00	2,00
5th percentile	4,00	3,09	3,00	3,00	2,30
Mean	6,89	5,44	4,41	4,97	3,92
95th percentile	10,11	9,00	7,00	7,70	6,50
Max	13,00	11,00	9,00	9,14	9,00
Std dev	2,02	1,67	1,21	1,27	1,33
B. Percentage of depleted capital before hoarding					
Min	10,57%	8,29%	8,34%	8,61%	7,29%
5th percentile	11,84%	8,87%	9,09%	8,93%	8,61%
Mean	17,01%	12,28%	11,69%	12,13%	11,34%
95th percentile	26,41%	17,03%	15,77%	16,19%	15,86%
Max	33,43%	21,67%	18,13%	20,73%	22,34%
Std dev	4,63%	2,60%	2,06%	2,34%	2,52%
C. Number of defaults after hoarding					
Min	4,00	3,00	3,00	3,00	2,00
5th percentile	5,00	3,81	3,01	3,06	2,31
Mean	7,62	5,90	5,31	5,31	4,11
95th percentile	11,71	9,01	8,51	8,00	7,00
Max	14,00	11,00	11,02	9,14	9,00
Std dev	2,24	1,82	1,72	1,33	1,39
D. Percentage of depleted capital after hoarding					
Min	11,25%	8,35%	8,34%	8,65%	7,29%
5th percentile	12,59%	9,38%	9,30%	9,10%	8,90%
Mean	18,13%	12,81%	12,40%	12,39%	11,72%
95th percentile	29,11%	17,76%	16,98%	17,25%	16,70%
Max	33,43%	24,18%	20,50%	20,73%	22,34%
Std dev	5,04%	2,72%	2,43%	2,44%	2,67%

Table 12: Summary statistics of simulation results : domestic and cross-country losses averaged over 500 schock scenarios and the defaults of an initial bank.

Table A. presents by-country distributions of average losses (over 100 network pairs) imposed by a bank on its domestic counterparties over the total capital of the system. Table B. presents by-country distributions of average losses (over 100 network pairs) imposed by a bank on its foreign counterparties over the total capital of the system.

	Year				
	2008	**2009**	**2010**	**2011**	**2012**
A. Losses imposed on domestic banking system					
Mean	1,60%	1,56%	1,49%	1,31%	1,86%
Min	0,00%	0,00%	0,00%	0,00%	0,00%
Median	1,00%	1,20%	1,34%	0,90%	0,68%
Max	7,59%	6,00%	7,03%	4,91%	12,33%
Std dev	2,08%	1,70%	1,75%	1,53%	3,06%
B. Losses imposed on a foreign banking system					
Mean	1,29%	0,87%	1,03%	0,86%	0,56%
Min	0,00%	0,00%	0,00%	0,00%	0,00%
Median	0,86%	0,52%	0,70%	0,37%	0,19%
Max	14,36%	10,59%	7,20%	15,47%	11,81%
Std dev	1,80%	1,20%	1,19%	1,50%	1,05%

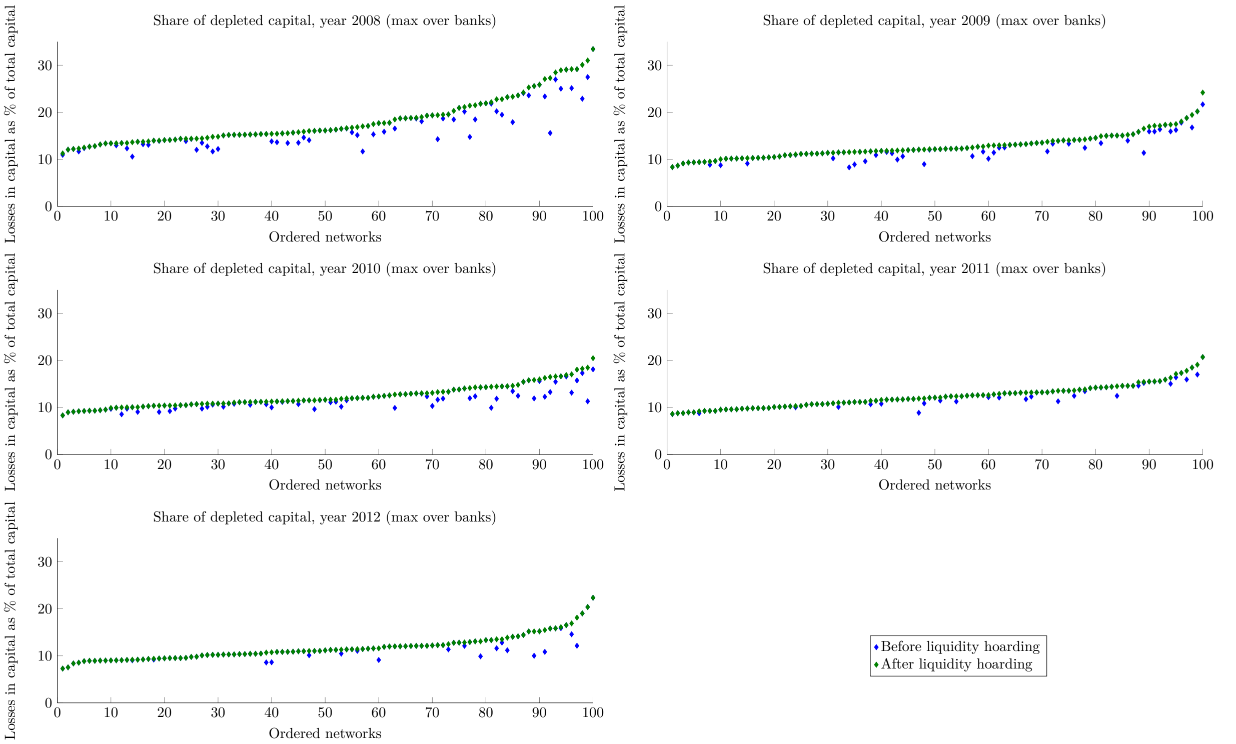

Figure 3: Share of interbank losses -before and after liquidity hoarding- ordered by the size of total losses (as % of total system capital)

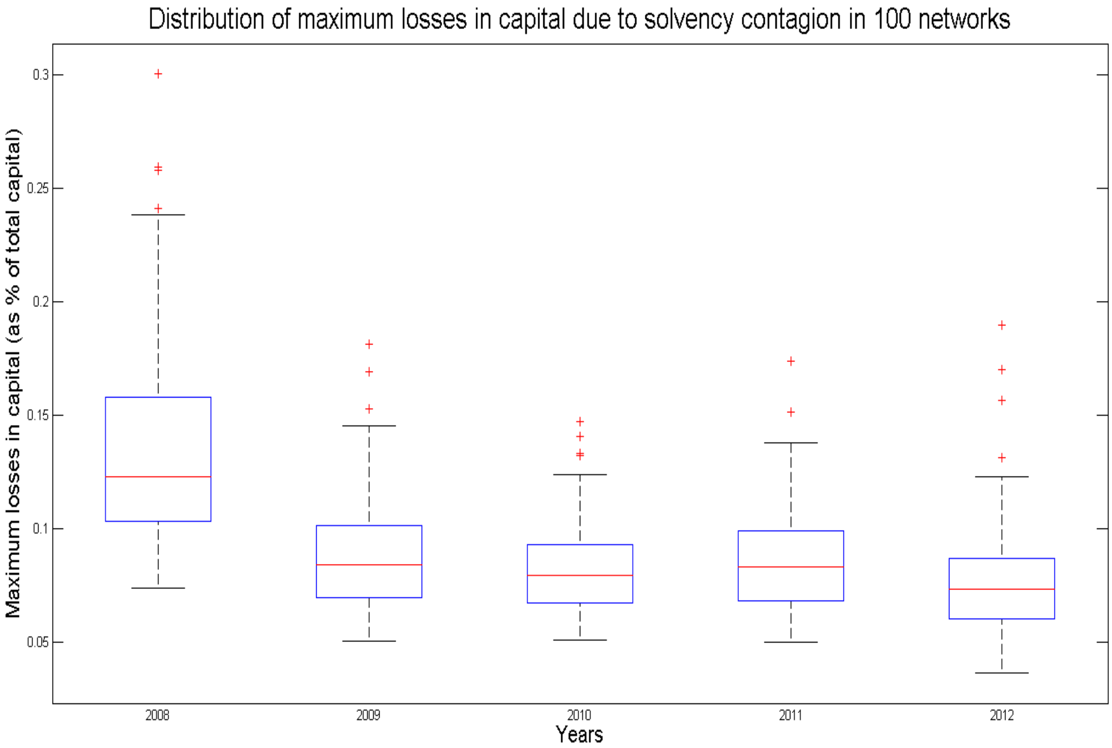

Figure 4: Distribution of losses due to solvency contagion (as % of total system capital)

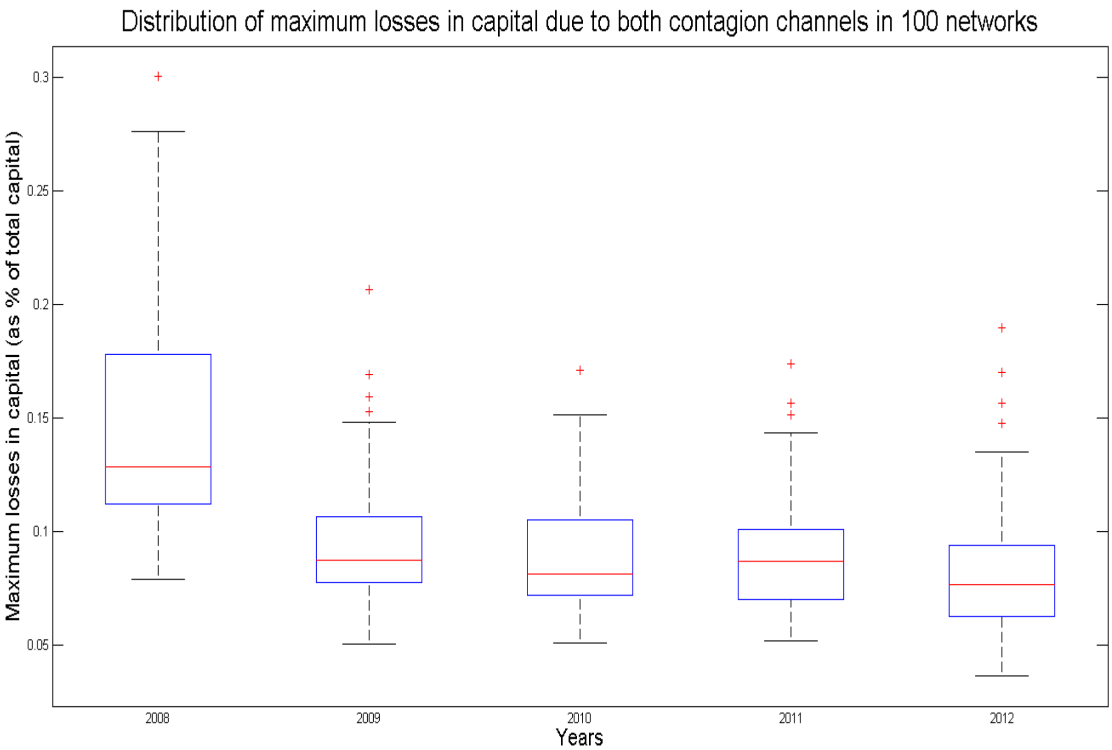

Figure 5: Distribution of losses due to both solvency and liquidity contagion (as % of total system capital)

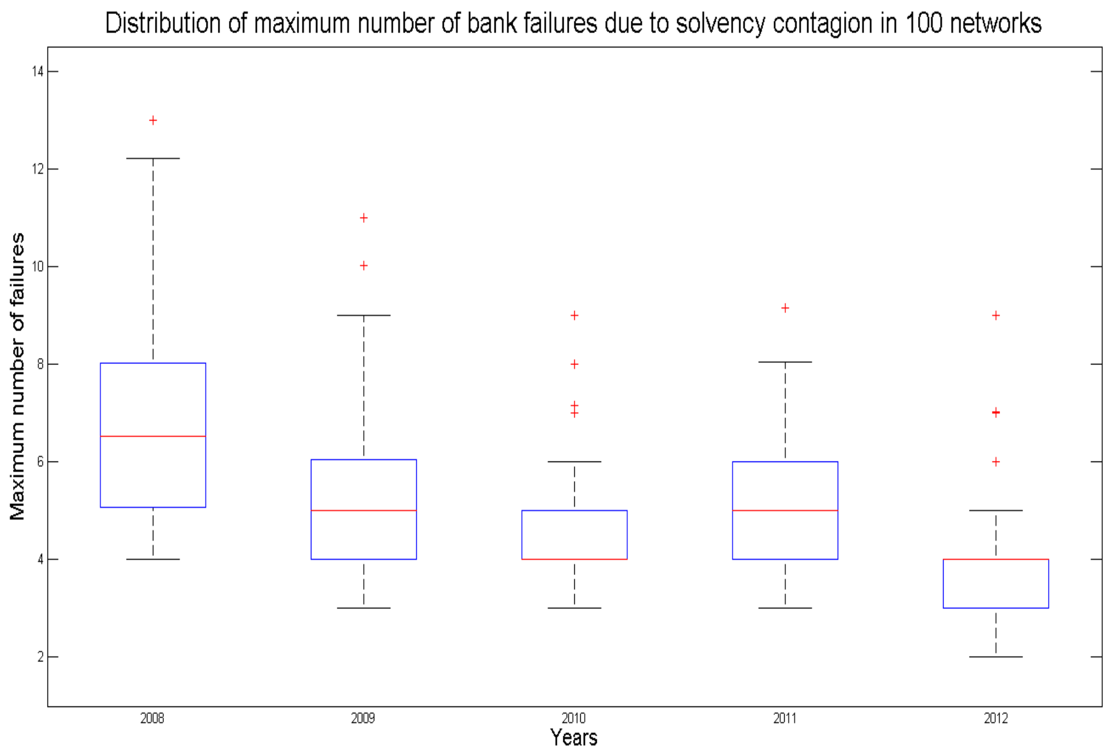

Figure 6: Distribution of maximum number of failures due to solvency contagion

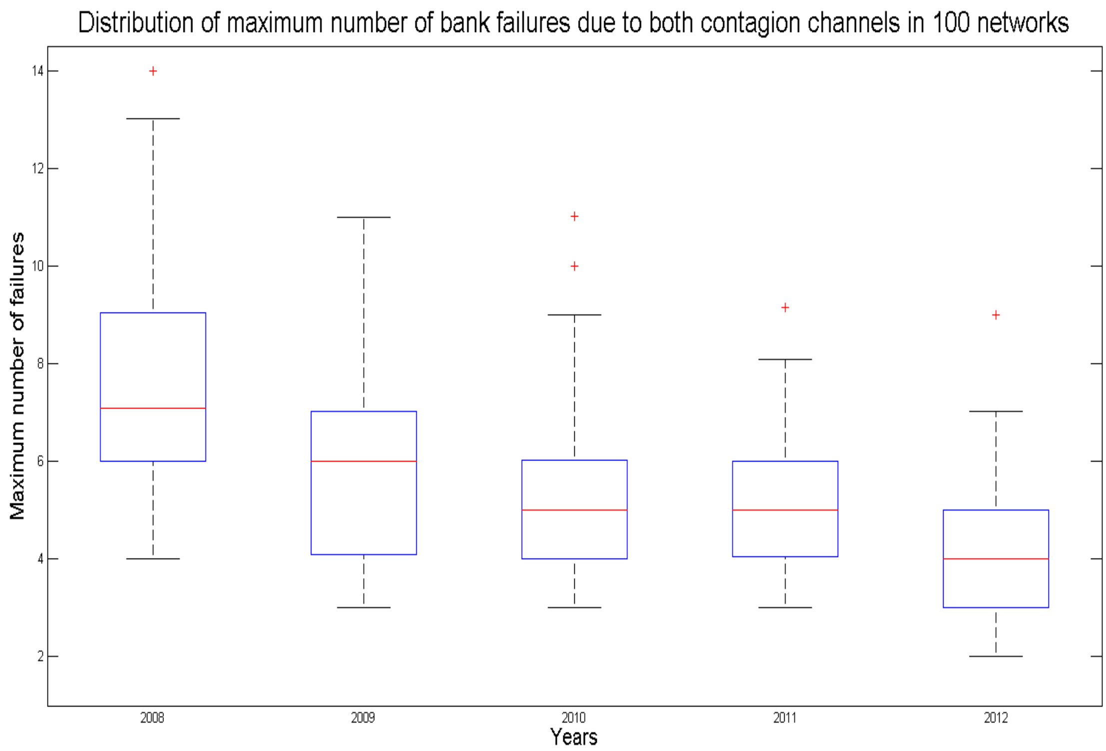

Figure 7: Distribution of maximum number of failures due to both solvency and liquidity contagion

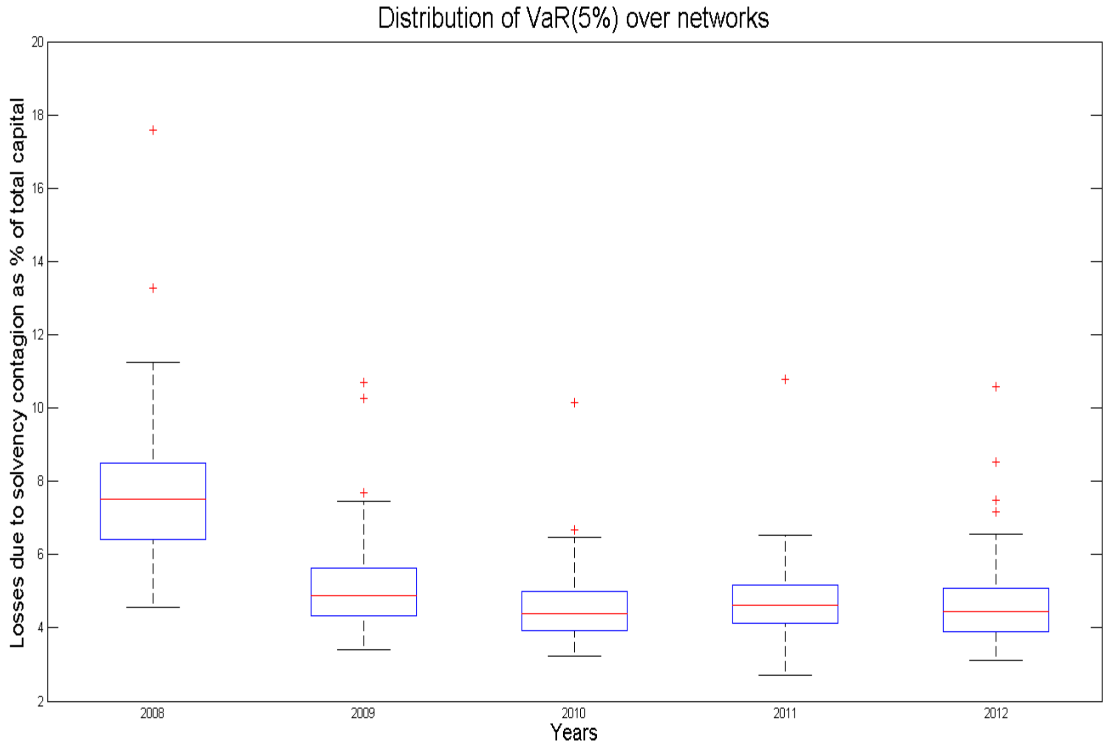

Figure 8: Distribution of the 5% worst losses due to solvency contagion over 500 shock scenarios and 100 network pairs (as % of total system capital)

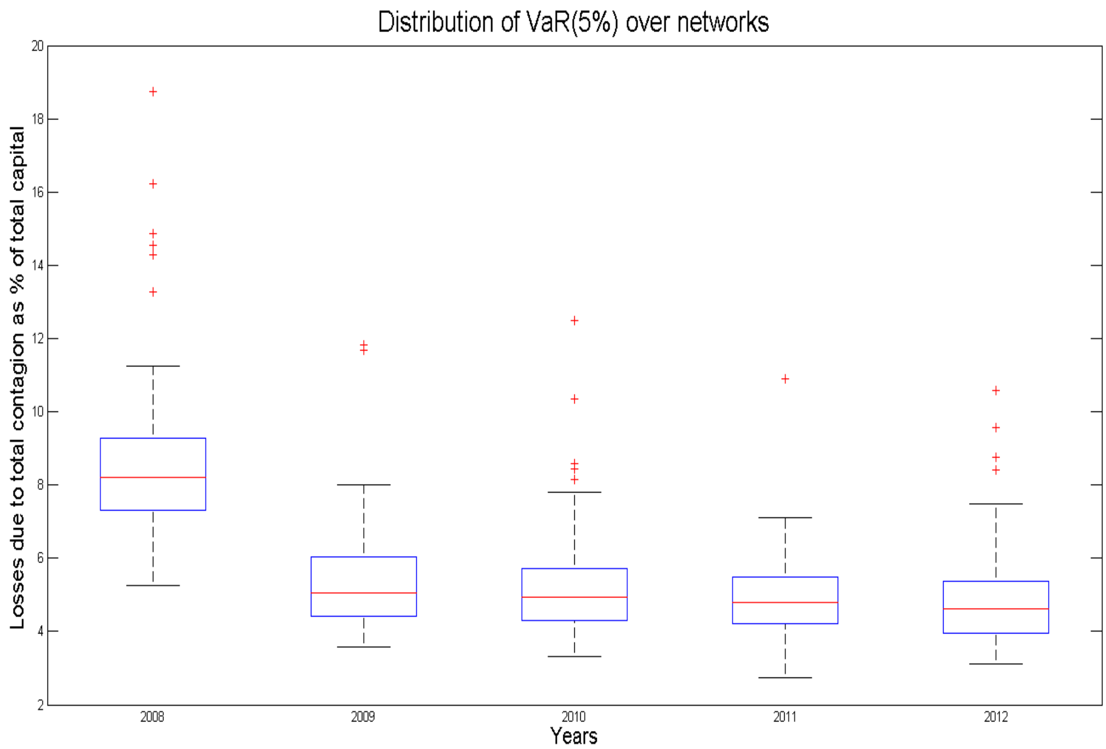

Figure 9: Distribution of the 5% worst losses due to both solvency and liqidity contagion over 500 shock scenarios and 100 network pairs (as % of total system capital)

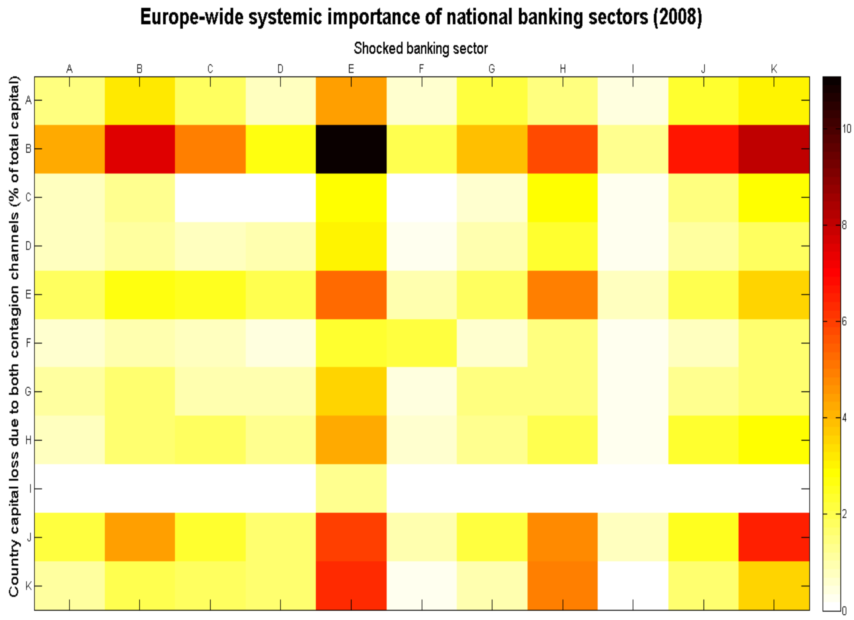

Figure 10: Total cross-border contagion in 2008
The cells $(A; B)$ of the map represent with colors the strength of the total capital loss experienced by country A's banking sector (as a fraction of its aggregate initial capital) given a common market shock and the default of a bank in the foreign banking system B. Total country capital losses are computed on average over 500 realizations of the market shock and 100 different pairs of long- and short-term exposure networks. They have been normalized to account for the different number of banks (and hence of simulations) considered for the various national banking sectors. Heatmaps have been anonymized for data confidentiality reasons; countries for which less than 3 sample banks are availble have been removed from the charts. Countries are ordered randomly, but the order is the same across years.

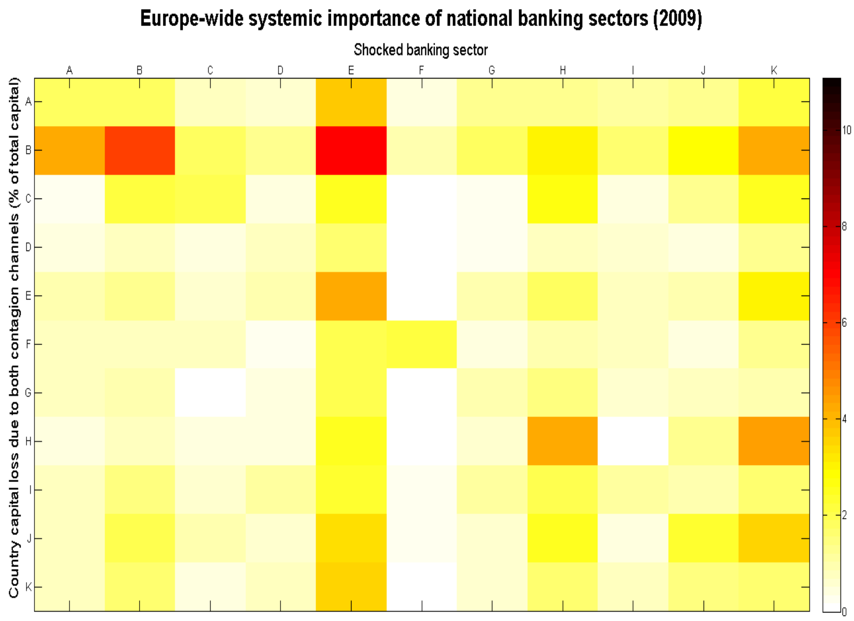

Figure 11: Total cross-border contagion in 2009
See caption in Figure 10.

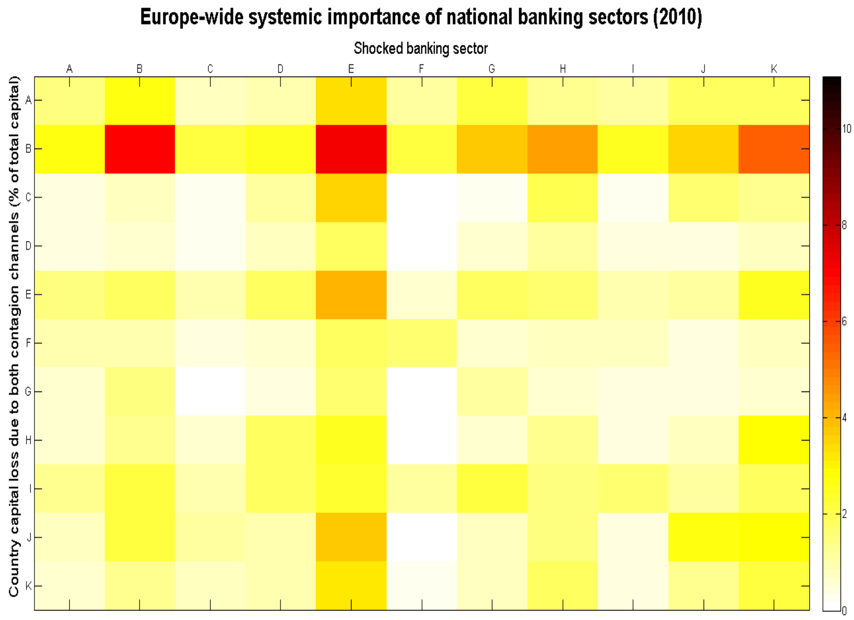

Figure 12: Total cross-border contagion in 2010

See caption in Figure 10.

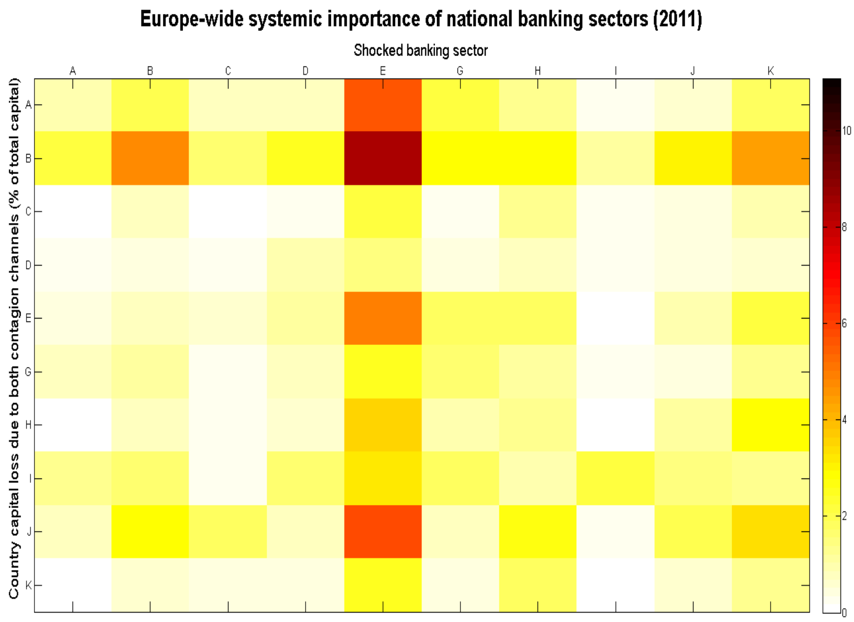

Figure 13: Total cross-border contagion in 2011

See caption in Figure 10. Note that one additional country has been removed from the 2011 heat map because of data unavailability for sample banks from this country in 2011.

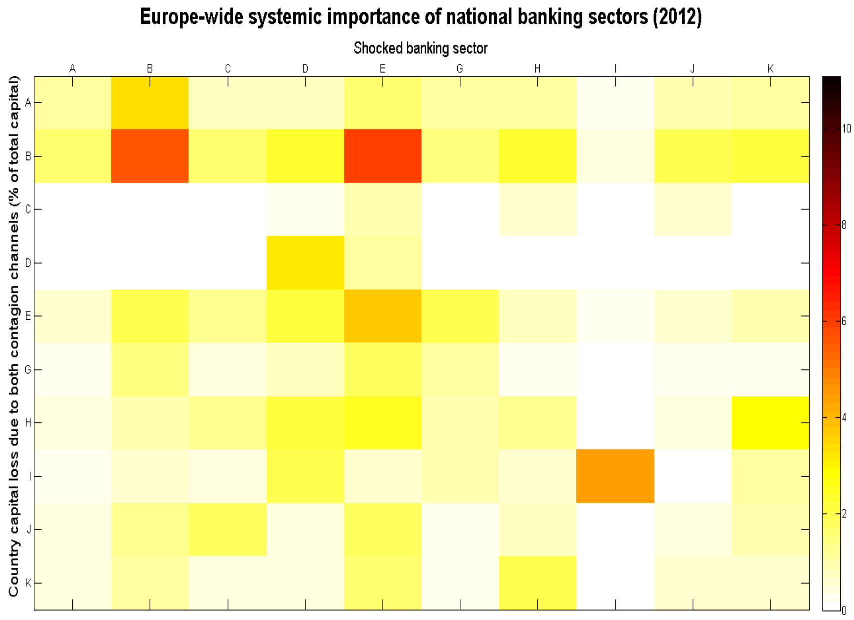

Figure 14: Total cross-border contagion in 2012

See caption in Figure 10. Note that one additional country has been removed from the 2012 heat map because of data unavailability for sample banks from this country in 2012.

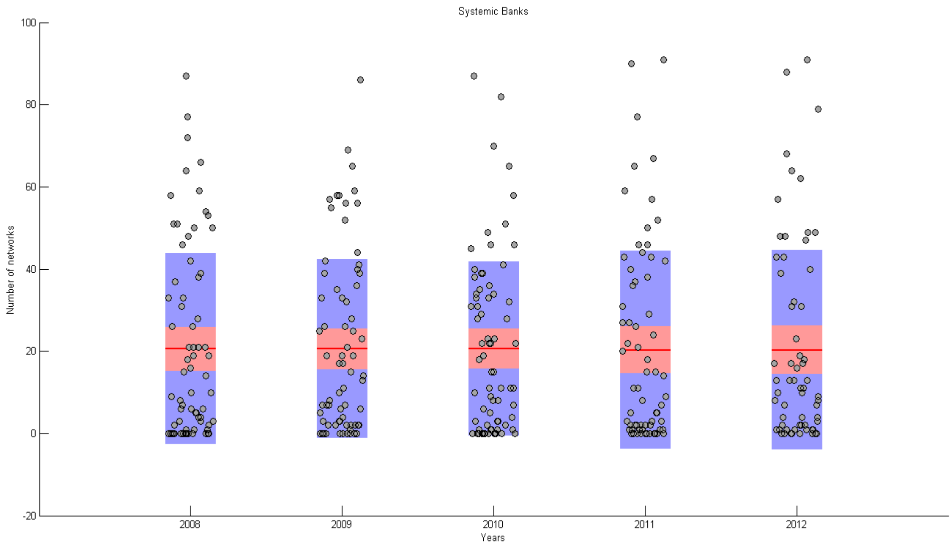

Figure 15: Systemic banks for each of the 5 years of analysis.
For each year, we have number of networks in which each bank is systemic. Most of the banks are either never systemic or rarely systemic, whereas some are systemic in almost all 100 simulated networks. We define a bank to be systemic, when losses (through both channels of contagion) imposed on the system by its default exceed 85th percentile of loss distribution.

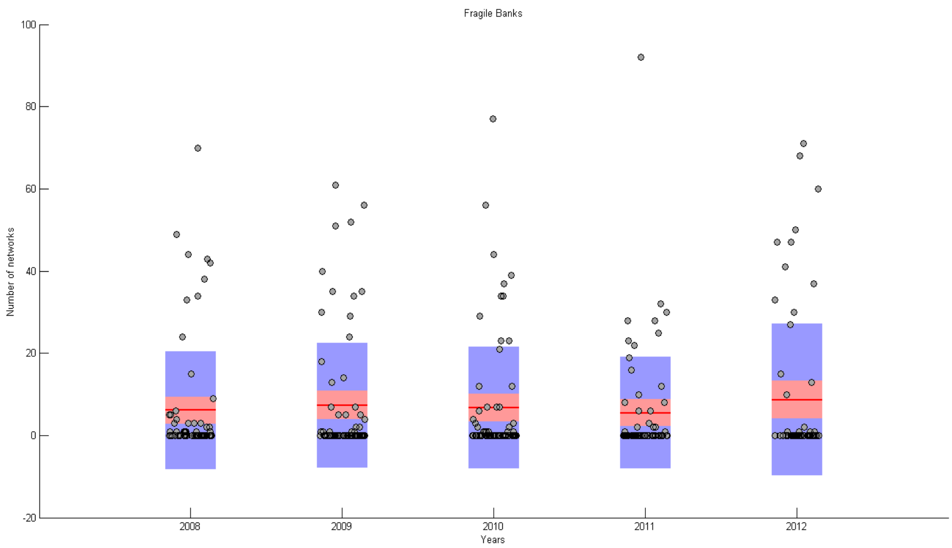

Figure 16: Fragile banks for each of the 5 years of analysis.
For each year, we have number of networks in which each bank is fragile. Most of the banks are either never fragile or rarely fragile, whereas some are fragile in more than half of 100 simulated networks. We define a bank to be fragile, when it defaults due to an initial default more frequently that 85% of other banks.

A.5 Econometrics

	(1)	(2)	(3)	(4)	(5)	(6)
	NBD	NBD	NBD	Capital loss	Capital loss	Capital loss
main						
Capital ratio	-88.87***	-88.88***	-88.80***	-18.17***	-18.15***	-18.16***
	(-10.35)	(-10.36)	(-10.33)	(-20.92)	(-20.93)	(-20.95)
ST funding / Assets	20.06***	20.08***	20.13***	5.110***	5.107***	5.104***
	(9.30)	(9.45)	(9.62)	(4.79)	(4.78)	(4.79)
Closeness	-16.10**	-16.28**	-16.96**	3.593*	3.918*	3.625*
	(-2.01)	(-2.02)	(-2.10)	(1.72)	(1.85)	(1.68)
EXP. low ST funding / Assets	1.710***	1.703***	1.665***	0.852***	0.845***	0.838***
	(4.49)	(4.50)	(4.38)	(5.30)	(5.31)	(5.28)
EXP. low Capital	0.977***	0.973***	1.020***	0.489***	0.486***	0.495***
	(5.12)	(5.08)	(5.31)	(6.52)	(6.41)	(6.55)
EXP. high N. Counterparties	-0.558***	-0.556***	-0.543***	-0.156***	-0.154***	-0.153***
	(-3.64)	(-3.65)	(-3.56)	(-3.70)	(-3.65)	(-3.64)
LT Clustering		-0.182	0.581		0.516	0.781
		(-0.05)	(0.16)		(0.50)	(0.75)
LT Avg. Path length		0.368	-0.0265		0.271	0.134
		(0.52)	(-0.04)		(1.38)	(0.68)
LT Max / Mean degree		0.0603	0.0467		0.128	0.120
		(0.19)	(0.15)		(1.46)	(1.36)
ST Clustering			-2.107			-0.806
			(-0.75)			(-0.96)
ST Avg. Path length			-0.105			-0.0429
			(-0.33)			(-0.49)
ST Max / Mean degree			-0.775***			-0.266***
			(-3.19)			(-4.26)
Observations	6500	6500	6500	6500	6500	6500
BIC	.	.	.	.	.	.

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Explaining bank fragility.
The dependent variable in columns (1), (2) and (3) is the frequency of defaults of bank i, for each network n, following the default of another bank j, $j \neq i$. The dependent variable in columns (4), (5) and (6) is the share of losses suffered by bank i, for each network n, following the default of another bank j, $j \neq i$.

	(1)	(2)	(3)	(4)	(5)	(6)
	NBD	NBD	NBD	Capital loss	Capital loss	Capital loss
main						
Capital ratio	-18.49***	-18.48***	-18.48***	-6.649***	-6.631***	-6.635***
	(-15.37)	(-15.36)	(-15.43)	(-20.03)	(-20.10)	(-20.16)
ST funding / Assets	1.574*	1.566*	1.538*	0.644**	0.639**	0.636**
	(1.92)	(1.90)	(1.88)	(2.46)	(2.45)	(2.44)
Closeness	27.79***	28.26***	28.58***	16.41***	17.01***	16.89***
	(6.71)	(6.74)	(6.62)	(11.37)	(11.68)	(11.32)
EXP. low ST funding / Assets	0.0117	0.00489	-0.0126	0.0510	0.0423	0.0383
	(0.08)	(0.03)	(-0.08)	(0.93)	(0.79)	(0.72)
EXP. low Capital	0.0818	0.0805	0.0974	-0.0928	-0.0970	-0.0939
	(0.35)	(0.34)	(0.42)	(-1.15)	(-1.22)	(-1.19)
EXP. high Beta	0.281***	0.281***	0.277***	0.156***	0.157***	0.157***
	(3.64)	(3.65)	(3.60)	(5.37)	(5.42)	(5.41)
LT Clustering		0.571	1.657		0.750	0.942*
		(0.35)	(0.97)		(1.38)	(1.68)
LT Avg. Path length		0.192	-0.0953		0.288***	0.214**
		(0.62)	(-0.31)		(2.65)	(1.96)
LT Max / Mean degree		0.146	0.127		0.199***	0.194***
		(1.54)	(1.35)		(5.91)	(5.75)
ST Clustering			-4.165***			-0.644
			(-2.59)			(-1.19)
ST Avg. Path length			-0.309			-0.0177
			(-1.51)			(-0.30)
ST Max / Mean degree			-0.634***			-0.143***
			(-5.34)			(-3.73)
Observations	6500	6500	6500	6500	6500	6500
BIC	.	.	.	.	.	.

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Explaining bank systemicity.
The dependent variable in columns (1), (2) and (3) is the frequency of failures imposed by the default of bank i, for each network n. The dependent variable in columns (4), (5) and (6) is the share of losses imposed by the default of bank i, for each network n.