Transmission Channels of Systemic Risk and Contagion in the European Financial Network*

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Abstract

We investigate systemic risk and how financial contagion propagates within the euro area banking system by employing the Maximum Entropy method. The study captures multiple snapshots of a dynamic financial network and uses counterfactual simulations to propagate shocks emerging from three sources of systemic risk: interbank, asset price, and sovereign credit risk markets. As conditions deteriorate, these channels trigger severe direct and indirect losses and cascades of defaults, whilst the dominance of the sovereign credit risk channel amplifies, as the primary source of financial contagion in the banking network. Systemic risk within the northern euro area banking system is less apparent, while the southern euro area banking system is more prone and susceptible to bank failures provoked by financial contagion. By modelling the contagion path the results demonstrate that the euro area banking system insists to be markedly vulnerable and conducive to systemic risks.

JEL Classification: G21, D85, G01, F37, G28.

Keywords: Systemic Risk, Maximum Entropy, Interbank Market, Financial Network, Sovereign Credit Risk, European Banks.

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1. Introduction

The collapse of Lehman Brothers in mid-September 2008 was the earthquake displaying that the modern financial system was severely fragile. Global financial market participants were directly impacted by its default and numerous repercussions were felt throughout the world, resulting from a plethora of cross-border and cross-entity interdependencies (De Haas et al. 2012; Acharya et al. 2014). The shock was rapidly spread in Europe, where by the end of September, euro area governments rescued the Belgian-French bank Dexia, demonstrating vividly that these interdependencies generate amplified responses to shocks and increase the speed of contagion in the financial system (Panageas 2010; Acharya et al. 2011; Aiyar 2012, Acharya et al. 2015 *inter alia*). Thus, in the aftershock era, the effects of both interconnectedness and contagion manifested themselves and systemic risk emerged as one of the most challenging aspects (Elliott et al. 2014; Acemoglu et al. 2015). The banking industry grappled with one overarching challenge; to measure and reduce systemic risk (for a definition and discussion on systemic risk and contagion see also Acharya et al. 2012; Liang 2013; and Allen and Carletti 2013) in order to improve the resilience of the financial system to adverse shocks and to prevent a repetition of the recent crisis.

While the euro area banking system was fundamentally solvent, according to several stress tests (Basel Committee on Banking Supervision 2011; European Banking Authority 2012), the contagion from the Lehman bankruptcy put at risk the stability of the European financial system, indicating that systemic risk has been enormously underestimated (Bartram et al. 2007; Engle et al. 2014). Synchronically, as contagion fears spread, the euro area sovereign debt crisis became apparent, and threatened the integrity of the Eurozone (Lane 2012; Claeys and Vašíček 2014). Emphatically, a sovereign default could lead to a disastrous financial instability and to an unprecedented failure of the European banking system (see also Caballero and Simsek 2013; Gennaioli et al. 2014).

The intensity and the speed with which shocks propagate in the entire financial system, highlights the need to identify, measure and understand the nature and the source of systemic risk in order to improve the underlying risks that banks face, to avert banks' liquidation ex ante and to promote macro-prudential policy tools (for an extensive review on macro-prudential policies see also Hanson et al. 2011). Thus, this study focuses on the euro area banking industry to examine the way systemic risk arises endogenously, the resilience of the Euro area banking system to systemic risk, and how shocks in economic and financial channels propagate in the banking sector. We also endeavour to answer the following questions: In the presence of a distress situation how the financial system performs? Have the new capital rules rendered the European banking industry safer? What is the primary source of systemic risk? How financial contagion propagates within the Eurozone? These fundamental themes remain unanswered, and hence obtaining the answers is critical and at the heart of most of the recent research on systemic risk.

Motivated by the absence of empirical evidence, we address these issues drawing on recent developments in the studies of systemic risk, contagion channels and advances in network theory, by constructing a unique interconnected, dynamic and continuous-time model of financial networks with complete market structure[1] (i.e. interbank loan market) and two additional independent channels of systemic risk (i.e. sovereign credit risk and asset price risk[2]). More precisely, we build on and extend the financial network models developed by Gai et al. (2011), Mistrulli (2011) and Castren and Rancan (2014) to employ counterfactual

[1] As discussed in the theoretical work of Allen and Gale (2000), and Freixas et al. (2000) the interbank market follows a multilateral pattern of banks' financial linkages - claims, the so called "complete market structure".
[2] In this study, asset price risk refers to the risk of depreciating a common asset which is financed by a loan (i.e. asset-backed loan).

simulations with entropy maximisation and to propagate shocks across the financial network[3], emerged from three systemic risk channels. Thus, our methodological approach provides two novelties. First, the financial network in this study consists of a unique set of various sectors which are neglected hitherto by the international literature. Specifically, we analyse the complexity of the system in terms of not only the bilateral linkages but also losses and cascades of defaults triggered by sovereign credit risk, and asset price risk. Second, in contrast with the existing literature, we are able to disentangle the effects of the shock in losses generated by the initial shock and losses spread by contagion. More concretely, we are able to capture multiple snapshots of the network structure and to measure accurately the direct and indirect effects. Consequently, the model allows us to provide novel evidence on the type of systemic risk which dominates the financial system and to measure and evaluate: i) the effects of shocks on one or more financial institutions (e.g. total losses, solvency and bankruptcy events); ii) the transmission mechanism which transfers and provokes the negative effects to the rest of the system; and iii) the variations in financial robustness, which display the boundaries of the European banking system.

Interestingly, at first glance we find that a shock in the interbank loan market causes the higher amount of losses in the banking network. This notwithstanding, remarkably we find that losses generated by the sovereign credit risk channel transmit faster through the contagion channel, triggering a cascade of bank failures. This shock can cause banks to stop using the interbank market to trade with each other and can also lead banks to liquidate their asset holdings in order to meet their short-term funding demands. Hence, the study provides empirical evidence that the Sovereign Credit Risk channel dominates systemic risks amplified in the euro area banking systems and hence, it is the primary source of systemic

[3] Our financial network uses the claims and liabilities of banks' balance sheets and excludes any leverage, in order to secure that any variation in the system is based on multiple equilibria. Shocks propagated in our model would penalize banks for being exposed to leverage and increase substantially their vulnerability in systemic risk and contagion. This approach also fulfils the criteria of Allen and Gale (2000), Shin (2008), Mistrulli (2011) and Castren and Rancan (2014).

risk. Moreover, we evaluate the impact of reduced collateral values and provide novel evidence that asset price contagion can also trigger severe direct losses and defaults in the banking system.

In addition to the above, we provide novel evidence that systemic risk in the euro area banking system didn't meaningfully decrease as it is evident that shocks in the three independent channels -interbank market, sovereign credit risk, asset price risk- trigger domino effects in the banking system. Likewise, we document a dramatic variation between northern and southern euro area countries in terms of their response to systemic risk. More concretely, there is much less systemic risk and the speed of contagion is much lower in banks based in the northern euro area than in banks based in the southern euro area. Furthermore, we find that the cross-border transmission of systemic shocks depends on the size and the degree of exposure of the banking sector in a foreign financial system. Particularly, the more exposed domestic banks are to the foreign banking systems, the greater are the systemic risks and the spillover effects from foreign financial shocks to the domestic banking sector. Finally, the results imply that the European banking industry amid the post-crisis deleverage, recapitalisation and the new regulatory rules, continues to be markedly vulnerable and conducive to systemic risks and financial contagion.

The study contributes and extends three strands of the literature. First, there is a recently growing literature on the construction of financial networks with mathematical models. Kroszner (2007), and Allen and Carletti (2013), document that the size of the financial network plays an important role on the propagation of systemic risk. We update their work and offer novel evidence that there are marked differences in the dynamic responses to systemic-risk related events across national banking systems, indicating that the network structure is time-variant. Allen et al. (2011) observe that full risk diversification is not optimal in the banking industry, while Battiston et al. (2012) find that the financial system can be more resilient for intermediate levels of risk diversification. In a similar vein, we document that even domestic banks with small financial exposures in a foreign banking sector may be severely affected by a systemic shock provoked by same.

Second, our study offers new insights on the critical role of endogenous complexity, betweenness, closeness and the importance of interconnectedness in the banking network. Leitner (2005), Gai et al. (2011), Billio et al. (2012), Castren and Rancan (2014), and Elliott et al. (2014) develop network models on monotonicity and identify the importance of complexity and concentration in the financial system. We extend their work demonstrating that the same shock would cause different losses in the banking network if emerged at different points in time. Importantly, we find that the propagated and the final losses differ substantially across the national banking systems reflecting the differences on the size, and the degree of interconnectedness across national banking systems. More concretely, the final losses appear to be lower in the post-crisis era, which may be due to cyclicality (i.e. deleverage, recapitalisation, new regulatory framework), but the risk of contagion remains substantially immense. Furthermore, we shed light on the debate for the suitability of the maximum entropy method on financial networks (Mistrulli 2011). Precisely, we employ several robustness checks by using the actual bilateral exposures in the four largest financial systems (Germany, France, Italy, and Spain) and compare the results with those obtained via the Maximum Entropy approach. On the empirical level, the findings indicate that Entropy Maximization neither over- nor under-estimates the bilateral exposures, while also this method is an appealing approach to calibrate losses generated by systemic shocks, and to measure the severity of financial contagion.

Third, our study relates to the vast literature on macro-prudential policies, the nature of systemic risk, and the spread of contagion in the banking industry developed by Allen and Gale (2004), Allen et al. (2009), Co-Pierre (2013), Drehmann and Tarashev (2013), Ang and

Longstaff (2013), among others. For instance, Allen and Gale (2004), and Allen et al. (2009) examine how shocks propagate through a financial network, based on interbank lending and model excessive price volatility. Co-Pierre (2013) compares systemic risk caused by contagion with the risk triggered by common shocks whilst Drehmann and Tarashev (2013) measure the systemic importance of interconnected banks. Ang and Longstaff (2013) study the nature of systemic sovereign credit risk and observe that it is strongly related to financial market variables.

To our knowledge this is the first study to explicitly compare different sources of systemic risk in the euro area banking industry. We provide novel evidence for the effects a negative shock generates by three independent systemic risk channels and document that contagious banks are not necessarily the large ones. The results enlighten the nature of systemic risk and provide a new perspective on financial contagion and domino effects in the banking sector. We also show that the sovereign credit risk channel is the dominant systemic risk and causes a plethora of defaults in the banking system. Importantly, we observe that a repetition of the recent financial crisis is apparent in the euro area banking system, implying that existing developments on macro-prudential policies fail to mitigate meaningfully the degree of systemic risk in the banking industry. In a similar vein, our results shed new light on the asset and liability management of banks. Specifically, the three systemic risk channels facilitate and improve the understanding of how systemic risk arises, thus providing with the optimal structure of both assets and liabilities, rendering the banking industry more resilient to systemic risk. Finally, these results have important implications for understanding systemic risk and for analysing policies designed to mitigate financial contagion in the euro area.

The rest of the paper is organized as follows. Section 2 provides the literature review. Section 3 describes the dataset, the methodology and the structure of the financial network.

Section 4 analyses the results from the simulation of the shock propagation. Section 5 presents robustness checks and section 6 provides the concluding remark.

2. Literature Review

2.1 Theoretical Framework

The global financial crisis of 2008 rendered systemic risk an area of escalated interest for researchers, whilst synchronically financial networks emerged as an appealing approach to study the way systemic risk propagates (see for example Elliott et al. 2014; Acemoglu et al. 2015). Hence, over the last years, studies on credit panics and bank runs departed from the traditional risk diversification framework (James 1991) and examined extreme interconnectedness (Ongena and Smith 2000; Caballero and Simsek 2013 *inter alia*) and ways to improve the stability of the financial system during turmoil periods (Gorton and Huang 2004 and 2006; Diamond and Rajan 2005), through financial interrelationships. A network describes a collection of nodes and the links between them, and thus, by using a network representation the structure of linkages among financial institutions (i.e. nodes) can be modelled and measured. Financial network theory can be instrumental in capturing risk associated externalities, triggered by a financial institution and the corresponding effects for the entire financial system. Thus, financial networks are employed as a suitable approach to study systemic risk, the way the banking system responds to contagion and to promote macro-prudential policies by examining network interdependencies.

Importantly, the financial network framework exhibits that excessive interconnectedness among banks and financial institutions increases systemic risk[4] and may lead to a plethora of bank failures and defaults (see also for informative reading Bae et al.

[4]According to the Bank for International Settlements (1994) systemic risk is the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader difficulties.

2003; Acharya and Yorulmazer 2008; Brunnermeier 2008 *inter alia*). The recent financial turmoil have made clear that there is a strong need for sound empirical work in this area, in order to enhance regulations that prevent a local crisis from becoming global, and to examine vulnerabilities that emerge from network interdependencies in the financial system. However, due to limited availability of data, empirical applications are hitherto at an early stage. Thus, entropy maximisation which calibrates systemic risk in the network structure has only recently served as the leading method for estimating counterparty exposures (Furfine 2003; Anand et al. 2014).

2.2 Systemic risk and financial networks

Kiyotaki and Moore (1997 and 2002), and Kaminski and Reinhart (1999) are among the first to search for systemic risk in banks, prompted by changes in macroeconomic developments. Allen and Gale (2000) employ a theoretical approach with banks' bilateral exposures in a financial network framework, to examine how the banking system responds to contagion. They build on Diamond and Dybvig (1983) where consumers have random liquidity preferences, and they find that incomplete networks are more susceptible to contagion. Interestingly, Dasgupta (2005) examines how linkages among banks can be a source of contagious breakdowns, and finds the way depositors react when they receive a negative signal about banks' fundamentals.

On the search for optimal financial network the size of each national banking sector play a dominant role. Freixas et al. (2000) use interbank credit lines to explore liquidity shocks emerged from uncertainty about where consumers will withdraw funds. They find that the stability of the banking system depends emphatically on whether depositors choose to consume at the location of a bank that functions as a money center or not. Allen et al. (2009), Brunnermeier and Pederson (2009), and Allen et al. (2011), use bilateral exposures in the interbank market to observe that a strongly connected banking network mitigates systemic risk by transferring the proportion of losses from one bank's portfolio to more banks through interbank arrangements. In a similar vein, Cocco et al. (2009), documents that interbank networks are typically sparse, because interbank activity is based on relationships, while Craig and von Peter (2014) identify that smaller banks use a limited set of money center banks as intermediaries.

An additional critical factor for the resilience of the banking network is the degree of interconnectedness. Allen and Gale (2004), Leitner (2005), Allen and Carletti (2006) and Gai and Kappadia (2010) find that banking systems respond differently in systemic risk due to changes on the degree of interconnectedness, idiosyncratic and aggregate liquidity shocks in the interbank market. In their theoretical approach, these studies account for the nature and scale bank-specific shocks, while also allowing asset prices to interact with balance sheets. Therefore, they propose central bank interventions to fix the short term interest rate and to provide extra liquidity in the market. Mistrulli (2011), and Trapp and Wewel (2013), observe not only that the network structures respond differently to the propagation of a shock, but the fragility of the system depends on the location in the network of the institution that was initially affected. Additionally, the first author simulates specific liquidity shocks in the Italian interbank market and observes that a bank default may spread to other banks through interbank linkages.

Several studies build on the network structure proposed by Upper and Worms (2004), to propagate shocks within the interbank loan market. Nier et al. (2007), Gai et al. (2011), and Hataj and Kok (2013) employ the epidemiology approach to test the resilience of the banking industry to systemic risk. Particularly, they construct dynamic banking networks to investigate how the likelihood of the market risk depends on the market conditions and the structure of the banking network. They document the key role of banks' financial linkages and observe that the spread of contagion depends on the degree of interconnection among banks. Furthermore, they find that contagion propagates within the financial network by aggregate and idiosyncratic shocks.

The network theory links balance sheets' claims and obligations into a network structure. This form allows researchers to model contagion risk and bank failures triggered by the propagation. Similarly, Castren and Rancan (2014) undertake an entropy maximization approach on macroeconomic data and bilateral exposures in the interbank market, to identify that the effects of systemic shocks depend on the underlying network structure. More recently, Elliot et al. (2014) and Acemoglu et al. (2015) explode how a propagation of shocks in banking networks and the extent of interbank connectivity increase systemic failures due to contagion of counterparty risk.

It is evident from the existing literature that sovereign credit risk and asset price risk are not examined as two important sources of systemic risk. On the contrary, freezes in the interbank market dominate the way researchers explore financial contagion in the banking sector. Departing from the financial network approach, Duffie and Singleton (1999), and Ang and Longstaff (2013) use the sovereign credit risk channel to propagate sovereign – specific credit shocks and observe that it causes a cascade of defaults in U.S. and Eurozone sovereigns. Additionally, Longstaff (2010), and Garratt et al. (2014), study the relationship between reduced collateral values and asset price contagion. They identify that defaults in the subprime market spread quickly through the global financial system and provide evidence for the critical role of asset backed securities on the transmission of the financial crisis.

3. Methodology

3.1 Data

We collect our dataset on a quarterly basis from the first quarter of 2005 till the fourth quarter of 2013 for sixteen Eurozone countries[5]. We obtain it from three sources: the Bank for International Settlements for the cross border quarterly exposures in the interbank market, the total banking exposures to each foreign country and the actual exposures in Sovereign Debt and asset-backed loans. For instance, we have information for the exposure of Austrian banks not just in French Sovereign debt, and asset-backed loans to companies based in France, but also for loans in French banks via the interbank market. Also, we collect data from the European Central Banks' sectoral balance sheets (flow of funds) for the local bilateral banking exposures. Finally, we obtain data from Bankscope on Tier 1 capital and Total Assets for 170 Eurozone based banks (see also Appendix A for more details).

3.2 The Network Structure

The study explores the consequences from a propagation of shocks in the banking network in two steps. First, we construct the financial network based on the banks' actual exposures in the interbank loan market, the sovereign debt (i.e. sovereign credit risk) and asset backed loans (i.e. asset price risk). We then propagate endogenous shocks commenced by the three channels described previously and measure the effects (i.e. losses) in the banking system. The losses are distributed into two components: the losses incurred by the initial shock and the losses resulting from the contagion process in order to measure the speed of the contagion.

The structure of the network is constructed by bank balance sheet interconnections (nodes in the interbank network), actual bilateral exposures and banks' exposures to sovereign debt and asset backed loans. For any missing information in the interbank bilateral exposures, we employ the entropy maximisation method with the complementary use of the

[5] Our sample consists of the following euro area countries: Austria (AT), Belgium (BE), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Latvia (LV), Luxembourg (LU), Malta (MT), Portugal (PT), Slovakia (SK), Slovenia (SI), and Spain (ES).

RAS algorithm which provides the advantage of minimizing any lost information in the priors. In particular, the financial network is generated based on the following three steps: First, we consider a Eurozone based economy with *n* financial intermediaries (i.e. banks). These are initially linked with each other based on the actual and simulated exposures in the local interbank market, and thus create a two-way interrelationship which is important for the spread of shocks within the network and for the analysis of the contagion path. Particularly, a bank is allowed to lend money to another bank and simultaneously the same bank may borrow money from a third bank. Using this structure for our network, we achieve to measure the potential benefits of diversification and to distinguish between losses incurred by risk sharing and losses incurred by risk spreading through the financial network. Consequently, we have the first systemic risk channel - "local interbank loan market"- represented in Figure 1, also called a "node" in the network structure (see also Newman 2002; and Gai et al. 2011 for informative reading on network structures).

-Please Insert Figure 1 about here-

Then, we create two additional systemic risk sources (or nodes) the "sovereign credit risk", and the "asset price risk" channels. The first contains banks' actual exposures in Sovereign Debt, and the second deals with banks' actual exposures in asset-backed loans. Our sample contains 16 countries, and thus corresponds to 48 nodes. Finally, we use the cross-border exposures to link and interconnect every local banking system (see also Figure 2).

-Please Insert Figure 2 about here–

As a result, we model the direct and the indirect effects from a systemic shock. For instance, assume that there is a bank based in country θ with interlinkages with a bank based in country ψ. During severe financial conditions, the bank in one country will be affected by the shock to a bank in another country. Moreover, the effects of the shock can also be spread via banks in a third banking system. Thus, the interdependence in the banking system over the network indicates that when a bank is under distress situation, may provoke a plethora of collapses throughout the financial network (see also Appendix B for the contagion path). Thus, similar to Shin (2008) and Castren and Rancan (2014) we construct an accounting framework of the financial system as a network of interlinked balance sheets where one sector's assets are another's liabilities.

3.3 Estimation

Since, we have different types of nodes, our financial network is defined as heterogenous. In order to estimate bank-to-bank exposures in the financial network, we employ the maximum entropy approach, which assumes that banks spread their lending as evenly as possible. Following Castren and Rancan (2014), two nodes i and j are connected through edges, labelled with $x_{ij,}$ where:

$x_{ij} = 1$, when there is a relationship; and

$x_{ij} = 0$, when there is no relationship.

Similarly, the link which connects two nodes is defined as x_{ij}. The links are directed, so that x is not symmetric (i.e. $x_{ij} \neq x_{ji}$). The strength of the link depends on the size and the degree of interconnection. In Appendix C we analyse the positions (i.e. degree, weight, centrality, betweenness, closeness) of the individual nodes in relation to the overall network, and provide the analytical structure of the financial network.

The bankings' sectors financial exposures to each other can be represented by an $N \, x \, N$ matrix $\boldsymbol{X}$ where each element x_{ij} is a bilateral exposure from sector i to sector j. This implies that an element x_{ij} is an asset of sector i *viz-a-viz* sector j and naturally is also a liability of sector j towards sector i.

$$
X = \left(\begin{array}{ccccc|c}
x_{11} & \cdots & x_{1j} & \cdots & x_{1N} & a_1 \\
\vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\
x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} & a_i \\
\vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\
x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} & a_N \\
\hline
l_1 & \cdots\cdots & l_j & \cdots\cdots & l_N &
\end{array}\right) \tag{1}
$$

Thus a sector's total assets are given by the sum of its row, the marginal $\boldsymbol{a_i}$ above given by formula (2) below:

$$
a_i = \sum_{j=1}^{N} x_{ij}\,, \qquad i = 1, \dots, N \tag{2}
$$

By the same rationale a sector's total liabilities are given by the marginal $\boldsymbol{a_i}$ as in formula (3) below:

$$
l_j = \sum_{i=1}^{N} x_{ij}\,, \qquad j = 1, \dots, N \tag{3}
$$

We do not have information for the element x_{ij} but we do have the column and row marginal from the euro area accounts collected from the European Central Bank. From these we want to extract a set of x_{ij} consistent with the row and column totals and also a set that is the most possible, given the values of the vectors $\boldsymbol{a_i}$ and $\boldsymbol{l_j}$. However, without any further assumptions about x_{ij} we cannot estimate the result analytically for N>2 since $N^2 - 2N$ unknowns have to be estimated. If we make a further assumption that the data are consolidated, that is a sector does not borrow or lend to itself, the main diagonal (x_{ij} for $i = j$) becomes zero and we can interpret the $\boldsymbol{a_i}$'s and $\boldsymbol{l_j}$'s as realisations of the marginal distributions $f(\boldsymbol{a_i})$ and f($\boldsymbol{l_j}$), and the x's as their joint distribution, $f(\boldsymbol{a_i}, \boldsymbol{l_j})$. If $f(\boldsymbol{a_i})$ and f($\boldsymbol{l_j}$) are independent, then $x_{ij} = \boldsymbol{a_i}\boldsymbol{l_j}$. According to the information theory (Jaynes, 1957), this gives us the matrix $\boldsymbol{X}^*$**.** Now we have $N^2 - 3N$ unknowns and the problem cannot be estimated analytically for $N > 3$.

$$X^* = \left(\begin{array}{ccccc|c} 0 & \cdots & x_{1j} & \cdots & x_{1N} & a_1 \\ \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ x_{i1} & \cdots & 0 & \cdots & x_{iN} & a_i \\ \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & 0 & a_N \\ \hline l_1 & \cdots\cdots & l_j & \cdots\cdots & l_N & \end{array}\right) \tag{4}$$

Standardising we can interpret the vectors $\boldsymbol{a_i}$ and $\boldsymbol{l_j}$ as the marginal distributions $f(\boldsymbol{a_i})$ and $f(\boldsymbol{l_j})$ while the x_{ij}'s are their joint distribution $f(\boldsymbol{a_i}, \boldsymbol{l_j})$. Then if $f(\boldsymbol{a_i})$ and $f(\boldsymbol{l_j})$ are independent it follows that $x_{ij} = \boldsymbol{a_i l_j}$ (see also Upper and Worms 2004 for further reading). In information theory terms, this amounts to maximising the entropy of the matrix $\boldsymbol{X}$**.** This independence assumption is consistent with each sector's assets and liabilities being spread equally over the other sectors based on their total assets and liabilities.

Of course independence is not always a good predictor of reality. There could be economic or political reasons why some sectors in some countries might be more exposed to some others. However by constructing the network of exposures with the independence assumption we are biasing it against contagion which would be more likely to manifest if some sectors were over-exposed to another infected sector. Thus if we observe significant contagion effects in our model we are more likely to view them in reality.

In order to solve for the x_{ij}'s we have to minimise the cross entropy of X^* with respect to a matrix with elements $x_{ij} = \boldsymbol{a_i l_j}$ for $i \neq j$ and $x_{ij} = 0$ for $i = j$.

$$\min_{\boldsymbol{x}^*} \boldsymbol{x}^{*\prime} \ln(\boldsymbol{x}^* \oslash \boldsymbol{x}), \text{ such that } \boldsymbol{x} > \boldsymbol{0} \textbf{ and } \boldsymbol{Ax} = (\boldsymbol{a}'\ \boldsymbol{l})' \tag{5}$$

where $\oslash$ refers to a Hadamard (element-wise) division; $\boldsymbol{x}$ and $\boldsymbol{x}^*$ are $N^2 - N$ vectors that are obtained by column-stacking the off-diagonal elements of matrices $\boldsymbol{X}$ and $\boldsymbol{X}^*$, such that all elements of $\boldsymbol{x}$ are strictly greater than zero; $\boldsymbol{A}$ is a $2N\, x\, (N^2 - N)$ selection matrix, containing zeros and ones; $\boldsymbol{a}$ is an $N-$dimensional column vector that row sums of the matrix $\boldsymbol{X}$, and $\boldsymbol{l}$ is an $N-$dimensional row vector that contains column sums of matrix $\boldsymbol{X}$. Because the objective function is strictly concave, we will get unique solution by solving (5) iteratively via using the RAS algorithm.

The RAS is an Iterative Proportional Fitting algorithm which adjusts an initial matrix **X** with row sums $\boldsymbol{a_0}$ and column sums $\boldsymbol{l_0}$ to a new matrix $\boldsymbol{X}^*$ that satisfies a new set of given row sums $\boldsymbol{a}$ and $\boldsymbol{l}$ such that $\boldsymbol{X}^* = \hat{\boldsymbol{r}}\, \boldsymbol{A}\, \hat{\boldsymbol{s}}$, where $\hat{\boldsymbol{r}}$ and $\hat{\boldsymbol{s}}$ are diagonal matrices with positive entries on the main diagonal. We employ it in order to achieve consistency derived from any missing or incomplete information between the entries in our matrix and the pre-specified row and column totals. Specifically, we have no information for actual bilateral exposures in the interbank loan market for some countries, and hence the actual linages are created through the RAS algorithm to guide us to a desired direction by excluding non-existent links. As a result, by using RAS round-by-round according to the sizes of the balance sheet linkages we reach a matrix where column sums and row sums are equal. Notably, the adjustments of the entries of the matrix are kept as close as possible to their initial values (i.e. bi-proportional), in order to preserve the structure of the matrix as much as possible. Hence, in order to estimate the bilateral exposures with the use of RAS in the new matrix X*, we minimise the cross-entropy between the matrix X* and the matrix X in equation, so that interbank exposures are as close as possible between the two matrices:

$$\min_{\hat{x}_{ij}} \sum_{i=1}^{N} \sum_{j=1}^{N} ln\,(\frac{\hat{x}_{ij}}{x^*{}_{ij}}) \qquad (6)$$

s.t. $\sum_{i=1}^{N} \hat{x}_{ij} = a_i$ and $\sum_{j=1}^{N} \hat{x}_{ij} = l_j$

for: $\hat{x}_{ij} \geq 0\ \forall\ i \neq j$ and also: $\hat{x}_{ij} = 0\ \forall\ i = j$

4. Empirical Findings

We simulate quarter-by-quarter three negative shocks emerged from: i) the Sovereign Credit Risk channel (or SCR), ii) the Interbank loan channel (or IB), and iii) the Asset Loan channel (or AL). We follow the mark-to-market accounting practices and assume that each bank has to deduct losses triggered by the shocks or to use the capital buffers when possible. Consequently, any losses imposed by the shocks imply a deduction in the banking sector's assets, which apparently renders a corresponding loss in its equity capital inevitable. We set a 10% shock derived from each channel and in the first step we measure the local (national) magnitude of the shocks. In our analysis, we are interested in examining losses and the contagion path occurred by the shock propagation, and thus we do not model any government or central bank interventions which require exogenous responses and might follow different rules. For instance, governments may decide to bail-out troubled banks, to force mergers between distress and healthy banks or to provide liquidity and funding through an asset purchase program with the intervention of central banks.

We then proceed on to measure the spread of the shock originated from the banks' domestic exposures, the banking systems most affected by the various shocks and hence the expected losses caused by the spread of the shocks across the euro area banking network. Hence, similar to Furfine (2003), Gai and Kapadia (2010) and Gai et al. (2011) our measure of systemic risk is the expected loss that the contagion channel imposes on a banking system. Finally, by assuming that banks cannot raise capital to compensate for the losses suffered from the shocks, we examine the resilience of the euro area banking sector, the way financial contagion propagates in the cross-border financial network, the speed of contagion and the ability of a local banking system to transmit cross-border systemic risks.

4.1 Shocks in the national banking systems

The sovereign credit risk channel simulates a scenario wherein the value of government bonds decreases by 10%. This shock is then propagated through the local banking network. Consequently, we exhibit to measure the interplay of financial interdependence among national banks and the financial acceleration in the development of systemic risk. Table 1 displays the impact (i.e. final losses) of a 10% shock over discrete periods of time, separately for each national banking sector. Notably, the impact of the shock is time-variant and also, changes widely across the national banking systems. This may be due to cyclicality (i.e. post-crisis deleverage process, recapitalisation, new regulatory framework), or the difference on the size and the banking structure of each economy. For instance, a 10% shock (i.e. decline in the price) to the Austrian Government Bonds causes €3.37 bn. losses to the Austrian banking sector, during the pre-crisis period. The losses increase during the crisis period (€4.08 bn.) and decrease in the post-crisis period (€ 3.33 bn.). This pattern characterises all national banking systems within our sample, implying that in the post-crisis era, banks reduced their exposures in sovereign debt holdings. Interestingly, in northern euro area countries, the majority of the losses are registered in the German banking system, while for southern euro area countries they are apparent in the French banking system. This is not entirely surprising given the size of banking sectors in these countries.

Figure 3 depicts the expected losses caused over time from a shock in the German and French sovereign debt accordingly. The results also indicate that a shock in the SCR channel triggers higher losses in the southern euro area, possibly due to the magnitude and the size of the Italian and Spanish sovereign debts (please see also Figure 4). It is worth noting that an intervention from a central bank could be at any point when the losses are propagated and can be through many ways. For instance, German banks can use their capital buffers to control a proportion of the losses. In this case the central bank will need to intervene with €3bn. in order to absorb the losses propagated by the shock in the German network. Similarly, a central bank intervention for the French banking system would cost €4.8 bn. for the post-crisis period.

-Please Insert Table 1 about here-

-Please Insert Figures 3 and 4 about here-

The interbank lending channel simulates a scenario wherein 10% of the total value of interbank loans will not be paid back. This shock is then propagated through the national banking networks. At first glance, Table 2 shows that expected losses triggered by the shock on interbank loans for the local banks exceed the expected losses driven by the SCR channel, implying that the interbank lending channel (IB) is systematically more important for the banking industry. Notably, the total expected losses decrease in the post-crisis period, as a result of the ensuing process of bank deleveraging. Furthermore, the final losses vary substantially across national banking systems reflecting the differences on the size of each interbank market. Figure 5 summarises the expected losses registered for the French (€ 63.57 bn. in the post-crisis era) and the German (€35.04 bn. in the post-crisis era) banking systems. Notably, a central bank intervention will cost €30.5bn. for the French and €12bn. for the German banking networks respectively, for the post-crisis period. Similar to the results obtained from the shock in the sovereign debt market, the Italian (€23.24 bn.) and the Spanish (€22.56 bn.) banking sectors are affected the most compared with the rest of the countries incorporated in our sample (see also Figure 6).

-Please Insert Table 2 about here-

-Please Insert Figures 5 and 6 about here-

Furthermore, Table 3 presents the expected losses after the propagation of a shock in the Asset Loan channel (AL), independently for each national banking system. More concretely, the asset loan channel simulates a scenario wherein the value of the collateral of the asset-backed loans declines by 10%. The expected losses propagated through the AL channel exceed the losses propagated by the SCR channel, but are lower than the losses propagated by the IB channel. For instance, the total amount of losses for France is €40.22 bn. in the post-crisis era and for Germany is €27.24 bn. (sees also Figure 7). Consequently, the results demonstrate that total expected losses decline in the post crisis era, confirming that banks reduced their exposure to asset-backed loans. Interestingly, a central bank intervention will cost €27bn. for the French and €3bn. for the German banking networks respectively. Figure 8 depicts that the same relationship holds for the effects of a shock in the Asset Loan channel for the Italian and the Spanish banking systems. Additionally, we find that each national banking system responds differently to systemic-risk related events (see also Figure 9). Particularly, the smaller is the banking sector, the lesser are the expected losses. From the three systemic risk channels, the interbank loan market constitutes the most important source of losses to the euro area banks. Moreover, we find that the same shock would cause different losses in the national banking sectors if emerged at different points in time. Interestingly, the results imply that euro area banks have strengthened their capital positions in the post-crisis era amid ongoing deleveraging.

-Please Insert Table 3 about here-

-Please Insert Figures 7, 8 and 9 about here-

4.2 Propagation of Shocks in the cross-border financial network

Next, we quantify the effects of shocks in the cross-border financial network, in order to examine the extent to which local banking systems transmit the losses to the European banking sector. Particularly, we examine how a national shock propagates and spreads within the euro are banking network. Table 4 depicts total losses in the banking systems from a 10% shock in the three systemic risk channels of Germany (Panel A) and France (Panel B), the two largest economies in the euro area. Interestingly, the results imply that the interbank market causes the higher expected losses when compared with the Sovereign Credit Risk and the Asset Loan channels. Additionally, the final losses vary substantially across the banking systems. Specifically, French banks suffer the wider losses due the size of its banking sector and due to large interconnectedness with the German financial system. Moreover, the results demonstrate that a 10% shock in the German systemic risk channels generates higher losses for the euro area banking sectors compared with a similar shock in the French channels. Thus, the German banking system is identified as systematically more important than the French banking system. The differences in the final losses are explained by the large differences on the size of the national banking sectors and on the degree of interconnectedness.

-Please Insert Table 4 Panel A and B about here-

Accordingly, the results in Table 5 suggest that a shock in the Italian economic system (Panel A) triggers wider losses in the euro area banking sector compared with a shock in the Spanish financial system (Panel B). Hence, the Italian financial system is systematically more important than the Spanish banking system for the euro area. The results indicate that a shock emerging from a given banking sector does not have the same impact than a shock propagating from some other banking sector. Furthermore, the results demonstrate that each of the systemic risk channels has a different impact on every local banking system and that the interbank risk channel generates the wider losses in the euro area banking network.

-Please Insert Table 5 Panel A and B about here-

Interestingly, a shock in a smaller banking system, like the Greek and the Portuguese (Table 6), originate a small amount of losses in the euro area banking systems. This can be explained to a great extent by the small size of their banking sectors and hence the small degree of interconnectedness with other European banking sectors. Consequently, we observe that the cross-border transmission of systemic shocks depends on the size and the degree of exposure of the banking sector in a foreign financial system. This result is in line with Kamber and Theonissen (2013) who observe that the more exposed domestic banks are to the foreign economy, the greater are the spillovers from foreign financial shocks to the home economy. As a result, each local banking system develops different propagation dynamics in the banking network, due to the differences in the financial structure (i.e. different magnitude of bilateral exposures and different size of sovereign debt and asset backed loans). Finally, we observe that final losses are time-variant, since the same shock propagated at different points in time diverse results[6]. This can be explained by the changes in the network structure triggered by changes in the degree of interconnectedness in the euro area banking sectors.

-Please Insert Table 6 about here-

4.3 The path and speed of contagion within the European banking network

In this section we analyse how systemic shocks originated in a national banking system, spread in the euro area banking network resembling to financial contagion. In particular, by using 170 banks from 16 euro area countries, we measure the speed and the path of cross-country financial contagion within the Eurozone. The simulation test is for a 10% propagation of shocks[7] in the three independent contagion channels, a scenario which is reasonable under severe financial conditions. Consequently, this approach allows us to capture the effect of variations in financial robustness from one bank to the others, rather than focusing exclusively on default events and bankruptcies.

Table 7 presents the results for a shock in the SCR channel and shows: i) the number of banks that default due to the shock and ii) the number of banks whose default cause at least one bank failure by contagion. The evidence indicates that financial contagion is highly

[6] More results for the pre and post-crisis effects on banks' losses are available upon request by the authors.
[7] Additional results with different scenarios are available upon request by the authors.

possible to occur in the euro area banking system. Moreover, we observe that the spread of the shock depends on the size of the bank that fails at the initial stage. More precisely, shocks in the German and French banking systems cause the wider failures. This can be explained by the size of their national banking sectors and from the large number of small banks which creates a cascade of defaults due to their interconnectedness. Thus, interestingly we find that contagious banks are not necessarily the large ones. This result is in line with Mistrulli (2011). Notably, there exists a certain threshold (30%) for the loss rate at which the shock spreads across the whole euro area banking industry, thus affecting all banks through contagion.

-Please Insert Table 7 about here-

Table 8 depicts the effects from a 10% shock that propagates through the Asset Loan channel. The results imply that the defaulted banks are lessen indicating that the SCR is the dominant systemic risk channel and the most systematically important for the spread of contagion in the euro area banking systems.

-Please Insert Table8 about here-

Table 9 shows the effects from a 10% shock in the Interbank lending channel (IB). The results demonstrate that the number of defaulted banks is higher when compared with the AL channel, but less than the number of banks that fail due to a shock in the SCR channel. Thus, a closer look at the contagion path reveals that the SCR channel is the most systematically important source to spread contagion within the euro area financial network.

-Please Insert Table 9 about here-

The findings presented in this section, demonstrate vividly that the change in the financial stability of a bank is affected at any point in time by the financial stability of the counterparties. Additionally, the results imply that if some banks default, this can trigger a cascade of defaults resembling to financial contagion. Consequently, the default of a bank decreases the value of the assets of each bank in the financial network down to the point where the value of assets becomes smaller than the value of liabilities. Thus, the bank defaults and spreads the crisis to other interconnected banks. These results complement the work of Gai et al. (2011) who observe that when risk sharing is maximised among counterparties, the default threshold hold the critical role for the spread of the shock.

Table 10 presents the results on how a default within the domestic banking system propagates in an international financial network. The most systematically important country is Germany and thus, we focus on the effects caused by a 10% shock in their interbank market[8]. The results obtained are based on the assumption that banks cannot react to the shock by raising capital while also governments and central banks cannot intervene at any stage. Indeed, whilst liquidity abruptly dries up when the financial system is under a distress situation, (see also Longstaff, 2010), central banks and governments need a sufficient amount of time to decide on the appropriate actions.

Notably, we observe that a shock generated in the German banking network may cause severe losses and defaults in the euro area banking system. Also, we find that a bank in a foreign country may not be financially linked with German banks, but it is possible to suffer from losses or even defaults to its banking sector due to financial contagion. This result is driven by the systemic importance of the German banking sector which lends to the periphery, and thus makes contagion effects more apparent. Moreover, the degree of losses varies substantially across national banking systems depending on the size and the degree of their interconnectedness. Thus, the speed at which losses are absorbed by the banking networks varies across countries. Consequently, we document that the spread of a shock depends on the systemic importance of a banking system, and the impact of a shock of a given magnitude strongly depends on its initial location. Thus, the probability of default does

[8] Results for the cross-border contagion path for all other euro area countries are available upon request by the authors.

not decrease monotonically with diversification in the interbank loan market, a result which corroborates the work of Allen et al. (2011). Interestingly, the propagation of a shock generated by other banking systems causes less contagious failures in the financial network, resembling to a non-monotonic connectivity of contagion, similar to Gai and Kapadia (2010). Albeit, we observe that even small banking systems (e.g. Greece and Portugal[9]) have the ability to transmit distress in stronger banking sectors. As a result, the smaller is the banking sector, the lesser are the expected losses and the cross-country contagion effects. These results are in line with the works of Allen and Gale (2000), and Freixas et al. (2000) who find that complete markets are not necessarily less conductive to contagion than incomplete markets.

In addition, from Table 10 we observe that there are marked differences in the dynamic responses across the national banking systems. Specifically, southern euro area banks react more strongly than northern euro area banks. This implies that southern euro area banks are more prone to financial contagion and more susceptible to systemic risks. Moreover, we find that as conditions deteriorate in the euro area banking system, the degree of interconnectedness in the financial network increases the possibility of a domino effect. Shocks generated in the German banking system create large losses in the financial network, and thus the domino effect is more apparent. This result corroborates and extends the theoretical work on endogenous complexity and the model of financial crises proposed by Cavallero and Simsek (2013). Finally, the propagation effects reveal that albeit the new regulatory framework and the deleveraging process, the risk of financial contagion has not substantially decreased.

- Please Insert Table 10 about here-

[9] More results on the way small banking systems transmit the shocks in larger banking systems are available by the authors upon request.

5. Robustness Check

The main finding of our study is that by employing the Maximum Entropy approach we capture three systemic risk channels which transform risk in the euro area financial network. In order to check the sensitivity of our findings we use the actual bilateral exposures in the four largest banking systems (Germany, France, Italy, Spain) to compare the results with those obtained with Maximum Entropy. This comparison is important, since it sheds light on the reliability of the maximum entropy approach for assessing the interbank market vulnerability to financial contagion. Following Mistrulli (2011) and Castren and Rancan (2014), the comparison between Maximum Entropy and observed interbank patterns can be interpreted as the theoretical comparison proposed by Allen and Gale (2000) between complete and incomplete markets.

Figures 10 presents the results with the Maximum Entropy method and the results obtained with the actual bilateral exposures for the German and French banking networks. We observe that both (estimated and actual) lines are fairly closed to each other, implying that the Maximum Entropy approach neither over- nor under-estimates the bilateral exposures. Indeed, the black line which represents the Maximum Entropy approach[10] of bilateral exposures produces very similar results with the actual exposures, implying that the Maximum Entropy approach is a suitable way to calibrate losses generated by systemic shocks.

-Please Insert Figure 10 about here-

Similar results are obtained for Figure 11 which depicts the Spanish and Italian banking systems. Specifically, the differences between the observed and the estimated values are fairly closed. Notably, the black line represents cross-country exposures in the interbank market, estimated with the use of RAS algorithm. On the other hand, the grey line represents

[10] The Maximum Entropy matrix of bilateral exposures contains the assumption that for each bank total interbank liabilities and total interbank assets are equal.

cross-country exposures in the interbank market, estimated with actual bilateral exposures with data constructed by the balance sheet items.

-Please Insert Figure 11 about here-

Moreover, we use the actual values to propagate shocks in the euro area interbank, sovereign and loan markets, and we observe that the estimated losses within the banking networks are quite similar to the estimated losses of the financial network computed with the Maximum Entropy approach[11]. In contrast to Mistrulli (2011) and in line with the work of Castren and Rancan (2014), this result asserts that the Maximum Entropy method does not underestimate the extent of the shock propagation.

6. Conclusion

This study models systemic risk by employing the Maximum Entropy approach for the euro area banking industry. We construct a unique interconnected, dynamic and continuous-time financial network and employ counterfactual simulations to propagate systemic shocks. In contrast to the existing literature, we use three independent channels of systemic risk: the interbank loan market, the sovereign credit risk market and the asset loan market, and provide novel evidence on the effects of shocks on financial institutions, the speed of contagion, the way shocks propagate and how euro area banks respond under severe financial conditions.

In response to the issues raised in the introduction, the findings have important implications for understanding systemic risk and for analysing policies designed to mitigate financial contagion in the euro area. Specifically, at first glance the empirical results reveal that a shock in the interbank loan market triggers the highest expected losses in the banking systems. However, by modelling the contagion path the findings reveal that a shock in the sovereign credit risk channel transmits faster through the banking network and leads to a

[11] Additional results on robustness checks are available upon request by the authors.

cascade of defaults. Thus, we conclude that the sovereign credit risk channel dominates systemic risks amplified in the euro area financial network. Additionally, we document that the propagated losses vary across the national banking sectors depending on their sizes and interconnectiveness, while also there is a dramatic variation across northern and southern euro area countries in terms of their response to systemic risk. In particular, the speed of contagion and the expected bank failures are markedly more prominent in southern euro area banking systems.

Moreover, by modelling the contagion path we observe that losses vary over time due to the post-crisis deleverage and to changes in the degree of interconnections among European banks. Interestingly, the findings reveal that the cross-border transmission of systemic shocks - and consequently the speed of contagion - depends on the size of the national banking sector, the initial location of the generated shock and the degree of interconnectedness. Finally, it is evident from the results that the European banking system remains highly vulnerable and conducive to financial contagion, implying that the new capital rules have not substantially reduced systemic risks, and hence, there is a need for additional policies in order to increase the resilience of the sector.

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Appendix A. Eurozone Banks.

The appendix below presents the sample of banks used in the study with quarterly data and the banks' place of origin. Our focus is the propagation of shocks in the Interbank, Asset-Backed Loan and Sovereign Credit Risk channels. Analytical information for the actual exposure of the banks is collected via the euro area Balance Sheet Items statistics. Notably, the propagation of shocks is employed for the largest banks (based on actual assets) in the euro area.

Bank	Country	Bank	Country
UniCredit Bank Austria AG-Bank Austria	Austria	Nordea Bank Finland Plc	Finland
Steiermärkische Bank und Sparkassen AG-Bank Styria	Austria	Danske Bank Plc	Finland
Raiffeisen Bausparkasse GmbH-Raiffeisen Wohn Bausparen	Austria	Aktia Bank Plc	Finland
Landes-Hypothekenbank Tirol-Hypo Tirol Bank	Austria	OP Mortgage Bank	Finland
Bausparkasse der Oesterreichischen Sparkassen AG	Austria	Helsinki OP Bank Plc	Finland
Bausparkasse Wuestenrot	Austria	Société Générale	France
Ageas	Belgium	BPCE Group	France
AXA Bank Europe SA/NV	Belgium	BPCE SA	France
BKCP scrl	Belgium	Credit Mutuel (Combined - IFRS)	France
RHJ International SA	Belgium	Fédération du Crédit Mutuel	France
Banque CPH	Belgium	Banque Fédérative du Crédit Mutuel	France
Deutsche Bank AG	Germany	Crédit Industriel et Commercial - CIC	France
Sparkassen-Finanzgruppen (Combined)-Sparkassen	Germany	HSBC France	France
DZ Bank AG-Deutsche Zentral-Genossenschaftsbank	Germany	La Banque Postale	France
Sparkassen-Finanzgruppe Hessen-Thuringen	Germany	Crédit Foncier de France	France
Deutsche Postbank AG	Germany	Caisse des Dépôts et Consignations-Groupe Caisse des Dépôts	France
FMS Wertmanagement Anstalt Des Oeffentlichen Recht	Germany	Credit Mutuel Arkea	France
NRW.BANK	Germany	Caisse d'épargne et de prévoyance Ile-de-France	France
Deutsche Bank Privat-und Geschaftskunden AG	Germany	Crédit du Nord	France
Wüstenrot & Württembergische	Germany	Crédit Mutuel Nord Europe	France
Landeskreditbank Baden-Wuerttemberg - Förderbank-L-Bank	Germany	Crédit Immobilier de France Développement - CIFD	France
Bausparkasse Schwäbisch Hall AG	Germany	Caisse d'épargne et de prévoyance Rhône Alpes	France
Hamburger Sparkasse AG (HASPA)	Germany	Caisse d'épargne et de prévoyance Provence Alpes Corse SA	France
HASPA Finanzholding	Germany	Lyonnaise de Banque	France
Dexia Kommunalbank Deutschland AG	Germany	Caisse d'Epargne et de Prévoyance Bretagne-Pays de Loire	France
Santander Consumer Bank AG	Germany	Caisse d'Epargne et de Prevoyance Nord France-Europe	France
BHW Bausparkasse AG	Germany	Caisse d'Epargne et de Prevoyance Normandie	France
Münchener Hypothekenbank eG	Germany	Caisse d'Epargne et de Prévoyance de Midi-Pyrénées	France
Deutsche Apotheker- und Aerztebank eG	Germany	Caisse d'épargne et de prévoyance de Bourgogne	France
Sachsen-Finanzgruppe	Germany	Crédit Coopératif	France
SEB AG	Germany	Caisse d'Epargne et de Prevoyance Côte d'Azur	France
Deutsche Hypothekenbank (Actien-Gesellschaft)	Germany	Caisse d'épargne et de prévoyance d'Auvergne et du Limousin	France
Sparkasse KölnBonn	Germany	Crédit Mutuel Océan	France
IKB Deutsche Industriebank AG	Germany	Banque Palatine	France
Kreissparkasse Köln	Germany	Crédit Mutuel de Maine-Anjou et Basse-Normandie	France
Wüstenrot Bausparkasse AG	Germany	Banque populaire Lorraine Champagne	France
LFA Förderbank Bayern	Germany	Banque Populaire Aquitaine Centre Atlantique	France
BMW Bank GmbH	Germany	Banque Populaire Val de France	France
Westdeutsche ImmobilienBank AG	Germany	Banque Populaire des Alpes	France
Frankfurter Sparkasse	Germany	Caisse d'épargne et de prévoyance du Languedoc Roussillon	France
InvestitionsBank Schleswig-Holstein	Germany	Banque Européenne du Crédit Mutuel	France

Stadtsparkasse München	Germany
Wuestenrot Bank AG Pfandbriefbank	Germany
Sparkasse Hannover	Germany
Sparda-Bank Baden-Württemberg eG	Germany
Bayerische Landesbausparkasse LBS	Germany
Stadtsparkasse Düsseldorf	Germany
Duesseldorfer Hypothekenbank AG	Germany
Targobank AG & Co KGaA	Germany
Mittelbrandenburgische Sparkasse in Potsdam	Germany
Die Sparkasse Bremen	Germany
Nassauische Sparkasse	Germany
LBS Landesbausparkasse Baden- Württemberg	Germany
Sparkasse Pforzheim Calw	Germany
LBS Westdeutsche Landesbausparkasse	Germany
InvestitionsBank des Landes Brandenburg	Germany
Berliner Volksbank eG	Germany
Kreissparkasse Ludwigsburg	Germany
Kreissparkasse Muenchen Starnberg Ebersberg	Germany
Sparkasse Nürnberg	Germany
Sparda-Bank Südwest eG	Germany
Investitions- und Strukturbank Rheinland-Pfalz (ISB) GmbH	Germany
Debeka Bausparkasse AG, Sitz Koblenz am Rhein	Germany
Deutsche Bank Bauspar AG	Germany
Sparkasse Leipzig	Germany
Sparkasse Münsterland Ost	Germany
Bank für Sozialwirtschaft Aktiengesellschaft	Germany
Sparda-Bank West eG	Germany
Landessparkasse zu Oldenburg	Germany
Frankfurter Volksbank eG	Germany
Kreissparkasse Esslingen Nuertingen	Germany
Sparkasse Krefeld	Germany
Bethmann Bank	Germany
Saechsische AufbauBank Forderbank	Germany
Stadtsparkasse Essen-Sparkasse Essen	Germany
BBBank eG	Germany
LBS Norddeutsche Landesbausparkasse Berlin-Hannover	Germany
Sparkasse Dortmund	Germany
DNB Pank AS	Estonia
AS LHV Pank	Estonia
Fund KredEx	Estonia
Tallinn Business Bank Ltd-Tallinna Äripanga AS	Estonia
Banco Bilbao Vizcaya Argentaria SA	Spain
Ibercaja Banco SAU	Spain
Catalunya Banc SA	Spain
Kutxabank SA	Spain
Liberbank SA	Spain
Caja Laboral Popular Coop de credito	Spain
Barclays Bank S.A.	Spain
Banco Grupo Cajatres SA-Caja 3	Spain
Caja Rural De Castilla-La Mancha	Spain
Casden Banque Populaire	France
National Bank of Greece SA	Greece
Piraeus Bank SA	Greece
Eurobank Ergasias SA	Greece
Alpha Bank AE	Greece
Bank of Ireland-Governor and Company of the Bank of Ireland	Ireland
Allied Irish Banks plc	Ireland
Permanent TSB Plc	Ireland
Bank of Ireland Mortgage Bank	Ireland
AIB Mortgage Bank	Ireland
EBS Limited	Ireland
ICS Building Society	Ireland
Credito Emiliano Holding	Italy
Casse del Tirreno	Italy
Bank Sepah	Italy
Espirito Santo Financial Group S.A.	Luxembourg
Standard International Holdings S.A.	Luxembourg
KBL European Private Bankers SA	Luxembourg
Jsc Latvian Development Financial Institution Altum	Latvia
GE Capital Latvia	Latvia
Caixa Geral de Depositos	Portugal
Banco Comercial Português, SA-Millennium bcp	Portugal
Banco Espirito Santo SA	Portugal
Banco BPI SA	Portugal
Santander Totta SGPS	Portugal
Banco Santander Totta SA	Portugal
Caixa Economica Montepio Geral	Portugal
BANIF - Banco Internacional do Funchal, SA	Portugal
Banco Popular Portugal SA	Portugal
Vseobecna Uverova Banka a.s.	Slovakia
Tatra Banka a.s.	Slovakia
Sberbank Slovensko, as	Slovakia
Prima banka Slovensko a.s.	Slovakia
Banka Celje dd	Slovakia
Banka Koper d.d.	Slovenia
Banka Celje dd	Slovenia
Gorenjska Banka d.d. Kranj	Slovenia
Postna Banka Slovenije dd	Slovenia

Appendix B. Modelling Financial Contagion

We model contagion stemming from unexpected shocks in our financial network, with banks' balance sheets[12] being the conduits for the transmission of the shocks as losses propagate through the banking system. The simulations are employed quarter-by-quarter between the first quarter of 2005 and the fourth quarter of 2013. Specifically, we consider sixteen Eurozone based countries, each with an economic system formed by N banks. We consider a credit cycle which lasts for four dates (t = 0, 1, 2, 3). At the initial date (i.e. t = 0), each bank i holds sufficient capital that it can either lend it to other banks via the interbank loan channel (N_i^{IB}) and/or invest in Government Bonds (N_i^{SB}) via the Sovereign Credit Risk channel, and/or invest in asset-backed loans (N_i^{AL}) via the Asset Loan Risk channel. All projects described above, provide a sufficient profit if held to maturity, i.e. at t = 3. However, the bank has the choice to liquidate its project (fully or partially) at t = 2, but will only recover a fraction of the project's full value.

We propagate shocks triggered by each channel independently at time t = 1. Then, we measure the losses realised for banks emanated from the shocks in each channel. Every bank has to meet interbank liabilities (L_i^{IB}) and thus, losses incurred by a shock in a channel (e.g. the asset loan risk channel N_i^{AL}) can be recovered by liquidating other projects (e.g. the Sovereign Debt holdings N_i^{SB}), at time t = 2. Consequently, systemic shocks in one channel may trigger fire sales, and hence losses in other channels. Thus, our approach allows us to distinguish between losses incurred by the propagation of a shock and losses incurred by contagion and the spread of systemic risk.

As a result, if there is a shock in the interbank loan channel, a bank i is solvent when:

---

[12] We follow the mark-to-market accounting practices and assume that each bank has to deduct losses triggered by the shocks or to use the capital buffers when possible. Consequently, any losses imposed by the shocks imply a deduction in the banking sector's assets, which apparently renders a corresponding loss in its equity capital inevitable.

$$(1-\sigma)N_i^{IB} + q_{SB}N_i^{SB} + q_{AL}N_i^{AL} - L_i^{IB} > CR \quad (1)$$

where σ is the fraction of banks with obligations to bank *i* that have suffered losses from the shock, q_{SB} is the resale price of the Sovereign Bond, $q_{AL}$is the resale price of the asset-backed loan, and CR is the bank's tier-1 capital. Moreover, the values of q_{SB} and q_{AL} are always less than one in the event of asset sales, since there are fire sales with the propagation of the shock in order a bank to meet its liabilities.

As a result, when $\sigma > CR + N_i^{IB}$, a bank has to liquidate other projects in order to be solvent:

$$\sigma < \frac{K_i-(1-q_{SB})N_i^{SB}-(1-q_{AL})N_i^{AL}}{N_i^{IB}}, \text{ for } N_i^{IB} \neq 0. \quad (2)$$

where $K_\iota = N_i^{IB} + N_i^{BS} + N_i^{AL} - CR$ is the bank's capital buffer which can be used in order to meet its liabilities.

All banks are allowed to fail one at a time, if the amount of the losses is greater than lenders' reported tier-1 capital (i.e. capital + reserves). Finally, we calculate the losses triggered in other banking systems from the initial shock. Notably, in this study we are interested in examining the effects of systemic risks in the euro area banking network and the resilience of the banking system. Thus, our financial network does not allow for a role of the central bank or for any government interventions in providing liquidity or rescue packages to the distressed banks which require exogenous responses and might follow different rules.

Thus, a bank is insolvent in our financial network when:

$$\sigma > \frac{K_i-(1-q_{SB})N_i^{SB}-(1-q_{AL})N_i^{AL}}{N_i^{IB}}, \text{ for } N_i^{IB} \neq 0. \quad (3)$$

Contagion occurs in the network system when either a bank is insolvent (equation (3)) or when fire sales - triggered by the propagation of a shock – are spread to other banks. Therefore, the likelihood of contagion corresponds and is directly linked to the size of the bank, the size of losses, the degree of interconnectedness and the size of the capital buffer.

The same relationship holds when the shock is propagated through the Asset Loan Channel. However, a shock propagated within the Sovereign Debt channel implies that the interbank loan and the asset backed securities markets are illiquid, because sovereign debt represents economic performance and credit conditions for a country and thus a priori liquidity will freeze in the interbank market while synchronically the price of collaterals will be severely harmed. Hence, amid to the direct interlinkages and obligations, the possibility of indirect financial contagion increases significantly when the shocks are triggered by the sovereign debt risk channel, such that equation (3) becomes:

$$\sigma > \frac{K_i}{N_i^{SB}}, \text{ for } N_i^{SB} \neq 0 \tag{4}$$

Appendix C. Network Measures

In order to take into account the information provided by the Maximum Entropy method, we identify the appropriate quantities characterising the structure and organisation of our network at the statistical level. The appendix provides a general characterisation of the heterogenous statistical properties presents the number of sector-level nodes, the estimated degree, closeness, centrality, and the clustering coefficient. Degree is the sum of the direct links that each node has with other nodes. With closeness we capture the influence for each node. With centrality and betweenness we clarify the absolute position of the node in the banking network. The clustering coefficient (CC) shows for a given node, the number of actual links to other nodes.

Statistical properties of the Banking Network

Network Measures	
Nodes	48
Degree	1.54
CC	0.42
K^{IN} - K^{OUT}	107,491
C_C^W	2.79
C_B^W	2.36

Figure 1. The graph presents the network structure for the Interbank Loan Market cross-banking exposures. The nodes are the Banking Sectors (i.e. BS) for each euro area country. The links are the actual exposures from the Bank of International Settlements statistics and the different strength of the arrows and the links represents the different volumes (sizes) and the difference in the degree of interconnections for the bilateral interlinkages. The domestic interbank exposures are estimated with the maximum entropy method**.**

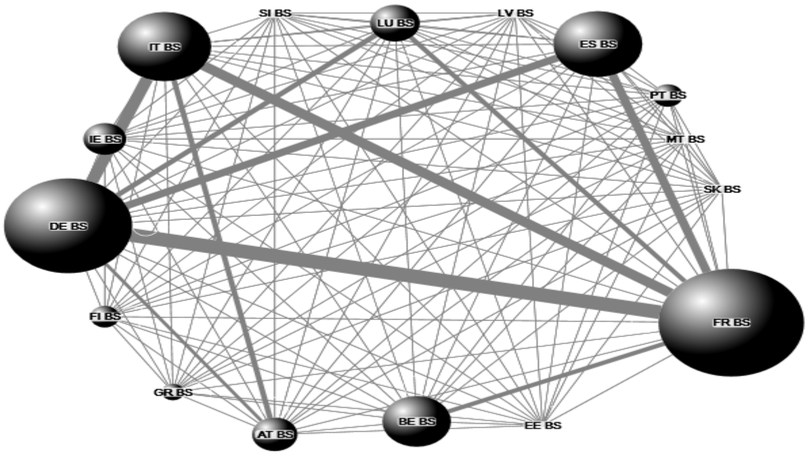


Figure 2. The graph depicts the network structure for the Asset-backed Loans (AL) and Sovereign Credit Risk (SCR) exposures. The nodes reflect actual exposures of each national banking sector. Each line represents the country from which the shock emerges. The strength of each link and each arrow exhibits the different volumes and the difference in the degree of interconnections for the bilateral interlinkages.

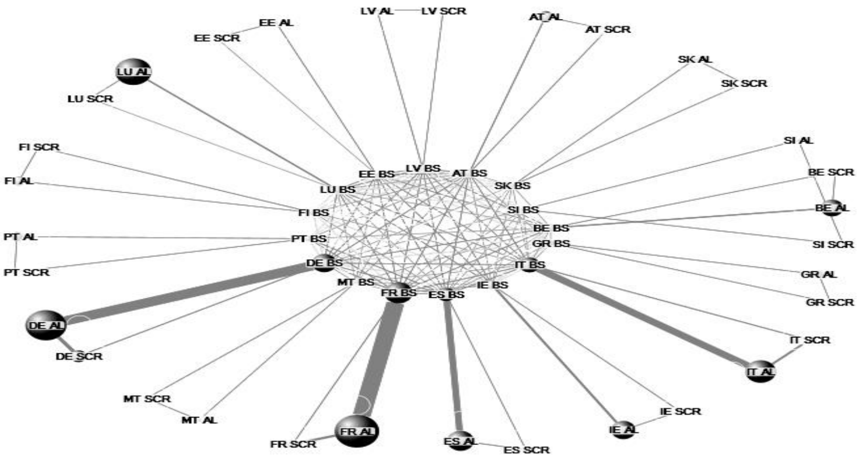
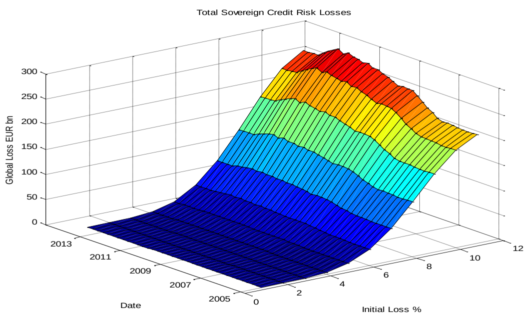


Figure 3. The graphs present losses in the German and French Banking Systems generated from a 10% negative shock in their Sovereign Debt Markets (Sovereign Credit Risk Channel). The simulation tests are propagated quarter-by-quarter from 2005 till 2013.

Losses in the German Banking Sector



Losses in the French Banking Sector

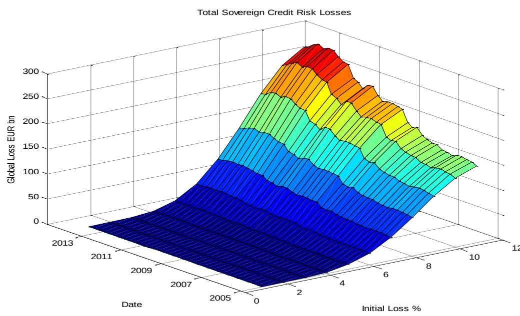
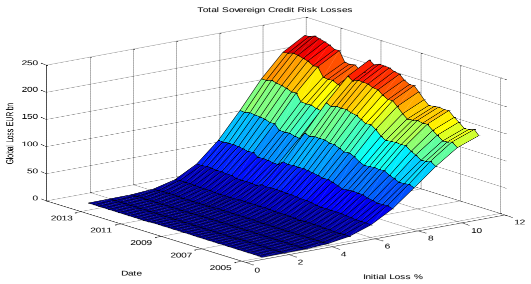


Figure 4. The graphs exhibit losses in the Italian and Spanish Banking Systems generated from a 10% shock in their Sovereign Debt markets (Sovereign Credit Risk Channel). The simulation tests are propagated quarter-by-quarter from 2005 till 2013.

Losses in the Italian Banking Sector



Losses in the Spanish Banking Sector

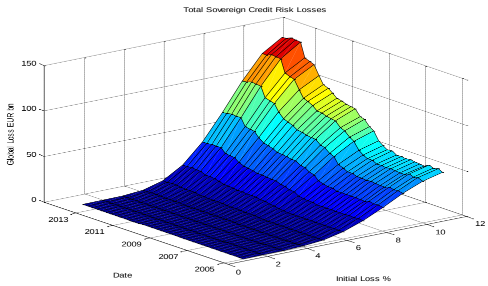
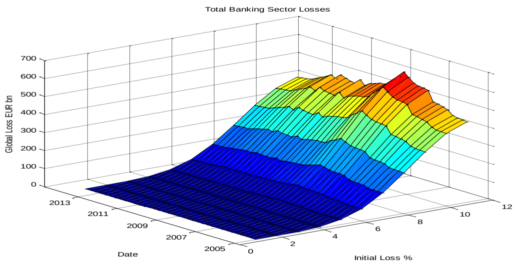


Figure 5. The graphs present losses in the German and French Banking Systems generated from a 10% shock in their national Interbank Loan markets. The simulation tests are propagated quarter-by-quarter from 2005 till 2013.

Losses in the German Banking Sector



Losses in the French Banking Sector

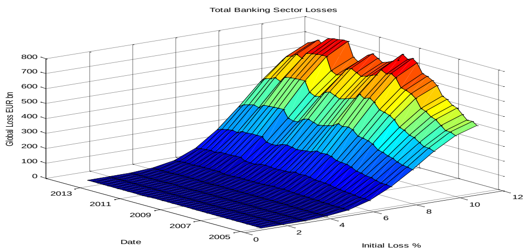
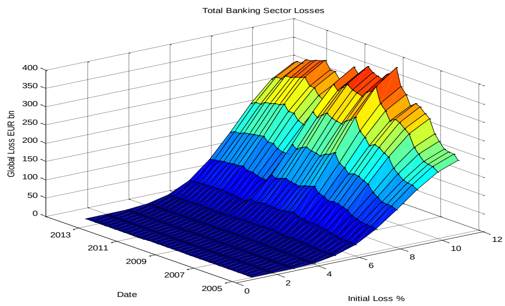


Figure 6. The graphs exhibit losses in the Italian and Spanish Banking Systems generated from a 10% shock in their national Interbank Loan markets. The simulation tests are propagated quarter-by-quarter from 2005 till 2013.

Losses in the Italian Banking Sector



Losses in the Spanish Banking Sector

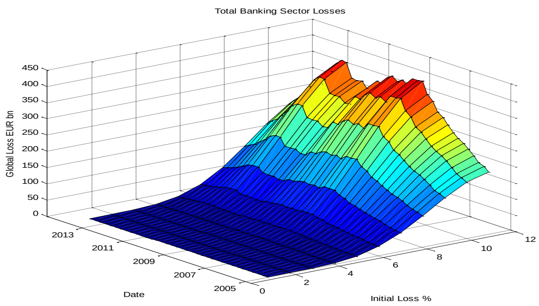
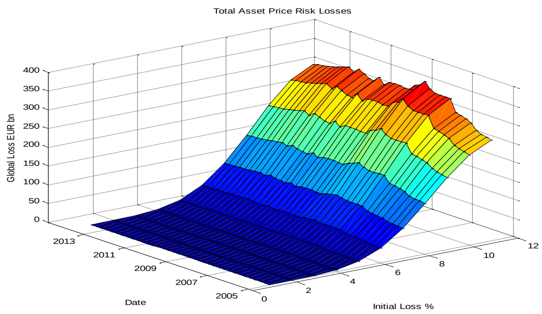


Figure 7. The graphs present losses in the German and French Banking Systems generated from a 10% shock in the German and French Asset-Backed Loans (Asset Loan Channel). The simulation tests are propagated quarter-by-quarter from 2005 till 2013.

Losses in the German Banking Sector



Losses in the French Banking Sector

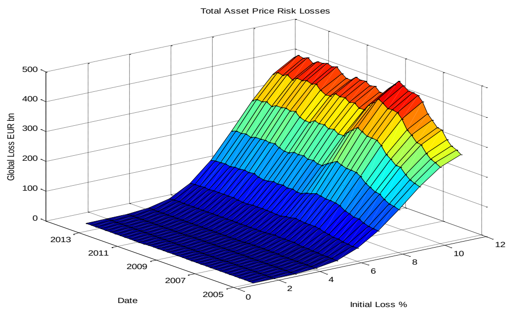


Figure 8. The graphs exhibit losses in the Italian and Spanish Banking Systems generated from a 10% shock in the Asset-Backed Loans (Asset Loan Channel). The simulation tests are propagated quarter-by-quarter from 2005 till 2013.

Losses in the Italian Banking Sector   Losses in the Spanish Banking Sector

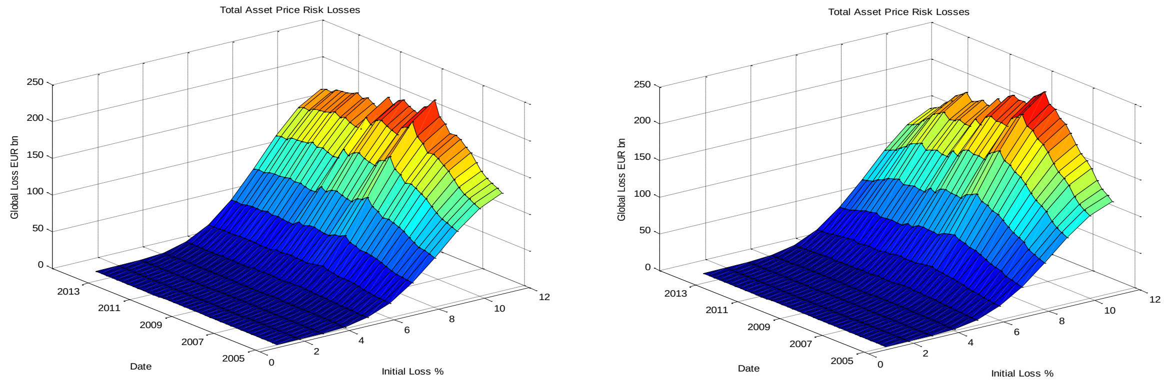


Figure 9. Total losses emerged in national banking systems from 10% negative shocks in three systemic risk channel. Panel A presents losses triggered in the Northern Euro Area banking sectors and Panel B exhibits losses caused in the Southern Euro Area banking sectors. The amounts are in EUR billions.

PANEL A   **PANEL B**

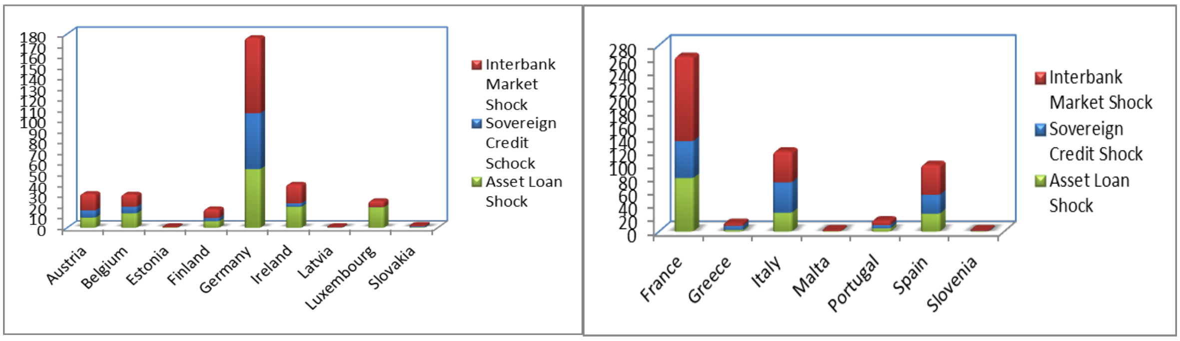


Figure 10. Losses estimated with Entropy Maximisation (estimate line) and losses generated by actual bilateral Exposures (actual line) from a 5% negative shock in the German (Panel A) and the French (Panel B) Banking Systems. The results are estimated quarter-by-quarter and the amounts are in EUR billions.

PANEL A   **PANEL B**

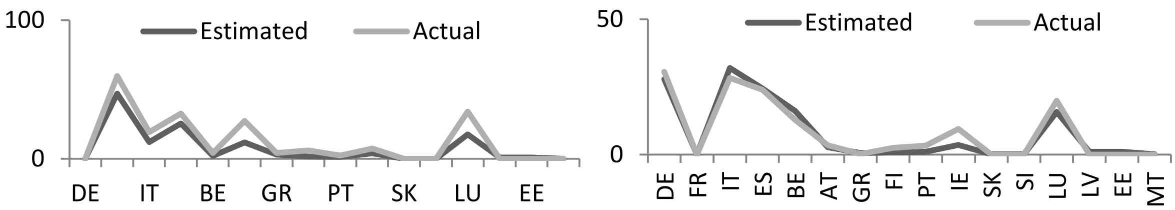


Figure 11. Losses estimated with Entropy Maximisation (estimate line) and losses generated by actual bilateral Exposures (actual line) from a 10% negative shock in the Italian (Panel A) and the Spanish (Panel B) Banking Systems. The results are estimated quarter-by-quarter and the amounts are in EUR billions.

PANEL A   **PANEL B**

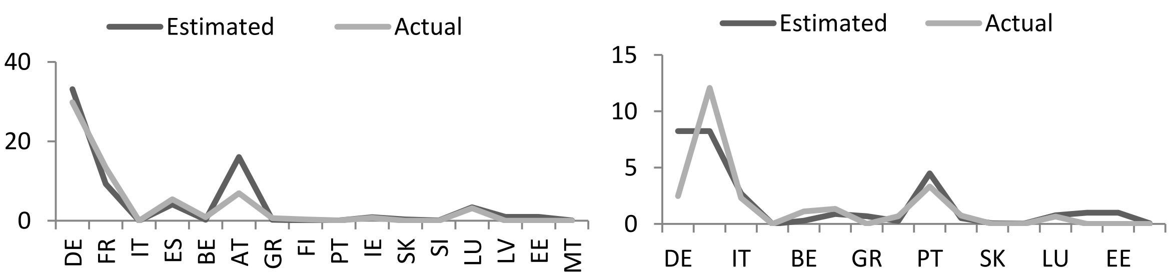


Table 1

Impact of a 10% shock in the Sovereign Credit Risk Channel. The table depicts the losses of a shock in the national banking sectors for the pre-crisis, the crisis and the post-crisis periods, quarter-by-quarter from 2005 till 2013. European countries are divided in two regions: Northern Europe and Southern Europe in order to reflect the effects based on the geographical region. All the amounts are in Euro Billions.

Northern Euro Area	Pre-Crisis	Crisis	Post-Crisis
Austria	- 3.377	- 4.089	- 3.336
Belgium	- 3.128	- 3.788	- 3.090
Estonia	- 0.025	- 0.031	- 0.025
Finland	- 1.504	- 1.821	- 1.485
Germany	- 29.201	- 31.880	- 26.003
Ireland	- 1.615	- 1.956	- 1.596
Latvia	- 0.087	- 0.105	- 0.086
Luxembourg	- 0.050	- 0.060	- 0.049
Slovakia	- 0.412	- 0.498	- 0.407
Southern Euro Area			
France	- 32.354	- 35.247	- 27.820
Greece	- 3.086	- 3.847	- 3.036
Italy	- 23.217	- 28.944	- 22.845
Malta	- 0.107	- 0.133	- 0.105
Portugal	- 2.485	- 3.098	- 2.445
Spain	- 14.447	- 18.011	- 14.215
Slovenia	- 0.299	- 0.363	- 0.296

Table 2

Impact of a 10% shock in the Interbank Loan Market. The table exhibits the losses of a shock in the national banking sectors for the pre-crisis, the crisis and the post-crisis periods, quarter-by-quarter from 2005 till 2013. European countries are divided in two regions: Northern Europe and Southern Europe in order to reflect the effects based on the geographical region. All the amounts are in Euro Billions.

Northern Euro Area	Pre-Crisis	Crisis	Post-Crisis
Austria	- 8.762	- 9.566	- 7.803
Belgium	- 6.518	- 7.116	- 5.804
Estonia	- 0.193	- 0.211	- 0.172
Finland	- 4.787	- 5.227	- 4.263
Germany	- 39.36	- 42.97	- 35.047
Ireland	- 9.918	- 10.828	- 8.832
Latvia	- 0.203	- 0.221	- 0.180
Luxembourg	- 3.357	- 3.665	- 2.989
Slovakia	- 0.384	- 0.419	- 0.342
Southern Euro Area			
France	- 73.933	- 80.545	- 63.571
Greece	- 2.350	- 2.560	- 2.020
Italy	- 27.035	- 29.453	- 23.246
Malta	- 0.775	- 0.844	- 0.666
Portugal	- 4.052	- 4.415	- 3.484
Spain	- 26.245	- 28.592	- 22.567
Slovenia	- 0.336	- 0.366	- 0.288

Table 3

Impact of a 10% shock in the Asset-Backed Loan Channel. The table depicts the losses of a shock in the national banking sectors for the pre-crisis, the crisis and the post-crisis periods, quarter-by-quarter from 2005 till 2013. European countries are divided in two regions: Northern Europe and Southern Europe in order to reflect the effects based on the geographical region. All the amounts are in Euro Billions.

Northern Euro Area	Pre-Crisis	Crisis	Post-Crisis
Austria	- 5.331	- 5.820	- 4.747
Belgium	- 7.531	- 8.222	- 6.706
Estonia	- 0.180	- 0.197	- 0.160
Finland	- 3.435	- 3.750	- 3.059
Germany	- 30.59	- 33.40	- 27.241
Ireland	- 10.975	- 11.982	- 9.773
Latvia	- 0.130	- 0.141	- 0.115
Luxembourg	- 10.698	- 11.679	- 9.526
Slovakia	- 0.319	- 0.348	- 0.284
Southern Euro Area			
France	- 46.784	- 50.967	- 40.227
Greece	- 1.367	- 1.490	- 1.176
Italy	- 16.545	- 18.025	- 14.226
Malta	- 0.305	- 0.332	- 0.262
Portugal	- 2.733	- 2.978	- 2.350
Spain	- 15.677	- 17.078	- 13.479
Slovenia	- 0.256	- 0.279	- 0.220

Table 4
Panel A Euro Area banking network final losses. The table depicts cross-border quarter-by-quarter impact of a 10% shock triggered by the three German Systemic Risk Channels: Sovereign Credit Risk (SCR), Interbank loan Market (IB) and Asset-backed Loan channel (AL). All the amounts are in Euro Billions.

Germany	SCR	IB	AL
France	- 0.564	- 3.209	- 2.049
Italy	- 0.404	- 2.298	- 1.467
Spain	- 0.134	- 0.759	- 0.485
Belgium	- 0.029	- 0.162	- 0.104
Austria	- 0.130	- 0.736	- 0.470
Greece	- 0.007	- 0.042	- 0.027
Finland	- 0.015	- 0.086	- 0.055
Portugal	- 0.009	- 0.051	- 0.032
Ireland	- 0.010	- 0.058	- 0.037
Slovakia	- 0.036	- 0.203	- 0.130
Slovenia	- 0.043	- 0.243	- 0.155
Luxembourg	- 0.032	- 0.184	- 0.117
Latvia	- 0.062	- 0.353	- 0.225
Estonia	- 0.064	- 0.361	- 0.231
Malta	- 0.121	- 0.686	- 0.438
Total Losses	**- 1.660**	**- 9.433**	**- 6.023**

Table 4
Panel B Euro Area banking network final losses. The table depicts cross-border quarter-by-quarter impact of a 10% shock triggered by the three French Systemic Risk Channels: Sovereign Credit Risk (SCR), Interbank loan Market (IB) and Asset-backed Loan channel (AL). All the amounts are in Euro Billions.

France	SCR	IB	AL
Germany	-0.202	-2.491	-1.352
Italy	-0.041	-0.501	-0.272
Spain	- 0.043	- 0.532	- 0.289
Belgium	- 0.028	- 0.351	- 0.190
Austria	- 0.029	- 0.352	- 0.191
Greece	- 0.003	- 0.036	- 0.019
Finland	- 0.008	- 0.096	- 0.052
Portugal	- 0.009	- 0.112	- 0.061
Ireland	- 0.012	- 0.143	- 0.078
Slovakia	- 0.018	- 0.218	- 0.118
Slovenia	- 0.021	- 0.260	- 0.141
Luxembourg	- 0.016	- 0.197	- 0.107
Latvia	- 0.031	- 0.378	- 0.205
Estonia	- 0.031	- 0.387	- 0.210
Malta	- 0.060	- 0.735	- 0.399
Total Losses	**- 0.551**	**- 6.789**	**- 3.686**

Table 5

Panel A Euro Area banking network final losses. The table depicts cross-border quarter-by-quarter impact of a 10% shock triggered by the three Italian Systemic Risk Channels: Sovereign Credit Risk (SCR), Interbank loan Market (IB) and Asset-backed Loan channel (AL). All the amounts are in Euro Billions.

Italy	**SCR**	**IB**	**AL**
Germany	- 0.301	- 1.536	- 0.689
France	- 1.116	- 5.692	- 2.554
Spain	- 0.081	- 0.411	- 0.184
Belgium	- 0.027	- 0.136	- 0.061
Austria	- 0.057	- 0.292	- 0.131
Greece	- 0.020	- 0.103	- 0.046
Finland	- 0.045	- 0.229	- 0.103
Portugal	- 0.013	- 0.068	- 0.031
Ireland	- 0.009	- 0.045	- 0.020
Slovakia	- 0.024	- 0.124	- 0.055
Slovenia	- 0.029	- 0.148	- 0.066
Luxembourg	- 0.022	- 0.111	- 0.050
Latvia	- 0.042	- 0.214	- 0.096
Estonia	- 0.043	- 0.219	- 0.098
Malta	- 0.082	- 0.416	- 0.187
Total Losses	**- 1.911**	**- 9.743**	**- 4.372**

Table 5

Panel B Euro Area banking network final losses. The table depicts cross-border quarter-by-quarter impact of a 10% shock triggered by the three Italian Systemic Risk Channels: Sovereign Credit Risk (SCR), Interbank loan Market (IB) and Asset-backed Loan channel (AL). All the amounts are in Euro Billions.

Spain	**SCR**	**IB**	**AL**
Germany	- 0.118	- 1.431	- 0.721
France	- 0.162	- 1.975	- 0.996
Italy	- 0.019	- 0.236	- 0.119
Belgium	- 0.012	- 0.145	- 0.073
Austria	- 0.009	- 0.104	- 0.053
Greece	- 0.007	- 0.087	- 0.044
Finland	- 0.016	- 0.191	- 0.096
Portugal	- 0.021	- 0.261	- 0.132
Ireland	- 0.005	- 0.061	- 0.031
Slovakia	- 0.008	- 0.102	- 0.051
Slovenia	- 0.010	- 0.122	- 0.061
Luxembourg	- 0.008	- 0.092	- 0.046
Latvia	- 0.015	- 0.177	- 0.089
Estonia	- 0.015	- 0.181	- 0.091
Malta	- 0.028	- 0.344	- 0.173
Total Losses	**- 0.453**	**- 5.510**	**- 2.778**

Table 6

Panel A Euro Area banking network final losses. The table depicts cross-border quarter-by-quarter impact of a 10% shock triggered by the three Portuguese Systemic Risk Channels: Sovereign Credit Risk (SCR), Interbank loan Market (IB) and Asset-backed Loan channel (AL). All the amounts are in Euro Billions.

Portugal	**SCR**	**IB**	**AL**
Germany	- 0.018	- 0.188	- 0.118
France	- 0.018	- 0.193	- 0.121
Italy	- 0.002	- 0.020	- 0.012
Spain	- 0.059	- 0.630	- 0.396
Belgium	- 0.005	- 0.050	- 0.031
Austria	- 0.003	- 0.028	- 0.018
Greece	- 0.003	- 0.030	- 0.019
Finland	- 0.006	- 0.065	- 0.041
Ireland	- 0.006	- 0.065	- 0.040
Slovakia	- 0.003	- 0.035	- 0.022
Slovenia	- 0.004	- 0.041	- 0.026
Luxembourg	- 0.003	- 0.031	- 0.020
Latvia	- 0.006	- 0.060	- 0.038
Estonia	- 0.006	- 0.061	- 0.038
Malta	- 0.011	- 0.117	- 0.073
Total Losses	**- 0.151**	**- 1.613**	**- 1.013**

Table 6

Panel B Euro Area banking network final losses. The table depicts cross-border quarter-by-quarter impact of a 10% shock triggered by the three Greek Systemic Risk Channels: Sovereign Credit Risk (SCR), Interbank loan Market (IB) and Asset-backed Loan channel (AL). All the amounts are in Euro Billions.

Greece	**SCR**	**IB**	**AL**
Germany	- 0.002	- 0.070	- 0.037
France	- 0.001	- 0.025	- 0.013
Italy	- 0.000	- 0.010	- 0.005
Spain	- 0.001	- 0.021	- 0.011
Belgium	- 0.001	- 0.019	- 0.010
Austria	- 0.001	- 0.028	- 0.014
Finland	- 0.001	- 0.025	- 0.013
Portugal	- 0.001	- 0.018	- 0.010
Ireland	- 0.001	- 0.025	- 0.013
Slovakia	- 0.000	- 0.013	- 0.007
Slovenia	- 0.001	- 0.016	- 0.008
Luxembourg	- 0.000	- 0.012	- 0.006
Latvia	- 0.001	- 0.023	- 0.012
Estonia	- 0.001	- 0.023	- 0.012
Malta	- 0.001	- 0.044	- 0.023
Total Losses	**- 0.012**	**- 0.372**	**- 0.194**

Table 7

Bank defaults caused by the Sovereign Credit Risk channel. The table presents bank-failures generated by a 10% negative shock at the Sovereign Credit Risk channel and by banks whose default triggers a bank failure from the propagation of financial contagion. The propagation takes into account the total capital buffers for each banking system, while most of the banks are contagious for a loss rate equal and greater than 0.1.

COUNTRY	**Banks failing by losses**		**Banks failing by Contagion**	
	Number of banks	Large banks	Number of banks	Large banks
Austria	2	0	4	1
Belgium	2	0	4	1
Estonia	1	0	4	1
Finland	2	0	4	1
France	10	0	19	2
Germany	21	0	29	1
Greece	1	1	4	4
Ireland	2	0	5	1
Italy	2	0	3	1
Latvia	2	2	2	2
Luxembourg	0	0	0	0
Malta	0	0	0	0
Portugal	4	0	8	2
Slovakia	3	0	5	1
Slovenia	1	0	4	3
Spain	2	0	6	1

Table 8

Bank defaults prompted by the Asset-backed Loan channel. The table exhibits bank-failures generated by a 10% negative shock at the Asset-backed Loan channel and by banks whose default triggers a bank failure from the propagation of financial contagion. The propagation takes into account the total capital buffers for each banking system, while most of the banks are contagious for a loss rate equal and greater than 0.1.

COUNTRY	**Banks failing by losses**		**Banks failing by Contagion**	
	Number of banks	Large banks	Number of banks	Large banks
Austria	0	0	0	0
Belgium	1	0	1	0
Estonia	0	0	0	0
Finland	1	0	1	0
France	2	0	6	0
Germany	3	0	9	0
Greece	0	0	0	0
Ireland	0	0	0	0
Italy	0	0	0	0
Latvia	1	1	2	2
Luxembourg	0	0	0	0
Malta	0	0	0	0
Portugal	1	0	0	0
Slovakia	1	0	0	0
Slovenia	1	0	1	0
Spain	1	0	2	0

Table 9

Bank defaults provoked by the Interbank Loan Market. The table exhibits bank-failures generated by a 10% negative shock at the Interbank Loan Market channel and by banks whose default triggers a bank failure from the propagation of financial contagion. The propagation takes into account the total capital buffers for each banking system, while most of the banks are contagious for a loss rate equal and greater than 0.1.

COUNTRY	Banks failing by losses		Banks failing by Contagion	
	Number of banks	Large banks	Number of banks	Large banks
Austria	1	0	3	1
Belgium	2	0	4	1
Estonia	1	0	4	1
Finland	1	0	2	0
France	6	0	11	0
Germany	13	0	17	0
Greece	1	1	1	1
Ireland	1	0	2	0
Italy	1	0	2	0
Latvia	2	2	2	2
Luxembourg	0	0	0	0
Malta	0	0	0	0
Portugal	2	0	6	0
Slovakia	1	0	3	0
Slovenia	1	0	4	3
Spain	1	0	3	0

Table 10

Cross-border Euro Area bank defaults provoked by a 10% negative shock in the German Interbank Loan Market. The table displays bank-failures in the Euro Area, generated by a 10% negative shock at the German Interbank Loan Market and by banks whose default triggers a bank failure from the propagation of financial contagion. The propagation takes into account the total capital buffers for each banking system, while most of the banks are contagious for a loss rate equal and greater than 0.1.

COUNTRY	Banks failing by losses		Banks failing by Contagion	
	Number of banks	Large banks	Number of banks	Large banks
Austria	3	0	5	1
Belgium	4	1	4	1
Estonia	2	0	4	1
Finland	2	0	4	1
France	14	0	21	3
Greece	4	0	7	2
Ireland	3	1	3	1
Italy	2	2	2	2
Latvia	0	0	0	0
Luxembourg	0	0	0	0
Malta	6	0	9	3
Portugal	5	1	5	1
Slovakia	4	3	4	3
Slovenia	6	1	7	2
Spain	3	0	5	1