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Cross-border interbank contagion in the European banking sector*

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Résumé

Cet article étudie la contagion trans-frontalière dans le secteur bancaire européen, en faisant usage de données d'exposition réelles. Sur la base d'un modèle séquentiel de défauts de solvabilité et de liquidité dans un réseau de banques, nous analysons la propagation géographique des pertes de 2008 à 2012. Nous étudions la distribution de l'étendue de la contagion après un choc agrégé et le défaut exogène d'une banque, sur des réseaux d'expositions simulés à partir de vraies données de prêts à court et à long terme. Nous utilisons une base de données nouvelle et unique de transactions sur le marché monétaire, estimées à partir des données de paiements TARGET2. Nos résultats montrent l'importance capitale de la structure sous-jacente des expositions pour la propagation des pertes. Une analyse économétrique des déterminants de la contagion montre que les expositions des banques aux contreparties les plus risquées dans le système et la position d'une banque dans le réseau avant le choc sont corréleés de manière significative avec les événements de défaut, au-delà de l'impact des seuls ratios financiers de la banque.

Codes J.E.L.: G01, G21, G28, F36.

Mots-clés: Contagion, Marché interbancaire, Stress Testing, Liquidité, Risque de contrepartie.

Abstract

This paper studies the scope for cross-border contagion in the European banking sector using true bilateral exposure data. Using a model of sequential solvency and liquidity cascades in networks, we analyze geographical patterns of loss propagation from 2008 to 2012. We study the distribution of contagion outcomes after a common shock and an exogenous bank default over simulated networks of actual long- and short-term claims. We exploit a novel and unique dataset of money market transactions estimated from TARGET2 payments data. Our results show the critical impact of the underlying network structure on the propagation of losses. An econometric analysis of the determinants of contagion shows that the position of a bank in the network and its exposure to the riskiest counterparties are significantly correlated with default outcomes, behind its own financial ratios.

J.E.L. Codes: G01, G21, G28, F36.

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

Non-technical summary

This paper investigates the scope for cross-border contagion in Europe using true bilateral exposure data at a bank level. We analyze geographical patterns of shock propagation between 73 European banking groups from end-2008 until end-2012. The extent of interbank contagion is assessed relying on Fourel et al. [2013]'s model. The model features both solvency defaults and liquidity defaults.

The scenarios we simulate include a common market shock on banks' capital and the exogenous default of a bank. We construct heat maps to identify both the banking sectors which are the most "systemic", in terms of the losses that the failure of one of their banks can impose to foreign banks, and the banking sectors are the most vulnerable to cross-border contagion from European counterparties.

We exploit for the first time a unique dataset of interbank money market transactions, with various maturities, estimated from TARGET2 payments data. We use true bilateral exposure data to simulate a large number of realistic exposure networks. Based on this simulated data, we conduct an econometric analysis 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.

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 our stress scenarios can be up to six times larger than the average number of defaults, depending on the underlying structure of interbank linkages.

1 Introduction

The 2007-2008 financial crisis revealed the fragility of financial institutions worldwide and the major role of interconnectedness among banks in the propagation of financial distress. Interconnections, in the form of bilateral contractual obligations, as well as exposures to common risk factors, have grown dramatically in the run-up to the crisis.[1] While higher interconnectedness is a 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.

This paper investigates the scope for cross-border contagion in Europe using true bilateral exposure data at a bank level. In Europe, cross-border contagion has taken a particular form during the sovereign debt crisis, in the form of market fragmentation. After the European Banking Authority's disclosure of the extent of European banks' common exposures to stressed sovereigns in 2011[EBA, 2011a], core banks have been reducing their exposure 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 markets).

We analyze geographical patterns of shock propagation between 73 European banking groups from end-2008 until end-2012. The extent of interbank contagion is assessed relying on Fourel et al. [2013]'s model. The model features both solvency defaults and liquidity defaults. We focus on the distribution of simulation outcomes (number of defaults and total losses) resulting from a common market shock on (listed) banks' capital, coupled with an exogenous bank default; the distributions are obtained over a large number of exposure networks simulated from true of long- and short-term exposure data. We construct heat maps to identify both the banking sectors which are the most "systemic", in terms of the losses that the failure of one of their banks can impose to foreign banks, and the banking sectors are the most vulnerable to cross-border contagion from European counterparties.

We use a novel database of cross-border interbank exposures. These exposures are generally not available to researchers. 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 payments data (see Arciero et al. [2013]). We use true bilateral exposure data to simulate a large number of realistic exposure networks, using the methodology proposed by Halaj and Kok [2013]. Based on this simulated data, we conduct an econometric analysis to identify both bank and network characteristics that make a bank/system more fragile/resilient to

[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.

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 the exogenous default of one bank, significant cross-border contagion may arise. 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 this impact has been reducing 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. 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, which can be interpreted as market fragmentation, and to an increase in banks' capitalization during these years, as 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 our stress scenarios can be up to six times larger than the average number of defaults, 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 scenarios. This is the first paper, to our knowledge, to document this feature by simulating interbank exposures based on actual bank-to-bank data.

A large literature exists that relies on counterfactual simulations in networks 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 primarily 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.

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]).

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 data. 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 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. 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 $OL(i)$.

	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 important as it makes it possible to define 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, i.e. to reduce or to cut their exposures to a counterparty when needed. As explained below, liquidity contagion 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). The network of long-term exposures is the main channel for the propagation of solvency contagion.

The model consists of three parts: *(i)* a shock with both a common and an idiosyncratic components, *(ii)* solvency contagion and *(iii)* 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.

The shock

The aggregate component of the shock takes the form of a common market shock. 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 by changes in banks' balance sheets. As depicted in figure 2, the shock represents a loss equal to 5% of bank capital on average over all scenarios but can reach up to 25% in extreme cases; such orders of magnitude are in line with bank capital losses observed during the recent crisis (see, e.g., Basel Committee on Banking Supervision [October, 2010] and Strah et al. [2013]).

The idiosyncratic part of the shock is modeled in a stylized way by assuming that one bank exogenously defaults. 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

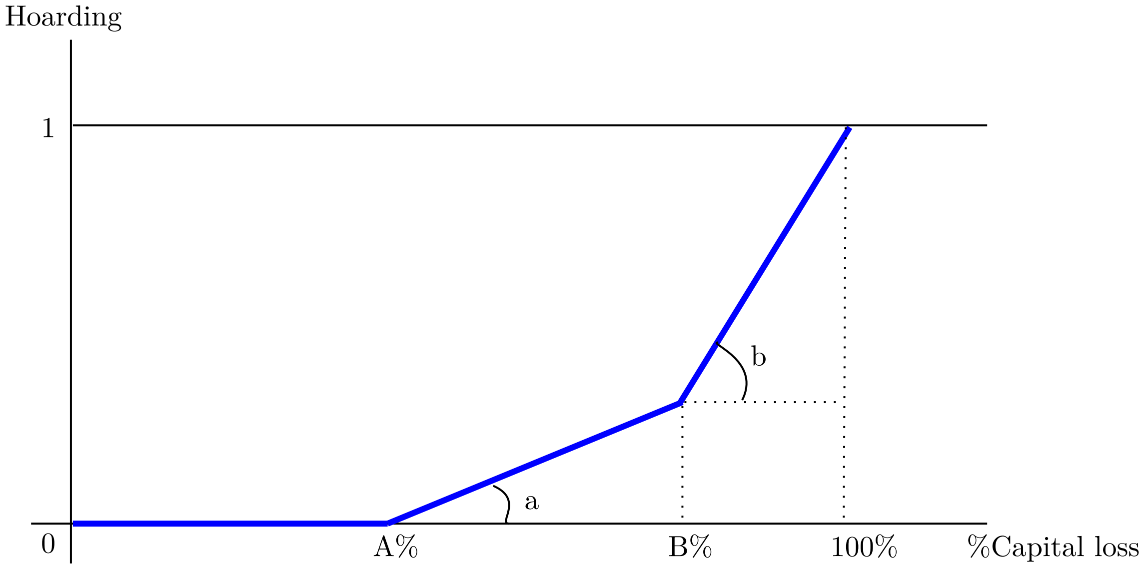

Figure 1: Liquidity hoarding behaviour.

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 the one hand, banks' assets become much more volatile, creating liquidity outflows in terms of margin calls and higher haircuts, 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 demand liquidity for precautionary reasons, hence to a *hoarding* behavior, by which they 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 when 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 the 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 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 hoard. A straightforward assumption is that the riskier the counterparty is, the more a bank hoards liquidity. Provided

[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.

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, 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 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]. 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 net evenly spread, either among banks within a national banking sector or across 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 exposure 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.

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 The sample of banks

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. In contrast with 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 participants.

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

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

[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`.

"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).[7] More specifically, we use loans with 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.[8] 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. [9] 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.[10]

[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.

[7]In this version of the paper, we use a dataset with distinction between originators and beneficiaries of TARGET2 transactions (i.e. indirect TARGET2 participants) that has been recently made available. Unlike the previous dataset where loans made on behalf of customers were attributed to the direct TARGET2 participants (i.e. settler banks), the new dataset allows us to obtain a more reliable representation of the universe of interbank money market loans and to estimate true exposures of the banks.

[8]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.

[9]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 2010 ECB euro money market study reports increasing market fragmentation in the euro money market in relation to the euro area sovereign debt crisis.

[10]Alternative calibrations, e.g. in which prior probabilities are based on the daily average amount lent to

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 200 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 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.[11] 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. [12]

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.

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

[12] 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.

3.2.4 Simulation dates

We repeat our counterfactual simulations at year-end for five dates, $t = \{2008, 2009, 2010, 2011, 2012\}$.[13] 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 200 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 with those observed for real interbank structures.[14] 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 200 networks, the most interconnected bank was about eight times more connected than half of the others; for one network the ratio between maximum and median degree was as high as sixteen. 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 200 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, however it is twice as dense as long-term networks.

Table 8 reports summary statistics of cross-country long-term exposures over 200 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 several times more exposed to their home counterparties, with domestic exposures reaching 24% of a country's capital and foreign exposures being around 3-5%. 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 and may be several times higher than national systems' capital. However, such high ratios of domestic and

[13] 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.

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

cross-border interbank exposures relative to a banking sector's total capital represent very few observations, and most of the cells in the $73x73$ exposure matrix are zeros which corresponds to low density of these networks.

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 being satisfied, but also because it allows capturing the 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.

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 200 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 200 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, thus identifying patterns of increasing or decreasing system resilience.

4.1 Contagion as a tail risk

Table 9 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 (the median is less than 2 and about 6% 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 9 show that the distributions of losses due to the shock and to solvency contagion are relatively thin-tailed across the 200 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 (6% 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 14% in 2008 and of 6.74% in 2012 (corresponding to more than 5 bank failures in 2008 and about 2 banks 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 10 shows that the exogenous default of one bank (always coupled with a common market shock) can lead to the default of other 15 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 larger in 2008 than afterwards.

Figures 3, 4 and 5 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 11% to 33% of total system capital in all years. Interestingly, liquidity hoarding plays a very different role from one year to another, and seems to be more important in years 2008-2010: for some networks, losses due to liquidity contagion can represent up to half of the total. On figures 4 and 5, we obtain maximum losses/failures resulting from the market stress coupled with one bank's default and plot distributions of these values for different networks. In these figures, we exclude losses due to the market shock. The number of defaults due to the market shock together with one bank's default can vary significantly depending on the underlying structure of interbank linkages: from 8.5% of system's capital (or 4 banks) in one network to 35% of capital (or 20 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 looked both at averaged and maximum contagion outcomes over the market shocks and 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 $VaR^2(5\%)$ 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 6 plots the distribution of $VaR(5\%)$ of losses due to contagion over 200 network pairs. We can see that the 5% worst capital loss stands on average at 8% and 6.5% over the networks in 2008 and all other years correspondingly, and that the loss distribution in 2008 has heavier tail. By comparing figure 6 and 4, 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 11 allows us to glance at the extent of domestic *versus* cross-border contagion in the whole European banking sector. Unlike the heat maps (figures 7 to 11) which cover national banking sectors with more than two banks, the table summarizes results for all 21 European countries: panel A. presents the distribution of the losses corresponding to the ones on the main diagonal 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 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 2009.

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 7 to 11, 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 of 14% of the country's aggregate initial capital, while white cells correspond to no loss at all.[15]

[15] Total country capital losses following the market shock and an idiosyncratic foreign bank default are computed on average over 500 realizations of the market shock; over 200 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.

In 2008 the banking sectors of countries E, H and K appear to be more systemic in terms of the number of foreign banking sectors that will be impacted by the default of an average bank in these countries, however losses are limited to around 6%. The systems B and J follow, however the aggregate losses that the default of an average bank in B imposes on A are much larger. Banks in country B are also noticeably more exposed to each other with losses reaching 13%. The default of a bank headquartered in D, F 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 K generally seem to experience the highest loss following a foreign default (more numerous colored cells). It is worth noting that banks in most of the countries are also exposed within the system, with level of losses comparing to the international.

The 2009 and 2010 maps show that the potential for cross-border contagion changed over time: on the one hand, the risks increased over time with more national banking systems experiencing higher losses, but at the same time, less countries became exposed. Interestingly, the risks got concentrated around several systemic countries, B, E and H. This phenomenon is particularly well observed for the most fragile banking sectors, A, B and K: in 2008-2009, they were exposed to the majority of the countries, whereas in 2010, losses from the three banking sectors B, E and H prevailed. Over time, banks became also more exposed domestically (the diagonal cells appear more pronounced).

In 2011 and 2012, we observe even more pronounced reduction in exposures with the same centers of risk concentration. Namely, E and H remained the most systemic banking sectors and imposed higher cross-border losses in 2011. The situation changed radically in 2012: B was the most systemic whereas E became the most fragile. At the same time, the prevailing of light colors in the map reveals a European banking system overall less vulnerable to cross-border contagion.

All in all, we find that the level of losses remains rather stable across the years: the highest losses suffered by a national banking sector remains within 12-14%; notwithstanding, the cross-border patterns do vary remarkably. In 2011 and 2012, banks reduce their interbank exposures (see table 5), and most notably so in the cross-country dimension (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 12 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.

Countries are ordered randomly, with the same order over time.

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 13 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 9 and Table 10 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.

Figure 6 demonstrates the evolution of the system resilience to contagion over time. The year when the system was the most fragile is 2008. In fact, the 2008 loss distribution is characterized by a statistically significant 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.

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 4% in 2008 to 2% in 2012); more skewed (the ratio of max to average degree jumped from 5.5 in 2008 to 7.75 in 2012); with increasing average shortest path length (in 2008, the median distance separating any two banks was of only 3.05 other institutions, whereas it reached 3.39 in 2011, and back to 3.04 in 2012) (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.

4.5 Robustness checks

We perform a number of robustness checks to test how different model parameters impact our results. We document that changes in all the model parameters - recovery rate, availability of cash and liquidity hoarding specifications - drive our results in the expected direction. More specifically, lower recovery rates increase impact of both contagion channels, less cash as well as more aggressive liquidity hoarding drive up losses due to funding issues. The levels of the impact, though, remain perfectly reasonable, with average increase of initial losses by 10-15%.

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:

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

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:

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

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: $Short-term\ funding\ /\ Total\ assets$. [16] 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,

[16] 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.

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.[17] 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.

Exposures to/from 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. Exposures to the "riskiest" counterparties are computed for the fragility regressions, since 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. For a bank being systemic, it is more important what types of banks are exposed to it, therefore we compute the share of bank i long-term interbank borrowing from the three "riskiest" banks in the system. If banks exposed to the defaulted peer are already risky, e.g. more leveraged, they may fail more easily.

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

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 12 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 significantly correlated to 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. Banks that are highly interconnected are more likely to default following a shock scenario and to suffer 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 banks' own financial ratios in economic terms. Being exposed to a larger banks, however, reduces both the probability of default and the losses suffered since they are more stable and less likely to default themselves. Finally, it is interesting to note that structural network characteristics do not explain different degrees of bank vulnerability. The two exceptions are clustering coefficient and average shortest path in long-term networks. More specifically, a system with longer intermediation chains and less triangles seems to be more resilient to the propagation of interbank losses.
Results are consistent across years with minor differences.

Bank systemicity. Table 13 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 significantly correlated with 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. As one would expect being big explains being systemic in both terms, imposing more defaults and more losses. Eigenvector centrality turns out to increase a bank systemicity: the more connected a bank due to its numerous direct and indirect 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. As for the fragility regressions, these tables show that when the riskiest counterparties, more leveraged, more exposed, larger and with higher beta, are exposed to a bank, it increases the bank's systemic importance.

6 Conclusion

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 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. These 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 a large number 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. We also analyze the determinants of system-wide and country-level contagion by exploiting within-year cross-network 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[18] 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.

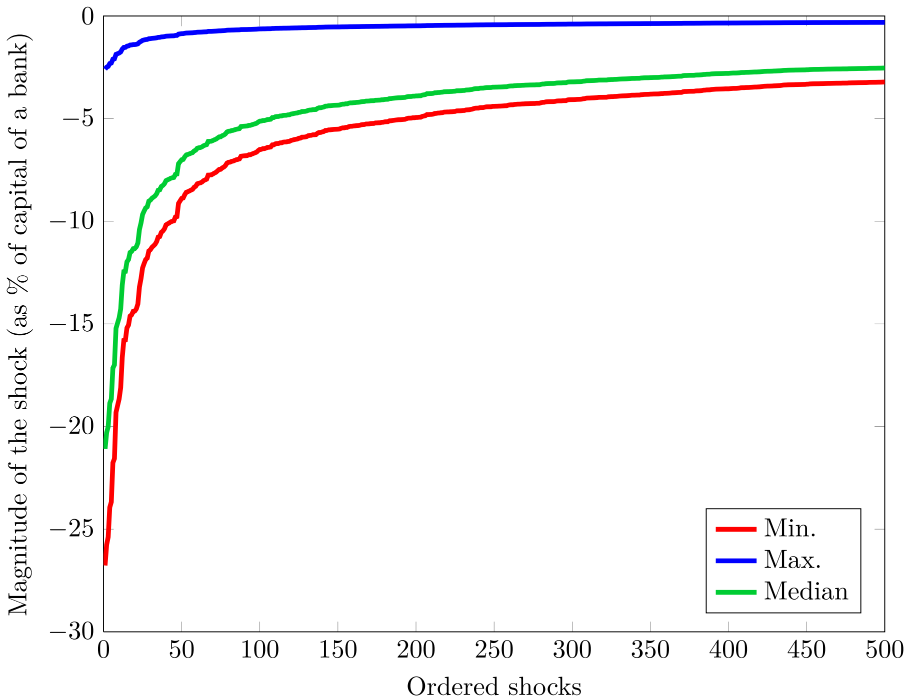

Figure 2: Distribution of the shocks to individual banks over 500 shock scenarios, measured as percentage of banks' capital

[18] 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

$$\begin{aligned} \mathbf{FD(C)} &= \left\{ i \in \mathbf{N} : C_0(i) + \underbrace{\epsilon(i)}_{\text{initial shock}} \leq 0 \right\} \\ &= \{ i \in \mathbf{N} : C_1(i) = 0 \} , \end{aligned} \tag{A.6}$$

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:

$$\begin{cases} C_2^0(i) = C_1(i) \\ C_2^k(i) = \max(C_2^0(i) - \sum_{\{j, C_2^{k-1}(j)=0\}} (1 - R^S) \times E_0(i,j); 0), \text{ for } k \geq 1, \end{cases} \tag{A.7}$$

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[19]. 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:

$$\lambda_t(i)E_t^{ST,k-1}(i) = \lambda_t(i)E_t^{ST,k-1}(i) \underbrace{\sum_{j, C_t^{k-1}(j) \geq 0} \frac{\mu_t(j)E_t^{ST,k-1}(i,j)}{\Sigma_h \mu_t(k)E_t^{ST,k-1}(i,h)}}_{=1}. \tag{A.8}$$

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:

$$\underbrace{Ca_t(i)}_{\text{cash}} + \underbrace{\lambda_t(i)E_t^{ST,k-1}(i)}_{\text{hoarding inflows}} - \underbrace{\sum_{j, C_t^{k-1}(j) \geq 0} \lambda_t(j)E_t^{ST,k-1}(j) \frac{\mu_t(i)E_t^{ST,k-1}(j,i)}{\Sigma_l \mu_t(l)E_t^{ST,k-1}(j,l)}}_{\text{hoarding outflows}} > 0. \tag{A.9}$$

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

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

$$
\left\{
\begin{array}{l}
C_t^0(i) = C_{t-1}(i) \\
\text{ for } k \geq 1, \\
\textbf{Solvency condition:} \\
C_t'^k(i) = C_t^0(i) - \sum_{\{j,\, C_t^{k-1}(j)=0\}} (1-R^L) E_t^{ST}(i,j) \\
\textbf{Liquidity condition:} \\
C_t''^k(i) = \left\{
\begin{array}{ll}
0 & \text{if } Ca_t(i) + \lambda_t(i) E_t^{ST,k-1}(i) - \\
 & \sum_{h, C_t^{k-1}(h) \geq 0} \lambda_t(h) E_t^{ST,k-1}(h) \frac{\mu_t(i) E_t^{ST,k-1}(h,i)}{\Sigma_l \mu_t(l) E_t^{ST,k-1}(h,l)} < 0 \\
C_t'^j(i) & \text{otherwise}
\end{array}
\right. \\
\textbf{Updating equation:} \\
C_t^k(i) = max(C_t'^k(i); C_t''^k(i); 0)
\end{array}
\right.
\tag{A.10}
$$

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)	1
Second hoarding threshold (B)	0,2
Amount hoarding (b)	1
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 200 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	180,00	223,00	194,00	146,00	100,00
Median	201,00	242,00	210,50	165,00	111,00
Maximum	216,00	264,00	226,00	181,00	122,00
Standard deviation	6,13	7,34	6,19	6,08	4,18
	Density				
Minimum	0,03	0,04	0,04	0,03	0,02
Median	0,04	0,05	0,04	0,03	0,02
Maximum	0,04	0,05	0,04	0,03	0,02
Standard deviation	0,001	0,001	0,001	0,001	0,001
	Average shortest path				
Minimum	2,82	2,79	2,97	3,10	2,45
Median	3,05	3,08	3,27	3,39	3,04
Maximum	3,93	3,45	3,70	3,72	4,09
Standard deviation	0,133	0,115	0,124	0,122	0,259
	Max / Median degree				
Minimum	3,80	2,71	3,40	4,50	6,50
Median	5,50	3,33	5,00	5,33	7,75
Maximum	7,67	4,33	6,50	8,50	16,00
Standard deviation	0,73	0,32	0,64	0,63	3,57

Table 7: Descriptive statistics of the 200 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		
Minimum	396	433	454	356	193
Median	428	465	486	389	213
Maximum	469	491	523	426	230
Standard deviation	12,34	12,65	14,14	12,24	6,44
			Density		
Minimum	0,08	0,08	0,09	0,07	0,04
Median	0,08	0,09	0,09	0,07	0,04
Maximum	0,09	0,09	0,10	0,08	0,04
Standard deviation	0,002	0,002	0,003	0,002	0,001
			Average shortest path		
Minimum	2,34	2,41	2,45	2,52	2,94
Median	2,55	2,63	2,65	2,80	3,48
Maximum	2,79	2,96	3,01	3,28	4,31
Standard deviation	0,09	0,08	0,10	0,16	0,25
			Max / Median degree		
Minimum	2,67	2,46	2,92	3,40	3,60
Median	3,36	3,29	3,67	4,22	5,00
Maximum	4,33	4,27	4,73	5,25	6,25
Standard deviation	0,35	0,34	0,30	0,36	0,62

Table 8: Descriptive statistics of domestic and cross-country exposures in the 200 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	24%	22%	15%	18%	12%
Min	0%	0%	0%	0%	0%
Median	0%	0%	0%	0%	0%
Max	306%	232%	166%	157%	136%
Std dev	66%	53%	36%	39%	33%
B. Cross-border interbank exposures (country level, % of country's capital)					
Mean	3.44%	3.20%	3.00%	5.07%	1.74%
Min	0%	0%	0%	0%	0%
Median	0%	0%	0%	0%	0%
Max	97%	177%	103%	942%*	89%
Std dev	10%	11%	10%	46%	8%

* This outlier value somehow confuses statistics. Without it, the maximum value is equal to 130% and the mean value to 2.93%.

A.4 Simulation results

Table 9: Summary statistics of simulation results averaged over 500 shock scenarios and the defaults of an initial bank.

Distribution of default outcomes over 200 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**
	Number of defaults before hoarding				
Min	1,28	1,27	1,17	1,22	1,18
Median	1,53	1,51	1,31	1,44	1,33
75th percentile	1,67	1,61	1,37	1,53	1,40
Max	2,18	2,16	1,68	1,84	1,77
	Share of depleted capital before hoarding				
Min	5,62%	5,66%	5,62%	5,61%	5,65%
Median	6,02%	5,95%	5,85%	5,84%	5,96%
75th percentile	6,20%	6,10%	5,97%	5,95%	6,13%
Max	7,32%	6,69%	6,68%	6,77%	6,72%
	Number of defaults after hoarding				
Min	1,30	1,29	1,19	1,29	1,18
Median	1,63	1,59	1,40	1,51	1,33
75th percentile	1,82	1,75	1,56	1,63	1,41
Max	5,55	5,28	3,12	3,67	1,79
	Share of depleted capital after hoarding				
Min	5,64%	5,67%	5,65%	5,63%	5,67%
Median	6,09%	6,01%	5,94%	5,90%	5,97%
75th percentile	6,41%	6,22%	6,13%	6,07%	6,14%
Max	14,00%	10,89%	8,91%	7,32%	6,74%

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

Distribution of maximum default outcomes over 200 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**
	Number of defaults before hoarding				
Min	5,00	3,05	3,00	4,00	3,00
Median	8,07	8,00	6,00	7,00	6,26
75th percentile	9,72	9,07	7,00	9,00	8,01
Max	15,00	13,09	11,16	14,00	11,00
	Share of depleted capital before hoarding				
Min	11,74%	11,19%	11,66%	11,09%	10,97%
Median	17,59%	16,29%	15,93%	17,05%	16,23%
75th percentile	20,66%	18,63%	17,67%	19,24%	18,60%
Max	32,57%	30,98%	27,56%	32,03%	29,33%
	Number of defaults after hoarding				
Min	5,00	3,24	3,00	4,00	3,05
Median	9,00	8,06	6,08	8,00	6,50
75th percentile	10,05	10,00	8,00	9,00	8,04
Max	15,00	13,09	12,12	15,00	11,00
	Share of depleted capital after hoarding				
Min	11,77%	11,69%	11,69%	11,46%	10,97%
Median	18,57%	16,79%	16,84%	17,33%	16,23%
75th percentile	21,54%	19,17%	18,77%	19,75%	18,60%
Max	32,57%	32,02%	27,56%	32,03%	29,33%

Table 11: 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 200 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 200 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 home banks					
Mean	1,96%	2,45%	2,46%	1,77%	1,53%
Min	0,00%	0,00%	0,00%	0,00%	0,00%
Median	1,06%	1,15%	1,60%	0,03%	0,03%
Max	13,03%	15,34%	10,89%	13,21%	10,90%
Std dev	3,18%	3,93%	2,99%	3,24%	2,84%
B. Individual Losses imposed on foreign banks					
Mean	1,21%	0,90%	0,82%	0,60%	0,43%
Min	0,00%	0,00%	0,00%	0,00%	0,00%
Median	0,31%	0,28%	0,26%	0,03%	0,00%
Max	34,56%	12,80%	25,22%	36,15%	15,64%
Std dev	2,81%	1,77%	1,94%	2,12%	1,28%

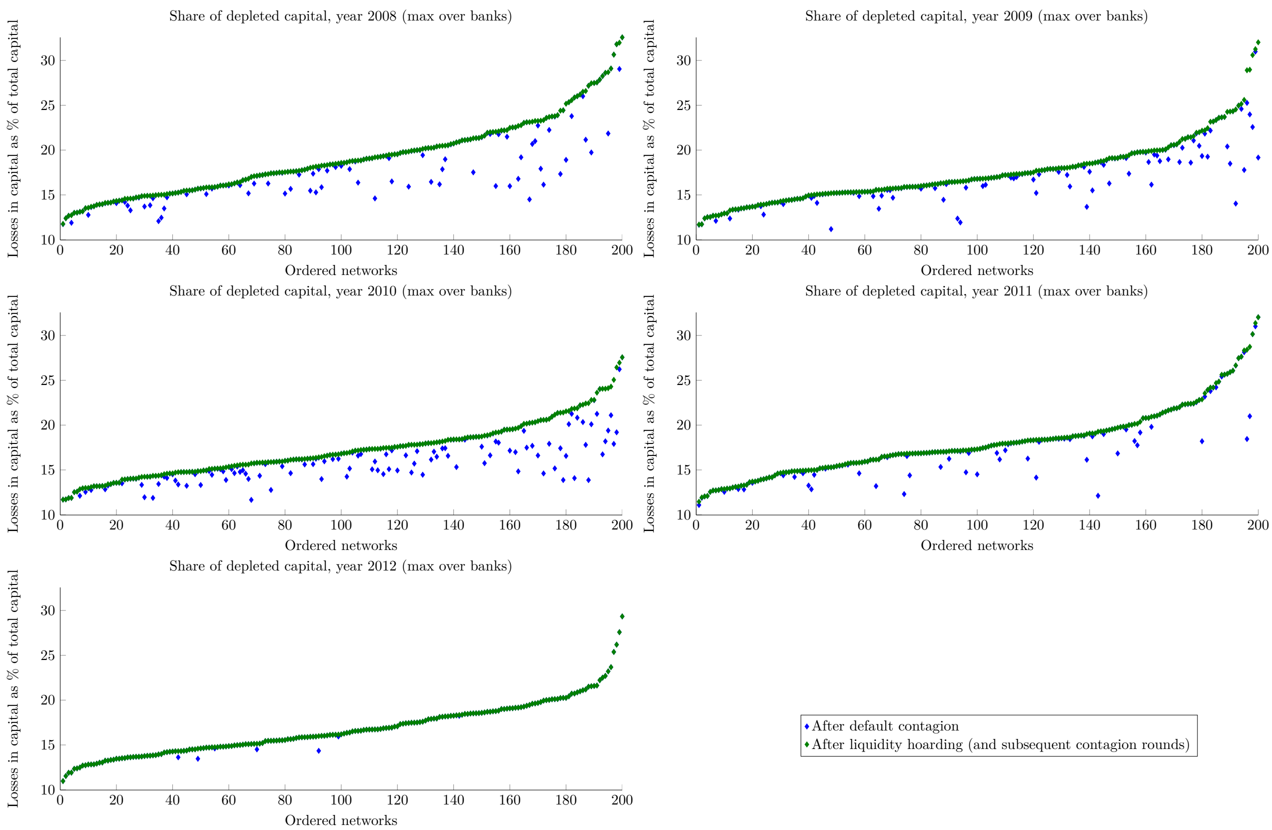

Figure 3: Share of interbank losses -before and after liquidity hoarding- ordered by the size of total losses (as % of total system capital)

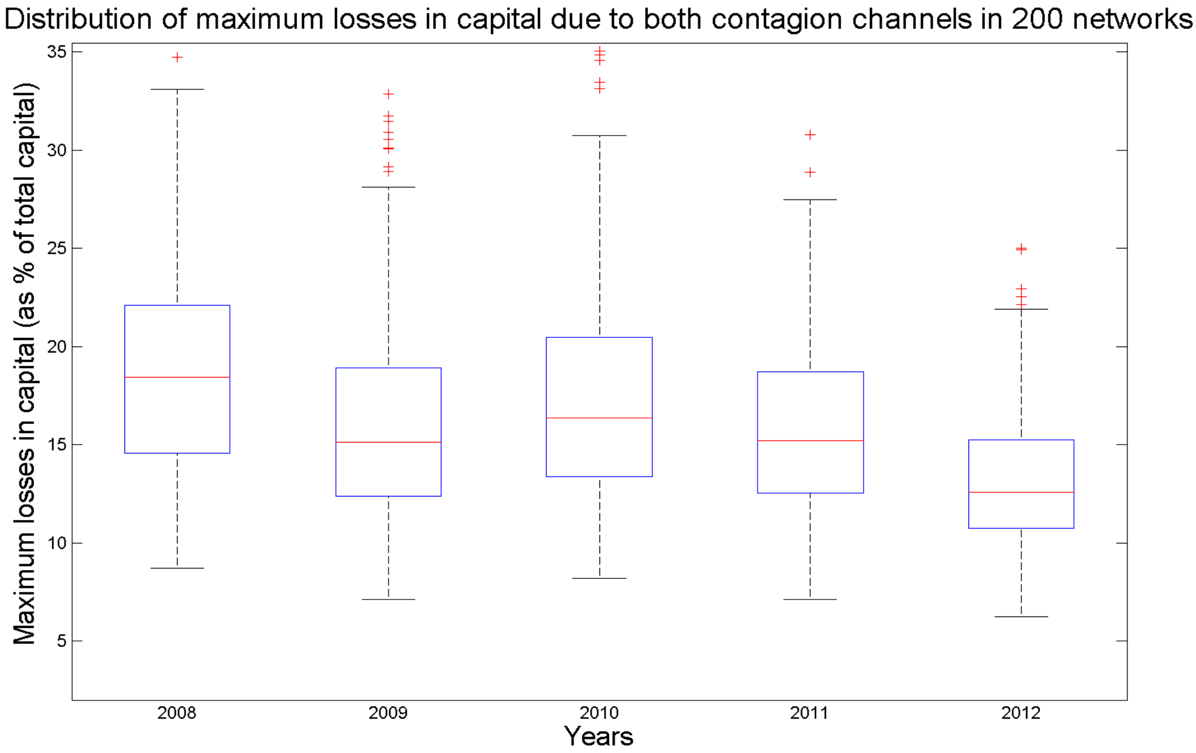

Figure 4: Distribution of losses due to both solvency and liquidity contagion (as % of total system capital)

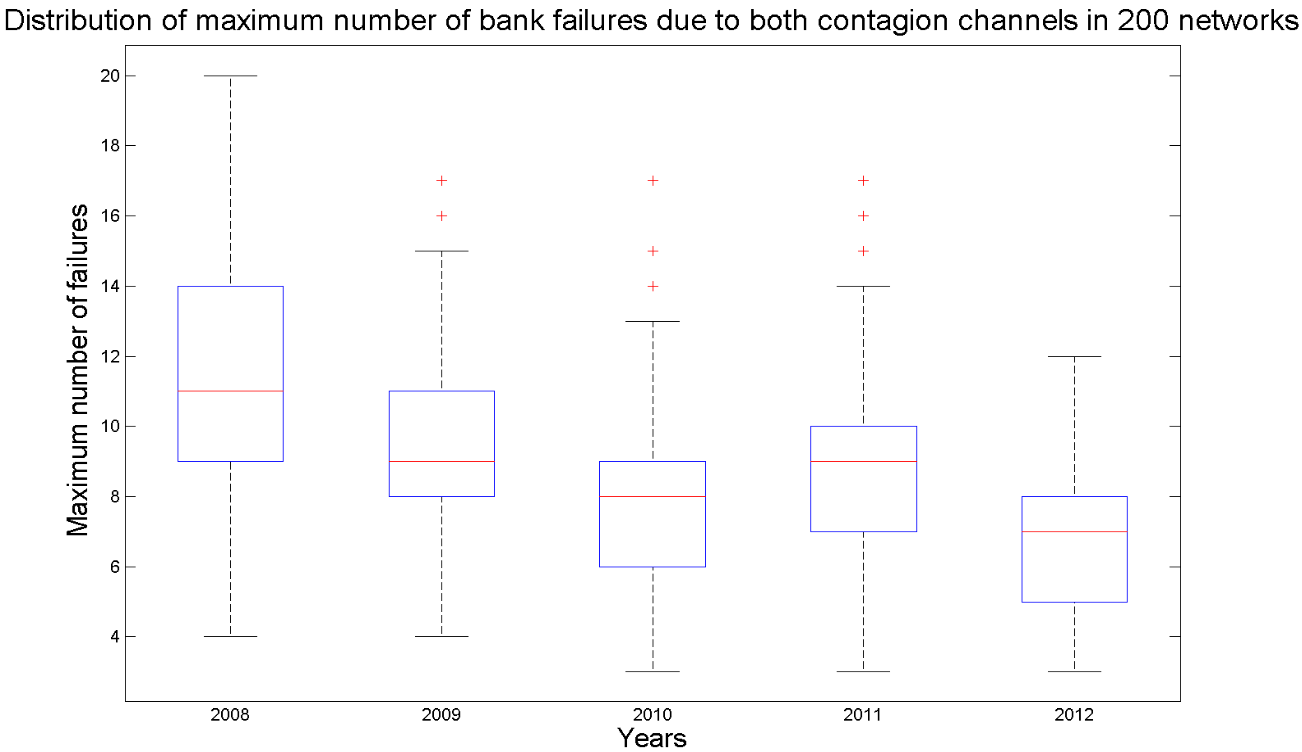

Figure 5: Distribution of maximum number of failures due to both solvency and liquidity contagion

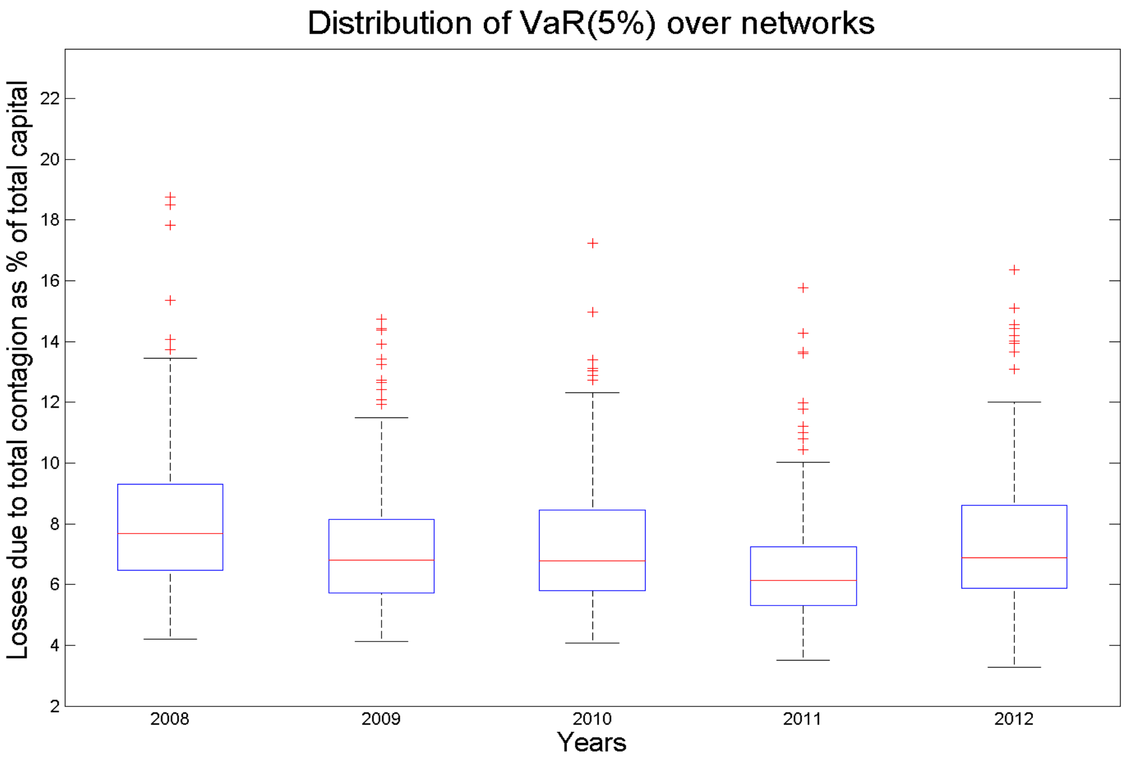

Figure 6: Distribution of the 5% worst losses due to both solvency and liquidity contagion over 500 shock scenarios and 200 network pairs (as % of total system capital)

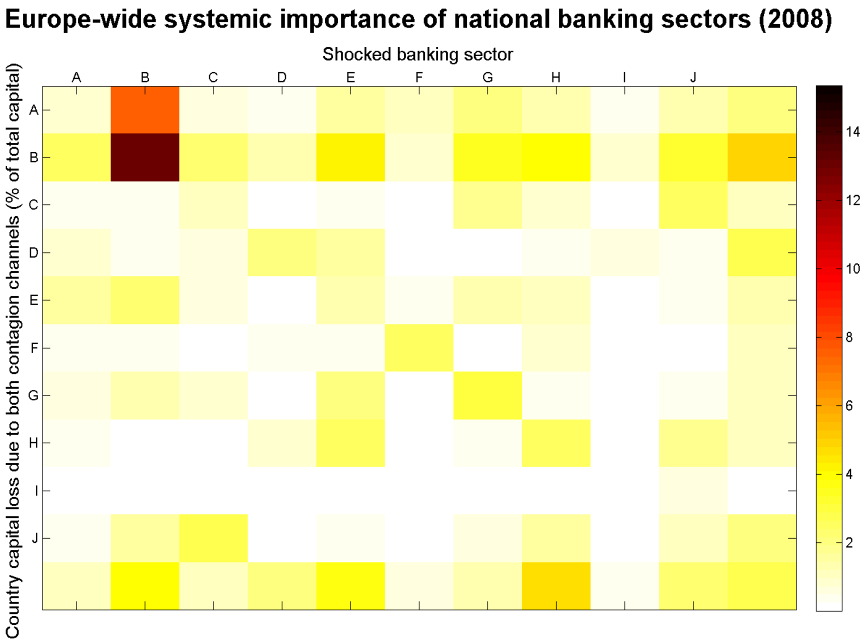

Figure 7: Total cross-border contagion in 2008

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 200 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 available have been removed from the charts. Countries are ordered randomly, but the order is the same across years.

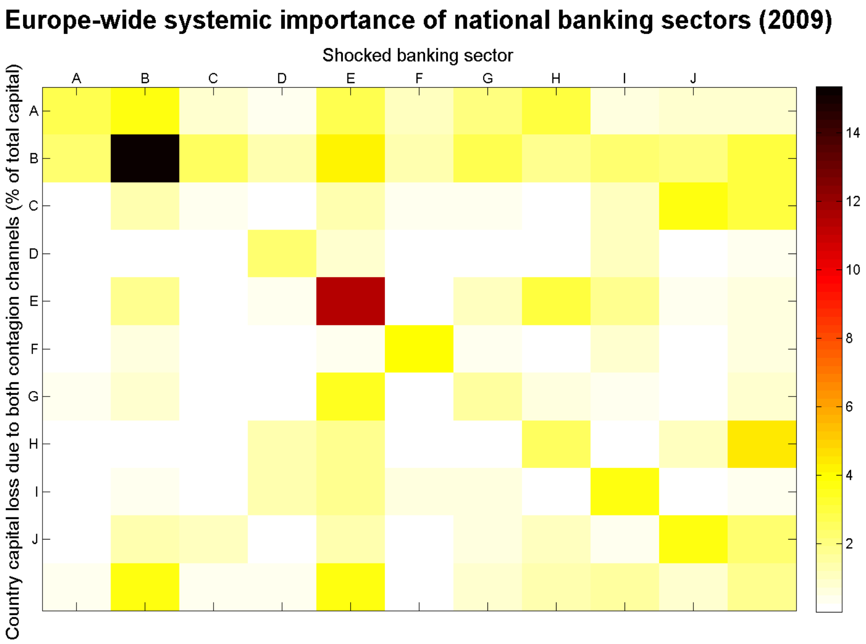

Figure 8: Total cross-border contagion in 2009

See caption in Figure 7.

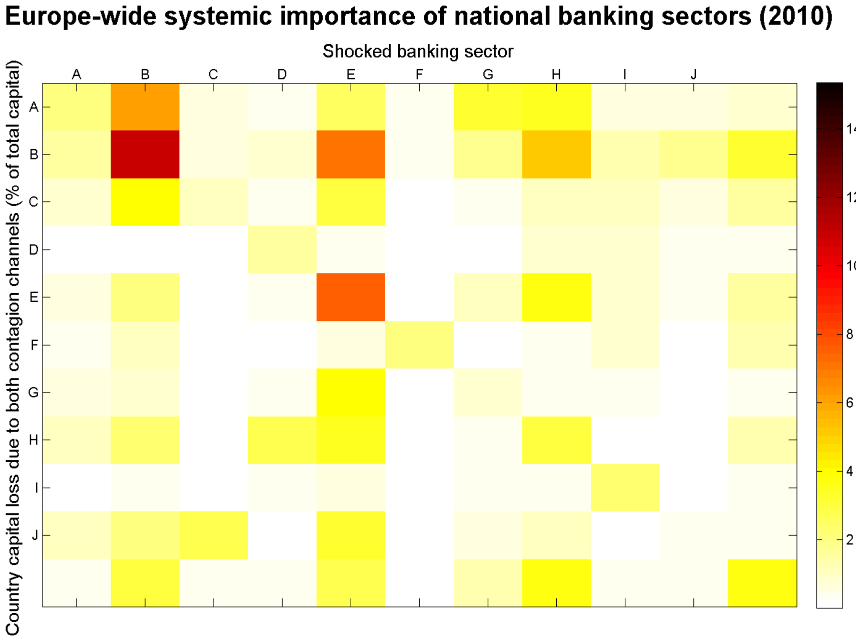

Figure 9: Total cross-border contagion in 2010
See caption in Figure 7.

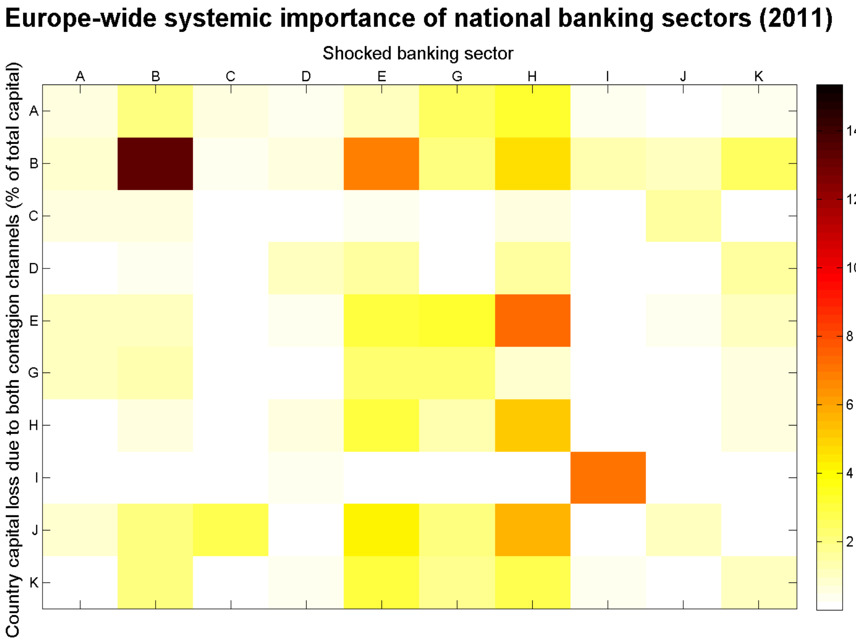

Figure 10: Total cross-border contagion in 2011
See caption in Figure 7. Note that one additional country has been removed from the 2011 heat map because of data unavailability for sample banks from this country in 2011.

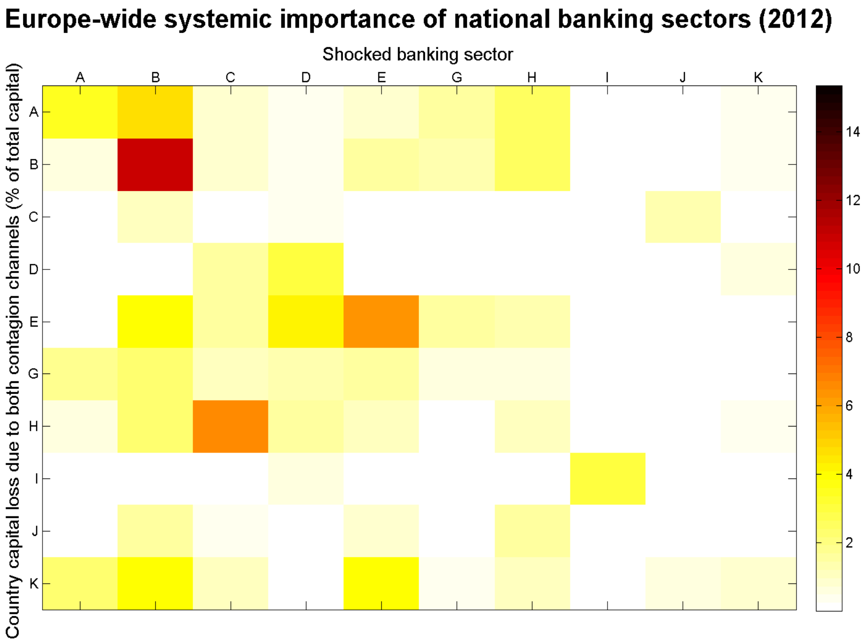

Figure 11: Total cross-border contagion in 2012

See caption in Figure 7. 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.

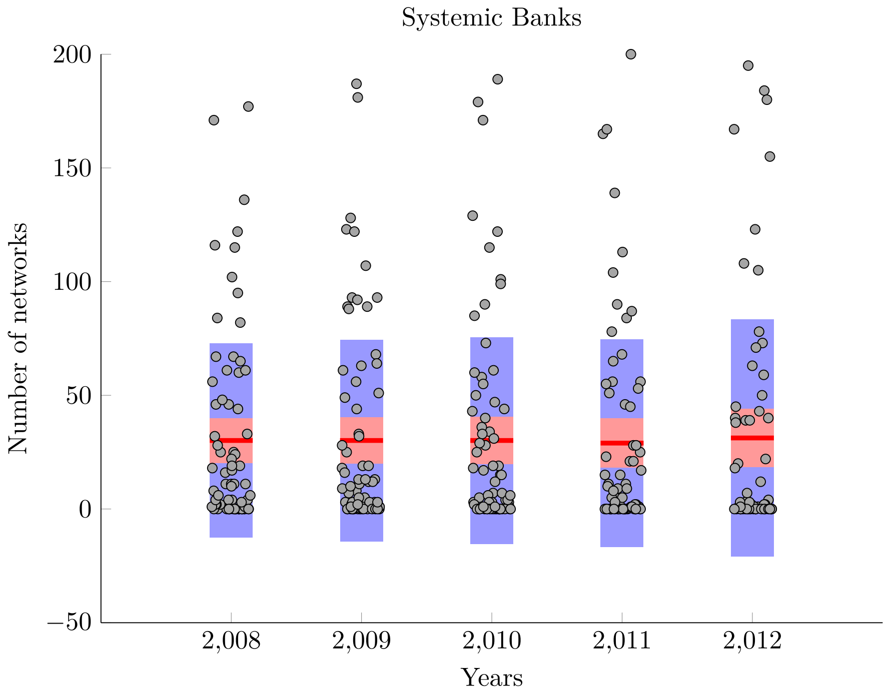

Figure 12: Systemic banks for each of the 5 years of analysis.
For each year, we have number of networks in which each bank is systemic. Most of the banks are either never systemic or rarely systemic, whereas some are systemic in almost all 200 simulated networks. We define a bank to be systemic, when losses (through both channels of contagion) imposed on the system by its default exceed 85th percentile of loss distribution.

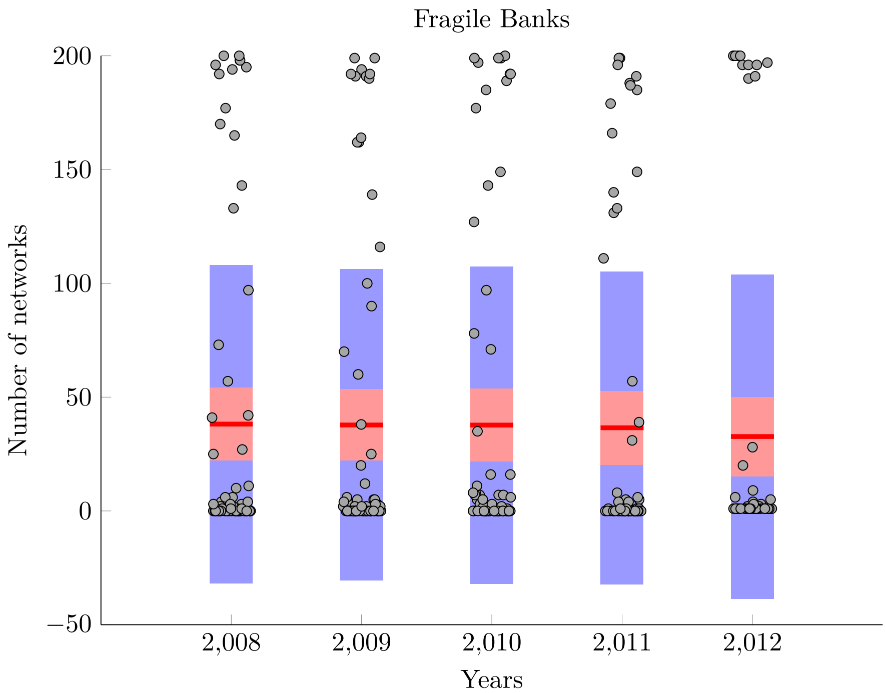

Figure 13: Fragile banks for each of the 5 years of analysis.
For each year, we have number of networks in which each bank is fragile. Most of the banks are either never fragile or rarely fragile, whereas some are fragile in more than half of 200 simulated networks. We define a bank to be fragile, when it defaults due to an initial default more frequently that 85% of other banks.

A.5 Econometrics

	(1) NBD	(2) NBD	(3) NBD	(4) Capital loss	(5) Capital loss	(6) Capital loss
main						
Capital ratio	-94.39***	-94.40***	-94.39***	-9.614***	-9.613***	-9.613***
	(-31.96)	(-31.95)	(-31.95)	(-36.31)	(-36.34)	(-36.35)
Log LT Interbank assets	0.160***	0.161***	0.161***	0.0797***	0.0797***	0.0797***
	(7.46)	(7.48)	(7.49)	(31.57)	(31.55)	(31.57)
ST funding / Assets	25.91***	26.04***	25.88***	3.475***	3.484***	3.470***
	(15.64)	(15.55)	(15.29)	(6.75)	(6.76)	(6.73)
Eigenvector centrality	0.361***	0.361***	0.364***	0.136***	0.136***	0.136***
	(4.15)	(4.14)	(4.17)	(5.19)	(5.19)	(5.20)
EXP. low ST funding / Assets	0.384***	0.385***	0.390***	0.0113	0.0123	0.0137
	(2.89)	(2.90)	(2.92)	(0.38)	(0.42)	(0.46)
EXP. low Capital	1.093***	1.090***	1.074***	0.434***	0.435***	0.432***
	(6.46)	(6.47)	(6.40)	(7.13)	(7.17)	(7.14)
EXP. larger banks	-0.535***	-0.536***	-0.533***	-0.0595**	-0.0591**	-0.0587**
	(-3.10)	(-3.10)	(-3.08)	(-2.15)	(-2.14)	(-2.12)
LT clustering		-3.203**	-3.362**		-0.831**	-0.868**
		(-2.02)	(-2.11)		(-2.45)	(-2.56)
LT Avg. Path length		0.296**	0.314**		0.0578*	0.0625*
		(2.00)	(2.08)		(1.78)	(1.89)
LT Max / Mean degree		-0.0573	-0.0805		-0.00259	-0.00890
		(-1.12)	(-1.50)		(-0.24)	(-0.79)
ST clustering			2.290			0.519
			(1.18)			(1.33)
ST Avg. Path length			-0.305			-0.0835
			(-1.04)			(-1.35)
ST Max / Mean degree			0.0635			0.0189
			(0.70)			(0.99)
Constant	-4.747***	-4.682***	-4.726***	-3.557***	-3.530***	-3.515***
	(-12.10)	(-6.73)	(-3.61)	(-77.11)	(-25.98)	(-13.30)
Observations	11000	11000	11000	11000	11000	11000

t statistics in parentheses

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

Table 12: 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, $j \neq i$. EXP. variables are computed as *exposures of the bank in question to the riskiest banks.*

	(1)	(2)	(3)	(4)	(5)	(6)
	NBD	NBD	NBD	Capital loss	Capital loss	Capital loss
main						
Log Total Assets	0.303***	0.303***	0.304***	0.105***	0.105***	0.105***
	(16.70)	(16.72)	(16.74)	(31.85)	(31.86)	(31.89)
LT liabilities / Assets	1.632***	1.643***	1.643***	0.330***	0.331***	0.333***
	(13.99)	(14.11)	(14.10)	(9.43)	(9.46)	(9.54)
Capital ratio	-21.99***	-22.00***	-21.99***	-2.279***	-2.279***	-2.279***
	(-14.11)	(-14.12)	(-14.11)	(-11.40)	(-11.40)	(-11.41)
ST funding / Assets	9.334***	9.327***	9.255***	3.185***	3.185***	3.162***
	(6.34)	(6.34)	(6.31)	(9.17)	(9.17)	(9.09)
Eigenvector centrality	0.497***	0.495***	0.496***	0.220***	0.220***	0.220***
	(7.26)	(7.22)	(7.22)	(9.29)	(9.30)	(9.34)
EXP. low Capital	0.904***	0.900***	0.897***	0.283***	0.283***	0.282***
	(8.38)	(8.35)	(8.30)	(6.41)	(6.41)	(6.41)
EXP. more Exposed	0.713***	0.706***	0.696***	0.339***	0.338***	0.338***
	(3.32)	(3.28)	(3.23)	(4.44)	(4.43)	(4.42)
EXP. larger Banks	0.715***	0.714***	0.713***	0.593***	0.593***	0.593***
	(4.55)	(4.55)	(4.56)	(9.70)	(9.71)	(9.71)
EXP. higher Beta	0.330	0.331	0.331	0.603***	0.603***	0.603***
	(1.39)	(1.40)	(1.40)	(7.59)	(7.59)	(7.60)
LT clustering		-2.062*	-2.241*		-0.409	-0.406
		(-1.75)	(-1.89)		(-1.64)	(-1.62)
LT Avg. Path length		0.248**	0.275**		0.0395	0.0485*
		(1.99)	(2.18)		(1.45)	(1.77)
LT Max / Mean degree		-0.0608	-0.0920**		0.00505	-0.00224
		(-1.37)	(-2.00)		(0.54)	(-0.23)
ST clustering			2.550*			-0.207
			(1.85)			(-0.72)
ST Avg. Path length			-0.461**			-0.176***
			(-2.08)			(-3.71)
LT Max / Mean degree			0.0710			0.0109
			(0.93)			(0.64)
Constant	-10.01***	-10.04***	-9.782***	-4.702***	-4.748***	-4.266***
	(-25.81)	(-16.02)	(-10.14)	(-71.11)	(-38.58)	(-21.14)
Observations	14600	14600	14600	14600	14600	14600

t statistics in parentheses

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

Table 13: 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. EXP. variables are computed as *exposures of the riskiest banks to the bank in question.*

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