Cross-border inter-bank contagion in the European banking sector*

Silvia Gabrieli† **Dilyara Salakhova**‡ **Guillaume Vuillemey**§

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Abstract

This paper studies the scope for cross-border contagion among a set of 73 European banking groups and analyses geographical patterns of loss-propagation from end-2008 until end-2012. The analysis relies on an enriched model of sequential solvency and liquidity cascades in a network setting. We look at the distribution of simulation outcomes resulting from *(i)* a common market shock on (listed) banks' capital, and *(ii)* an exogenous bank default ; the distributions are obtained over 100 different simulated networks of long and short-term exposures. To obtain a realistic representation of how European banks are connected through their long- and short-term claims, we exploit for the first time a unique dataset of interbank money market transactions, with various maturities, estimated from TARGET2 payment data. And we conduct an econometric analysis of both the network and the balance sheet determinants of contagion in different networks over five years.

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

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*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Banque de France or the Eurosystem and its staff.

†Banque de France, silvia.gabrieli@banque-france.fr

‡Banque de France, Université Paris Ouest Nanterre, dilyara.salakhova@banque-france.fr

§Banque de France, Sciences-Po, Paris guillaume.vuillemey@banque-france.fr

1 Introduction

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

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

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

The extent of interbank contagion is assessed relying on Fourel et al. [2013] model of sequential solvency and liquidity cascades in a network setting. More specifically, we look at the distribution of simulation outcomes resulting from a common market shock on (listed) banks' capital, coupled with

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.

an exogenous bank default ; the distributions are obtained over 100 different simulated networks of long- and short-term exposures. We observe the total number of defaulted banks after several rounds of solvency and liquidity contagion, and the total capital loss experienced by a certain country's banking sector when contagion is triggered by the default of a foreign bank. Heat maps are used to assess, on the one hand, which banking sectors are the most "systemic" in terms of the losses that the failure of one of their banks can impose to foreign countries' banks and, on the other, to identify which banking sectors are the most prone to cross-border contagion from European counterparties.

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

Our study contributes to this literature both from a modelling and an empirical point of view. With regard to the modelling part, by using the enriched model of default cascades in a network set up of Fourel et al. [2013] we take into account one possible form of banks' reaction to distressed financial conditions. Notably, banks experiencing losses - either due to a market shock or the default of one of their bank-counterparties - but still solvent, will start hoarding liquidity in the short-term interbank money market. Our sequential algorithm thus enables us to consider *(i) fundamental* losses due to exposure to common risk factors, *(ii) solvency* contagion, whereby banks suffer losses due to their long-term exposures to other banks, and *(iii) liquidity* contagion, by which banks experience liquidity withdrawals from counterparties in the interbank money market. While we do not model other important forms of banks' endogenous reaction to a shortage of funding (such as the sale of part of their assets possibly igniting a market fire-sale), we do not see a major drawback in considering banks' capital as constant throughout the rounds of contagion as raising capital under stressed market conditions and at very short notice is notoriously very hard (if possible at all).

Empirically, the paper enriches the existent simulations studies in several respects. First, considering both long- and short-term interbank exposures among a large set of European banks, it addresses a number of theoretical and empirical questions that arise once one moves from domestic only to cross-border exposures. For instance, the home bias and international lending patterns are accounted for when the matrices of exposures are reconstructed relying on actual interbank trading data. Thus the international scope of our empirical exercise enables us to focus not only on bank-to-bank contagion, but also on the geographical patterns of financial distress and the distribution of losses EU-wide.

Second, methodology-wise we consider the joint impact on the banking system of a common shock (on stock returns of listed banks) and an idiosyncratic shock (i.e. a bank default). This allows for a more realistic stress scenario, since correlated exposures have one more time proved to be a major source of systemic risk in the 2007-2009 financial crisis. [3] Moreover, the use of the algorithm developed by Halaj and Kok [2013] to simulate, for each year-end, a large number of interbank networks increases remarkably the realism of our results. Differently from existing simulations of national contagion, losses propagate upon highly sparse and concentrated interbank network structures, which reveal the empirically documented core-periphery property of interbank exposures, hence a high heterogeneity across banks. [4] Also, running the stress scenario over a large number of simulated networks - all very close to the "true" one - we obtain for each year a distribution of contagion results, i.e. VaR-like metrics. In this respect, our results account for the fact that the structure of a stressed interbank network may change substantially over very short time horizons, so that what matters is not a particular state of the interbank network at one date as such, but a probability distribution over possible network structures.

Third, with regard to the data, we reconstruct interbank exposures matrices based on a unique source of information on interbank relationships, namely all euro-denominated money market loans settled via the Eurosystem's Large Value Payment System TARGET2. Our simulations are repeated five years in a row, so that, for the same shock scenario, we can track our results over time and estimate whether the European banking sector has strengthened to interbank contagion over the last years.

Fourth, we conduct an econometric analysis of both the network and the balance sheet determinants of contagion. First, we analyze the determinants of contagion at a system level, therefore considering the European banking sector as one system. Second, we refine the analysis at a more granular level by investigating the country-level determinants of cross-border contagion. Up to our knowledge, we the first who such an analysis with the use of the real data.

The remainder of this article is structured as follows. In section 2, we make an overview of the related literature. In section 3, we present the theoretical model for the imputation of losses and the liquidity hoarding mechanism. In section 4, we describe the interbank exposures data and present the algorithm to generate interbank networks. The results of simulations are presented and commented on in section 5. Section 6 discusses an econometric exercise. Section 7 introduces robustness checks, section 8 concludes. Most tables and figures are presented in appendix.

2 Literature review

This paper is related to two strands of the empirical literature, *(i)* on contagion within financial networks and *(ii)* on cross-border financial interconnectedness in Europe.

3. This issue is studied in different papers, e.g., Cont and Wagalath [2013], Allen et al. [2012], Gai and Kapadia [2010]

4. A core-periphery interbank network is characterized by a densely connected small core of banks and a sparsely connected periphery. Banks in the periphery are connected to the core only. National interbank networks typically have a core-periphery structure, see Craig and von Peter [2010].

2.1 The empirical literature on contagion in financial networks

A growing literature investigates the contagion dynamics in national interbank networks. In reaction to a shock - either idiosyncratic or systematic - one or several propagation channels are modeled. A number of articles focus on solvency risk only, i.e. on direct losses imputed on a bank's capital ratio. In these papers, spillovers propagate within the network via direct "domino effects", whereby the default of one financial institution on its obligations leads to losses on the balance sheets of other institutions, which may lead to further defaults, and so on. Important contributions in this respect include Furfine [2003] for the United States or Upper and Worms [2004] for Germany. Upper [2011] provides a comprehensive survey of the literature on solvency "default cascades".

More recently, a handful of papers model both solvency and liquidity contagion channels. Cifuentes et al. [2005] include fire sales in a model of capital losses and investigate the amplification of contagion and the determinants of the fixed point where no more bank fail using simulated data. Arinaminpathy et al. [2012] study liquidity hoarding in simulated interbank networks subject to shocks, whereas Karas and Schoors [2012] and Fourel et al. [2013] investigate its empirical features using respectively data on Russian and on French banks. One essential result is that risk and contagion can be significantly underestimated if liquidity risk is not accounted for.

Finally, recent models of contagion in financial networks suggest that the probability and extent of distress from unexpected shocks is likely to vary depending not only on the asset market's liquidity but also on changes in the interbank network structure (see Gai and Kapadia [2010], or Georg [2013]).[5] This literature points to the need for empirical studies of contagion to account for the evolving nature of the web of interbank exposures. Our paper further investigates this direction by repeating the stress scenarios at multiple dates, and by running all simulations over an over-arching distribution of probable network structures at each date.

2.2 The literature on cross-border interconnectedness in Europe

Another key aspect of our paper with respect to the existing literature is that it focuses not on one national banking sector but on both domestic and cross-border exposures of European banks. In that respect, it is related to several papers investigating the structure or the resilience of the European financial sector. Gropp et al. [2009] analyze cross-border contagion using market-implied distances-to-default to estimate the probability of several financial institutions experiencing a large shock. If it finds potentially important contagion between European financial sectors, this paper does not provide information regarding the channels of contagion (common exposures, money market, ownership links, etc.). A few papers, in particular by Castren and Kavonius [2009] and Castren and Rancan [2013], focus on macro-financial linkages between Euro area financial sectors, using either

5. The seminal theoretical contribution to the analysis of contagion in a network setup is that of Allen and Gale [2000]. However, the latter use a highly simplified banking network consisting of four banks only. Allen and Babus [2009] review the use of network models in finance.

balance sheet or flow of funds data. The main contribution by Castren and Rancan [2013] is to document the network topology of these flows over time. One drawback, however, is that they rely on maximum entropy estimation techniques, whose fit at an international level is likely to be worse than at a national level (see below) and that they do not rely on direct bank-to-bank exposures. Finally, Vuillemey and Peltonen [2013] investigate contagion at a European scale through bond and CDS exposures following a sovereign credit event.

The only attempt to investigate contagion *per se* in the European interbank market is by Halaj and Kok [2013]. They use the contagion algorithm first proposed by Eisenberg and Noe [2001] together with a simple model of solvency contagion and of fire sales to propose a metrics (the "Systemic Probability Index") that captures the likelihood of contagion from the failure of a given bank to honour its interbank obligations. Their empirical exercise provides evidence for a "knife-edge" effect of contagion, i.e. only a small share of the simulated networks are prone to substantial contagion, whereas it remains essentially negligible in most instances. While our paper relies on Halaj and Kok [2013]'s algorithm, it also differs from their paper in several important respects. First, simulation of interbank networks is based on a considerably richer dataset, as we use bank-to-bank TARGET2 data rather than country-level exposure-at-default data to obtain much more realistic exposure matrices. Second, our model is less mechanistic as it features behavioural aspects of liquidity hoarding, implying that each bank's hoarding behaviour is driven by its own counterparties' characteristics. Third, we investigate in greater details the geographical patterns of cross-border contagion and repeat our simulations at 5 dates so as to track the European banking sector's robustness over time. In that respect, our theoretical exercise is considerably richer.

3 The model

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

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

Banks are interconnected by two types of links : short-term and long-term exposures. The distinction between these links is essential within the present model as it enables defining two channels of contagion (liquidity vs. solvency contagion). Short-term exposures are represented mainly by short-term loans, e.g. with overnight or one-week maturity, and a link can be easily cut from a certain day/week to the subsequent one. This property of the link allows banks to hoard liquidity, that is, to reduce or to cut their exposures to a counterparty when needed. As explained

	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

below, liquidity contagion here propagates through the network of short-term exposures. On the contrary, long-term exposures represent a more stable source of funding and can not be cut before maturity. Therefore, only if a bank defaults do its counterparties lose all their long-term exposures to it (taking a recovery rate into account). A network of long-term exposures is the main channel for the propagation of solvency contagion.

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

Common market shock

The way a market shock is simulated is essential. The latter weakens the resilience of the system, thus revealing more plainly the potential for contagion (see Upper [2011]). In the absence of national supervisory data allowing to shock various asset classes in bank balance-sheets (as in Elsinger et al. [2006a], Elsinger et al. [2006b], or in Fourel et al. [2013]), we implement a common shock directly on all listed banks' capital using a one-factor model for equity returns (see details in Appendix 1). The same shock is consistently applied over the whole time period, 2008-2012, which allows us to make sure that contagion in the system is driven purely by the change in the network structure and banks' capitalization level.

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

Solvency contagion

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

$$\underbrace{[C(j) - \epsilon(j)]}_{\text{Capital after initial shock}} - \underbrace{\sum_i R^S(i)E(j,i)}_{\text{non-recovered exposures}} < 0 \tag{3.1}$$

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. The detailed implementation of the algorithm is reported in Appendix 2.

Liquidity hoarding

Banks regularly perform liquidity management, estimating their liquidity stock, outflows and inflows for the next period. In normal times, they can foresee with some certainty how much liquidity they will need to satisfy reserve requirements or other commitments ; to this end they can borrow from other banks in the interbank market as well as from the central bank (e.g. through weekly main refinancing operations). In a well functioning interbank market banks with excess liquidity can lend it to those who lack short-term funding. This situation can however radically change during times of increased uncertainty. On one hand, banks' assets become much more volatile creating liquidity outflows in terms of margin calls, higher haircuts and requirements for collateral, which are difficult to foresee. On the other hand, confidence in the market evaporates quickly, counterparty risk rises, and banks fear both their inability to get liquidity when needed as well as counterparty risk. All this can lead banks to a precautionary demand for liquidity hence to *hoarding* behavior, by which they reduce lending to each other in order to secure own liquidity needs and to reduce exposure to counterparty risk. [6]

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

Banks will decide how much to hoard based on their own perception of market uncertainty. But they also have to decide how much and from which counterparty they will hoard. A straightforward assumption is that the riskier the counterparty is, the more a bank hoards liquidity. Provided banks have no private information about the riskiness of other banks' portfolios, they can rely on leverage μ as a proxy for the riskiness of a counterparty (Das and Sy [2012], Lautenschlager [2013]). The

6. 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.

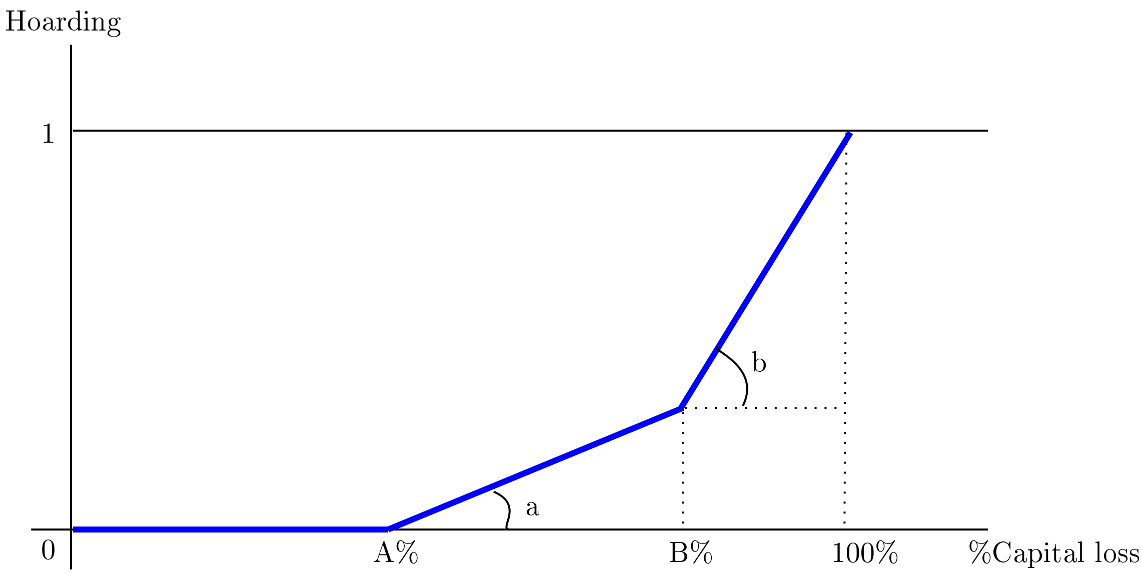

FIGURE 1 – Liquidity hoarding behaviour.

easiest way for a bank to hoard liquidity is to stop rolling over short-term loans. After all the banks decide how much to hoard and make claims, the following condition has to be satisfied for a bank to be liquid :

$$[Cash] + [To\,Be\,Recieved] - [To\,Be\,Paid] > 0 \tag{3.2}$$

4 Interbank exposures data 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. The data used to construct the matrices of interbank exposures and additional balance sheet items used in the simulations are also presented.

4.1 The algorithm

We apply the algorithm proposed by Halaj and Kok [2013] to simulate a large number of interbank networks that are used to run the stress scenarios. In the absence of interbank lending and borrowing data, one common method in the literature relies on their estimation through entropy maximization (see Sheldon and Maurer [1998], Wells [2004] and Mistrulli [2011] for a comparison of this methodology with actual exposure data). We adopt an alternative methodology proposed by Halaj and Kok [2013] for different reasons. First, one essential drawback of the entropy maximization method is that the obtained matrix of bilateral exposures is such that strictly positive links are estimated between any two banks which have a strictly positive aggregate interbank exposure, i.e.

the obtained network is not sparse and does not display the empirically documented core-periphery structure (averaging bias). When national banking systems are considered, such an undesirable feature may be neglected, as domestic banks within a country are typically densely interconnected. On the contrary, applying the same methodology when cross-border exposures are considered would amount to neglect either a possible home-bias in interbank exposures or the fact that financial interconnections are evenly spread nor among banks within a national banking sector neither among different countries' banking sectors. In other words, preferential banking relationships do exist, as well as strong geographical patterns. Second, the entropy maximization method yields a unique solution for the bilateral exposures matrix, and may therefore badly account for the fact that interbank exposures are likely to change quickly. In addition, performing stress scenarios on a unique exposures matrix typically fails to obtain a probability distribution over the simulation outcomes. By contrast, the methodology introduced by Halaj and Kok [2013] addresses these two issues by enabling the construction of a large number of sparse and concentrated networks that all match the aggregate exposure levels. Third, this methodology enables us to make use of additional information from TARGET2 data, which could not be used otherwise.

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, relies on 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.

4.2 Data and calibration

4.2.1 The sample

We run our contagion analysis using a sample of 73 European banking groups, whose list is provided in appendix. Given our focus on the resilience of the European banking system, we select our sample starting from the list of banks that underwent the 2011 stress tests ran by the European Banking Authority (EBA).[7] This list includes all the banking groups headquartered in Europe

7. See EBA [2011b].

that are part of the list of Global Systemically Important Banks (G-SIBs) [8], while it excludes some Spanish "cajas" to avoid an over-representation of the Spanish banking sector. Worth noting is that our sample also includes savings and cooperative banks, hence non-listed European institutions : differently from the extant empirical literature on contagion that relies on market data, this allows us to assess also the impact of a shock hitting relatively smaller market players.

4.2.2 Long-term interbank exposures

Information on the total interbank loans L_i granted by any bank i to all its counterparties within the network is retrieved via the balance sheet item named "Net loans to banks" available in *SNL Financials.* [9] 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.

4.2.3 The probability map : TARGET2 data

The probability map Π_t is obtained based on term interbank money market loans settled in TARGET2 during each year t. [10] More specifically, we use loans with maturities ranging from more than one month and up to six months to compute shares of preferential lending. The latter 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. [11] 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

8. The latest list has been published by the Financial Stability Board in November 2012 and is available at `http://www.financialstabilityboard.org/publications/r_111104bb.pdf.`

9. "Net loans to banks" are defined as *Net loans and advances made to banks after deducting any allowance for impairment.*

10. See Arciero et al. [2013] for details on the identification methodology. Note that in 2012 TARGET2 settled 92% of the total large value payments traffic in euro. The remaining fraction of the total turnover is settled mostly via the EURO1 settlement system. See ecb.2013.

11. 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.

stronger geographical patterns emerge. This is especially so in periods of heightened uncertainty about counterparties' solvency. [12]

4.2.4 Short-term interbank exposures

[TO BE COMPETED]

4.2.5 Cross-border interbank exposures

[TO BE COMPETED]

4.2.6 Additional balance sheet data

[TO BE COMPETED]

4.2.7 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.

5 Simulation results

[TO BE COMPLETED]

12. 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. ECB money market study reports increasing market fragmentation in the euro money market in relation to the euro area sovereign debt crisis.

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.

6 Econometric analysis

[TO BE COMPLETED]

7 Robustness checks

[TO BE COMPETED]

8 Conclusion

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9 Appendix

9.1 Appendix 1 : The model

9.1.1 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 [14] 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 0.05% 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.

9.1.2 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

$$\begin{aligned} \mathbf{FD(C)} &= \left\{ i \in \mathbf{N} : C_0(i) + \underbrace{\epsilon(i)}_{\text{initial shock}} \leq 0 \right\} \\ &= \{ i \in \mathbf{N} : C_1(i) = 0 \} \,, \end{aligned} \tag{9.3}$$

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 :

$$\begin{cases} C_2^0(i) = C_1(i) \\ C_2^k(i) = \max(C_2^0(i) - \sum_{\{j,\, C_2^{k-1}(j)=0\}} (1 - R^S) \times E_0(i,j); 0), \text{ for } k \geq 1, \end{cases} \tag{9.4}$$

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

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.

9.1.3 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 [15]. 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 :

$$\lambda_t(i)E_t^{ST,k-1}(i) = \lambda_t(i)E_t^{ST,k-1}(i) \underbrace{\sum_{j, C_t^{k-1}(j) \geq 0} \frac{\mu_t(j)E_t^{ST,k-1}(i,j)}{\Sigma_h \mu_t(k)E_t^{ST,k-1}(i,h)}}_{=1}. \tag{9.5}$$

Liquidity condition

When a bank hoards liquidity, it improves its short-term funding position, whereas liquidity

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

withdrawals by its counterparties deteriorate it. The following liquidity condition must hold :

$$\underbrace{Ca_t(i)}_{\text{cash}} + \underbrace{\lambda_t(i)E_t^{ST,k-1}(i)}_{\text{hoarding inflows}} - \underbrace{\sum_{j,C_t^{k-1}(j)\geq 0} \lambda_t(j)E_t^{ST,k-1}(j)\frac{\mu_t(i)E_t^{ST,k-1}(j,i)}{\Sigma_l \mu_t(l)E_t^{ST,k-1}(j,l)}}_{\text{hoarding outflows}} > 0. \tag{9.6}$$

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

$$\begin{cases} C_t^0(i) = C_{t-1}(i) \\ \text{ for } k \geq 1, \\ \textbf{Solvency condition :} \\ C_t'^k(i) = C_t^0(i) - \sum_{\{j,\, C_t^{k-1}(j)=0\}}(1-R^L)E_t^{ST}(i,j) \\ \textbf{Liquidity condition :} \\ C_t''^k(i) = \begin{cases} 0 & \text{if } Ca_t(i) + \lambda_t(i)E_t^{ST,k-1}(i) - \\ & \sum_{h,C_t^{k-1}(h)\geq 0} \lambda_t(h)E_t^{ST,k-1}(h)\frac{\mu_t(i)E_t^{ST,k-1}(h,i)}{\Sigma_l \mu_t(l)E_t^{ST,k-1}(h,l)} < 0 \\ C_t'^j(i) & \text{otherwise} \end{cases} \\ \textbf{Updating equation :} \\ C_t^k(i) = max(C_t'^k(i); C_t''^k(i); 0) \end{cases} \tag{9.7}$$

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.

9.1.4 Model calibration

9.2 Appendix 2 : The sample

9.3 Appendix 3 : Descriptive statistics

9.4 Appendix 4 : Simulation results

9.5 Appendix 5 : Robustness checks