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Agent-Based Risk Assessment Model of the European Banking Network

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Agent-Based Risk Assessment Model of the European Banking Network[1]

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Abstract

The 2007-2009 financial crisis highlighted the vulnerabilities in the global banking system and shifted research focus to the study of systemic risk. Network theory and agent-based simulation have been used to investigate complex banking systems that would be difficult to model analytically. Nevertheless, the difficulty of obtaining accurate data, as well as the computational complexity of running such models, are limiting their ability to capture the complexities that are emerging in real-world scenarios. In this paper, we use an agent-based simulation combined with innovative calibration techniques in order to model the European banking system as accurately as possible. We extend the existing network approach by adding the ability to model banks of different sizes as well as the detailed connections of individual banks across countries. Our model consists of 286 banks in 9 European countries. We believe that the experiments in this model provide valuable insights into systemic risk within the European banking system as well as useful guidelines for creating new policies.

Keywords: *C63, D85, G21*

JEL Classification: *agent-based models, bank, contagion, network models, systemic risk*

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1 INTRODUCTION

A noticeable trend of increasing complexity and interdependencies has been observed in contemporary financial systems. Modern markets bring together a diverse group of stakeholders that form a rich network of interdependencies through a wide set of possible actions. The wide use of financial products such as collateralized debt obligations and exotic derivatives are further convoluting the balance sheets of their users as well as the overall structure of interconnections. Over recent decades, the international integration and regulation relaxations have added even more interconnectedness and concentration to the global financial system. In such an environment, systemic risk emerges as a key issue, as a failure of individual banks may impose large costs on the entire system.

As dramatically demonstrated during the global financial crisis of 2007-2009, the relevance of systemic risk was significantly underestimated. Before the crisis, financial regulators and central banks were mostly focused on ensuring the liquidity of individual banks and the risk of contagion was, in general, considered to be low (Furfine, 2000). However, the collapse of Lehman Brothers and American International Group (AIG) has shown that feedback elements in interconnected networks have the potential to amplify the shocks in financial systems. These highly undesirable effects of systemic risk, interconnectedness and shock propagation have attracted significant research interest (Gai and Kapadia, 2010; Chui et al., 2010, Haas and Horen, 2012).

The regulatory bodies responded to the crisis as well, for example by updating the Basel II recommendations – the revised version, Basel III attempts to add robustness to the system by adding mechanisms for increasing the resilience of banks to transient shocks (Basel Committee, 2013). Additionally, the European Banking Authority has performed stress-tests of the EU banking sector (Basel Committee, 2010). Despite the soft assumptions that were taken in these tests, these results were subject to criticism, as well as the overall Basel III framework (Sutorova and Teply, 2014).

Current research typically uses two central concepts: (1) *network theory* and (2) *agent-based modelling*. Network theory is a branch of mathematics that studies relations of mutually connected entities (Sneppen, 1997). It is a natural choice for representing banking networks as it offers various methodologies for studying their structure and properties. Using the network theory, banking systems are represented as networks of interconnected nodes. Agent-based modelling provides tools for studying collective behaviour under various conditions, using computer simulations. This approach consists of precisely defining the behavioural rules for each agent and the set of data available to agents. In a computer simulation, the agents are brought together in an environment that can be set up according to the experimental goals. If the behavioural rules are sufficiently detailed and realistic, such simulations can bring valuable insights into the interactions of agents, and their influence on each other as well as the environment. In the agent-based simulations of banking systems, mutually connected agents represent individual banks, data they hold, their balance sheets and a set of behavioural rules e.g. when to sell assets or when to default etc. Combining the network theory and agent-based modelling approaches provides a set of tools that can be used to predict how the actions of individual banks on the market in case of a shock propagated through the banking system.

Current research in applying these methods to the field of banking system stability divides into two main streams: (1) *empirical research* and (2) *theoretical models.* Theoretical models examine how system behaviour is influenced by general characteristics of the system. Some of the key research questions these papers cover are related to the level of interconnectedness – higher risk sharing lowers the risk of a default; however if a default happens, a high number of connections increases the likelihood it will disperse (Upper, 2010; Gai et al., 2011).

The first network model based research of systemic stability was performed by Allen & Gale (2000) who investigated the liquidity shocks contagion. Other early research was carried out by Freixas, et al. (2000), who studied banks with systemic importance and provided recommendations for central bank interventions. Cifuentes, et al., (2005) and Shin (2008), add a market liquidity contagion channel which decreases the price of illiquid assets. There are studies that analyse systemic stability by simulation experiments on random networks, under varying conditions such as connectedness and exposure (Nier, et al., 2007; Gai & Kapadia, 2010; Georg 2013), risk diversification, innovation and leverage (Devereux & Yetman, 2010; Battiston et al., 2012; Caccioli et al, 2012; Corsi et al., 2012, Wincoop, 2013). Regulatory requirements are investigated in Klinger & Teply (2014a) and Chan-Lau (2014) who estimate the influence of capital buffers on system stability, bank solvency and interconnectedness as well as measures to contain the contagion during a financial turmoil. Finally, Klinger & Teply (2016) add state aid to the banks as a means of mitigating systemic crises.

These works are theoretical rather than empirical, with exceptions such as Upper and Worms (2004) focusing on the German interbank market or Van Lelyveld and Liedorp (2006) analysing the Dutch market. More recently, several realistic models of the global bank market were devised (Hale et. al., 2011; Hale 2012; Montagna & Kok, 2013; Gross & Kok, 2013;

Minoiu & Reyes, 2013). Additionally, Nirei et al. (2015) calibrate the loan syndication networks model to the broad market data. The limited empirical literature of systemic risk modelling is understandable, since the simulation of network structures is computationally very costly (Halaj and Kok, 2013).

Several studies concentrate on real-world interbank exposure modelling. For example, Boss, et al. (2004), Upper & Worms (2004), Wells (2004), van Lelyveld & Liedorp (2006) and Muller (2006) analyse the banking systems of Austria, Germany, the United Kingdom, the Netherlands and Switzerland respectively. Recently, Halaj and Sorensen (2013) tried to approximate a network of the banks that reported during the 2010 and 2011 EBA stress tests (EBA, 2011). Finally, Craig & Peter (2014) investigated the tiered structure of the real-world German banking network. However, most researchers face the problem of virtually non-existent reliable data on individual interbank exposures. This work combines theory and empirics as the model is calibrated to the real-world data of the European banking network.

Our approach builds upon the probabilistic network model proposed by Gai et al., 2010. and the simulation models by Nier et al., 2007 and Klinger & Teply (2013). We devise a realistic model of the European banking system, based on the available data on interconnections among the banks. In this way, we would like to help bridge the aforementioned gap between theoretical insights and practical research based on current real-world data. We simulate the behaviour of the European banking system when hit by an adverse shock event such as a bank default. Unlike in Klinger & Teply (2013), where the banking system of each country is represented by a single node, we take into account the multitude of banks in each country. We also add further detail to the simulation, by introducing the ability to model banks of different sizes. Banking networks within individual countries are modelled based on real data, including the market concentration, competition and relative power of large vs. small banks, in order to represent the market structures across countries as faithfully as possible. Put differently, the value-added of our research is adding bank heterogeneity to the modelling.

The main goal of this research is to shed a light on the real interconnectedness between 9 Eurozone banking sectors and estimate the levels of shock propagation in large-scale events such as defaults of multiple banks, as well as smaller events such as defaults of an individual bank. It is our hope that these findings might assist EU policy makers, including the European Central Bank (ECB) when estimating systemic effects of bank defaults. This paper is organised as follows: Section 2 brings the description of the used network model while the agent-based shock modelling is described in Section 3. System calibration to real data is described in Section 4 and Section 5 brings the results. Section 6 concludes.

2 THE MODEL

We devise a model of the European banking system for evaluating the systemic risk of various inter-banking connection patterns. Our approach consists of (1) the network structure and (2) policies for shock modelling. The network model is a general representation, that can be used for simulating an arbitrary banking system and is, therefore, a highly flexible framework for experiments with hypothetical scenarios as well as the modelling of current, real-world banking networks. Nevertheless, it is a static data structure to which a dynamic component is added through the means of agents, representing individual banks. As precise descriptions of bank behaviour are added, the interdependent banks can interact in a simulation. Having defined the initial connections network and the rules of the dynamic behaviour, it is possible to simulate the system behaviour when hit by an adverse shock. The network model is described in Section 2.1 while the behaviour specification for agents is given in Section 2.2.

2.1 BANK NETWORK MODELLING

The banking network $\mathrm{G} = (\mathrm{V}, \mathrm{C})$, is a directed weighted network consisting of a set of nodes *V* and a set of connections *C*. Each bank corresponds to a single node from the set *V*. Two nodes *j* and *k* are connected if, and only if, there is debt exposure between the banks corresponding to nodes *j* and *k*. If there is a connection between *j* and *k*, set *E* contains the ordered pair (*j*, *k*). All connections in the network are directed, meaning that debt exposure from *j* to *k* doesn't imply the opposite. Furthermore, each connection is weighted, meaning that a debt value is associated with each connection. Each node is associated with (1) balance sheet information and (2) debt exposure data for the bank.

For each pair of banks (*j*, *k*), the debt exposure of *j* to *k*, denoted $w_{jk}^{IN} = w_{kj}^{OUT}$ is defined as bank *k* owing the quantity *w* to the bank *j*. Notice the symmetry of the debt, denoted with the superscript "out" and the exposure, denoted with the superscript "in". Combined together, all the debt data forms the debt structure in the system.

The balance sheet data associated with each node contains the bank assets and liabilities. During the simulation run, the balance sheet is being updated to reflect the current bank balance. An example bank sheet is given in Table 1.

At the moment of network initialization, the total value of assets for bank *i* is defined as a sum of interbank assets (i_j), sovereign debt (s_j) and external assets (e_j):

$$a_j = i_j + s_j + e_j.$$

The value of *interbank assets* of the bank is the sum of all loans in the network and for an individual bank *i*, it is equal to the sum of exposures towards other banks in the system:

$$i_j = \sum_{k \in N(j)} w_{jk}^{IN} ,$$

Where $N(j)$ is the set of nodes connected to the node *j*.

Sovereign debt, denoted s_j is defined as the sum of a bank's exposures towards the local sovereigns. Finally, the *external assets*, denoted e_j for a bank is the sum of the bank's exposures outside the banking network, such as households, foreign sovereigns and non-national financial institutions. The sum of all external assets in the network, denoted *E* is the sum of external assets of all individual banks.

The value of *liabilities* for a bank *j*, denoted l_j is defined as a sum of interbank liabilities (b_j), external liabilities (d_j) and the capital reserve:

$$l_j = b_j + d_j + c_j.$$

The *interbank liabilities* are the sum of all loans in the network, and for an individual bank *i* is the sum of debt to other banks in the system:

$$b_j = \sum_{k \in N(j)} w_{jk}^{OUT} ,$$

where $N(j)$ is the set of nodes connected to the node *j*.

External liabilities are defined as a sum of bank exposures outside the network, such as loans to households, foreign sovereigns and non-national financial institutions. The value of *capital reserve* represents the security buffer for covering potential losses.

*Table 1: Balance sheet of the bank **j** in the network*

a_j TOTAL ASSETS	l_j TOTAL LIABILITIES
i_j **interbank assets**	$\boldsymbol{b_j}$ interbank liabilities
s_j **sovereign debt**	$\boldsymbol{d_j}$ external liabilities (deposits)
e_j **external assets**	$\boldsymbol{c_j}$ capital reserve

Note: For simplicity we assume that all the interbank assets and interbank liabilities are unsecured.

Source: Authors

2.2 Agent-based Contagion Simulation

To investigate the interactions among a network of banks, bank behaviour is modelled by rules of agent behaviour under various possible conditions. We focus on the actions of banks under stress and develop behaviour rules for events related to the systemic shock propagation: when to default and when to perform asset fire-sales. The simulation starts by deduction of a share of external assets from the balance sheet of a selected bank or a group of banks. A balance sheet shock originating from that bank follows in the entire system. Similarly, at the beginning of each next simulation iteration, every bank may receive a total asset-side shock of Δ=δ+*PriceShock*, whose individual components are described in detail below. The stress propagates through the network triggering actions of distressed banks and the simulation continues until the initial shock is completely dissolved and stops being transmitted further onto other agents.

If the banks affected by the primary shock do not possess sufficient capital buffers, a process of cascade contagion might unfold, as manifested by further transmission of the shock to other banks in each iteration. Each iteration is assumed to last an unspecified period of time. In reality, this depends on the maturity structure of the debt and the regulation regarding the procedure of writing off bad debts. Every shock is reflected in the balance sheet of banks that were affected, as they lose a certain part of their assets, and in the simulation the bank writes off an equal value of liabilities in order to balance assets with liabilities. The bank first tries to absorb the shock using the owners' equity; however, if the capital buffers are not large enough, the banks default on the claims of other creditors.

The shock a j-th bank receives is a total shock received from all exposures and translates into a gap between its assets and liabilities. When the bank j suffers a shock of size $\Delta_{j,t} = \mathrm{l}_{j,t} -$

$a_{j,t}$ during the simulation iteration t, its external behaviour depends on the shock size relative to its balance sheet structure. The behaviour of the bank is defined as follows:

a) The bank tries to absorb the shock using its capital reserve. If $c_{j,t} \geq \Delta_{j,t}$, the bank is able to cover the losses by its own funds, and the capital covers the cost. The bank does not propagate the shock further to other banks in the system.

b) If $c_{j,t} < \Delta_{j,t}$, the bank cannot cover the losses using its own reserve and therefore it defaults. [2]The residual shock overflows to interbank liabilities b_j. In this case, its value up to the value of interbank liabilities $b_j$is uniformly divided into losses of all creditor banks. In the case of m creditor banks, in the next simulation iteration, each creditor k will receive a shock $\delta_{jk,t+1}$ from the bank j:

$$\delta_{jk,t+1} = min\left(\frac{\Delta_{j,t} - c_{j,t}}{m_{j,t}}, \frac{b_{j,t}}{m_{j,t}}\right). \quad (1)$$

As the bank defaults, it is removed from the network and doesn't participate in the system in subsequent iterations. Furthermore, each creditor bank evaluates the received shock in the next iteration.

Additionally, it holds that:

i. If $b_{j,t} \geq \Delta_{j,t} - c_{j,t}$, the shock is absorbed by the bank's capital and interbank liabilities.

ii. If $b_{j,t} < \Delta_{j,t} - c_{j,t,}$, the shock overflows to external liabilities, meaning that the residual loss is covered by the depositors.

Two types of liquidity issues can affect a stressed financial system: (1) *market illiquidity* and (2) *funding illiquidity*. Market illiquidity, first described by Kyle, 1985, is a situation when asset selling negatively impacts their prices. The funding illiquidity is the inability to meet the due obligations. During the recent financial turmoil, both issues were evident as an unexpected gap in short-term bank financing caused funding illiquidity on the liability side and the resulting fire-selling of assets promoted a further rapid decline in asset prices. To

[2] The model as described in the paper allows banks to operate with capital close to a zero level. However, in reality supervisors claim they would revoke the license much earlier, e.g. at 4.5%. However, given a major systemic shock, the regulators cannot easily afford to close banks down immediately and the regulatory behaviour is subject to dynamic inconsistency. The rationale is discussed in more detail in Klinger & Teply (2014a).

enable realistic simulations of the system, both illiquidity types are accounted for in our model.

Following Gai, et al. (2010), we assume that the banks in default have to liquidate all their assets before they can be removed from the network. The sovereign debt is entirely liquidated as it is assumed to be more liquid. However, the low market depth might limit the capacity to absorb external and interbank assets and under these conditions it will not be possible to sell them for the prices on the bank's balance sheet. Based on Cifuentes, et al, (2005), we calculate the discounted external asset price at iteration *t*, denoted $P(\boldsymbol{x})_t$ is calculated using an inverse demand function:

$$P(\boldsymbol{x})_t = \exp\left(-\frac{\alpha}{E_t}\sum_{j=1}^{|V|} x_{j,t}\right), \quad (2)$$

where α represents the market's illiquidity (the speed at which the asset price declines) $|V|$ is the number of banks (nodes) in the network, E_t is the total value of external assets in the system and $x_{j,t}$ is the initial value of external and interbank assets being sold by the bank *j* during the iteration *t*. The additional loss caused by the asset sales are added to the initial shock on the i-th bank in the current lap and transmitted accordingly.

Using the mark-to-market accounting procedure, at the end of each iteration, the external assets of each bank are revaluated, so that the value during the iteration *j+1* is defined as:

$$e_{j+1} = e_{j,t} P(\boldsymbol{x})_t.$$

Therefore, the value of price shock for all banks in the iteration t+1 is the result of losses resulting from these price adjustments:

$$PriceShock_{j,t+1} = e_{j,t}(P(\boldsymbol{x})_{t-1} - P(\boldsymbol{x})_t).$$

Furthermore, as the failing bank liquidates all of its assets, it may withdraw a certain part of short-term credit claims on other banks. For this reason, the debtors of the failing bank may receive an additional funding liquidity shock. This shock is evaluated using the above rules, as a decrease in the liabilities and may require them to sell a part of their assets to balance out the gap in funding (Chan-Lau, 2010). More formally, if the bank *j* defaults, the related part of interbank liabilities $b_{kj} = i_{jk}$ of its debtor k gets erased from the debtor k's total liabilities so that

$$l_{k,t} = l_{k,t-1} - b_{kj,t}.$$

As a result, the k-th bank is forced to fire-sale external assets equal to the value of the funding shock. This amount of external assets is added to the total amount that the banks in the current iteration offer on the market for sale and the k-th bank receives for it the amount of $P(\boldsymbol{x})_t b_{kj,t}$, which is the price of the assets under current market valuation. The value of the loss $b_{kj,t} - P(\boldsymbol{x})_t b_{kj,t}$ is added to the k-th bank's credit shock.

3 System Calibration

The focus of this research is insight into the real-world banking network in Europe and providing a contribution to the ongoing debates about the banking sector stability and systemic risk. While the simulation approach described is applicable to arbitrary banking networks and behaviours, the key goal of the study is to find realistic data and calibrate the devised model to represent the real-world environment with a high degree of accuracy and realism.

We include the following countries in our simulations: Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain. However, as documented by many authors, e.g. Mistrulli, (2011), the full data on mutual exposures of the real-world banks is not available. Therefore, we resort to proxy data inferred from available sources to build the interbank network approximation which is as close to the real-world as possible. The banks in our system are approximated based on their home country parameters, such as the total asset amount and structure of the banking sector (EBA, 2011), the number of banks and market concentration in the given country (ECB, 2014). The structure of the interbank network is approximated from high-level aggregate data on banking systems according to the positions reported to the BIS (BCBS, 2009; BCBS, 2013).

The calibration consists of (1) bank market structure estimation in each country and (2) interbank debt structure estimation. Unlike the previous work in Klinger & Teply (2014), where banking systems for each country were highly simplified and represented as a single node, we wanted to add more detail to the study and model individual banks in each country. For this reason, we developed a set of tools to use the incomplete data about the bank interdependencies to estimate both the market structure in the countries we simulate as well as the connections among the banks (both locally and internationally).

3.1 BANK SIZE ESTIMATION

As the banks in the countries of our model are different, the homogeneity assumption of Klinger & Teply (2014) is relaxed. In this work, we provide more detail in the model and take bank sizes into consideration. We introduce three types of bank sizes: small, medium and large banks. To determine the number of banks and the relative asset share in each category, we investigate the structure of the real-world banking networks: the aggregate balance sheet data and the market concentration in each country of the model.

We created representative balance sheets for each bank type, i.e. for large, middle and small banks (Table 2). The size definitions are based on the asset size criterion and the representative balance sheet for each size is derived by analysing the patterns in the balance sheets of real-world banks (Gambacorta & Rixtel, 2013.; European Central Bank, 2015).

Table 2: Illustrative balance sheets of large, middle and small bank

LARGE BANK			
Share	**TOTAL ASSETS**	**TOTAL LIABILITIES**	**Share**
15.0%	sovereign debt	interbank liabilities	25.0%
25.0%	interbank assets	external liabilities (deposits)	70.0%
60.0%	external assets	equity (capital buffer)	5.0%

MIDDLE BANK			
Share	**TOTAL ASSETS**	**TOTAL LIABILITIES**	**Share**
20.0%	sovereign debt	interbank liabilities	10.0%
10.0%	interbank assets	external liabilities (deposits)	80.0%
70.0%	external assets	equity (capital buffer)	10.0%

SMALL BANK			
Share	**TOTAL ASSETS**	**TOTAL LIABILITIES**	**Share**
30.0%	sovereign debt	interbank liabilities	5.0%
5.0%	interbank assets	external liabilities (deposits)	80.0%
65.0%	external assets	equity (capital buffer)	15.0%

Source: Authors based on ECB and BIS

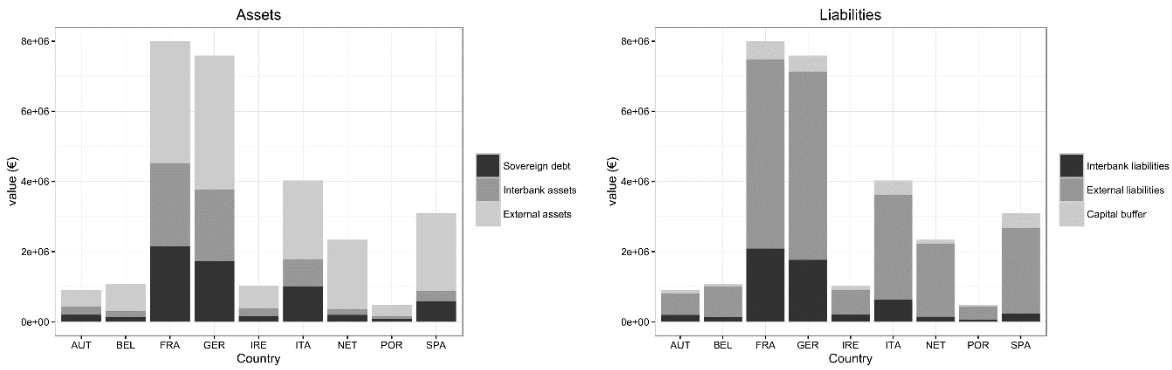
We classify bank markets into three categories: low, medium and highly concentrated, and use the Herfindahl index (HI) to determine categories for each market. The HI values are in between 0 and 10,000. Values below 500 indicate low market concentration, values in between 500 and 1100 indicate medium and the values above 1100 correspond to high concentration (Hake, 2012). Based on the real-world data for the banks in the model (BCBS, 2009; BCBS, 2013), we define prototype country market shares, depending on the market concentration and assume that the markets with low concentration have small banks summing up to 45% market share, 15% market share for medium-sized banks and 40% share of large banks. In the moderately concentrated market prototype, small banks have 15% market share, mid-sized 25% and large 60%. Finally, the highly concentrated market prototype has the small bank market share of 10%, medium-sized 20% and the remaining 70% is composed of large banks. The resulting estimates of the shares are detailed in Table 3.

Table 3: Estimated shares of different sizes of banks in the observed banking sectors

Country	Herfindahl index (2013)	Market concentration	Small banks share	Medium banks share	Large banks share
AUT	405	LOW	0.45	0.15	0.40
BEL	979	MEDIUM	0.15	0.25	0.60
FRA	551	MEDIUM	0.15	0.25	0.60
GER	266	LOW	0.45	0.15	0.40
IRE	674	MEDIUM	0.15	0.25	0.60
ITA	406	LOW	0.45	0.15	0.40
NET	2104	HIGH	0.10	0.20	0.70
POR	1196	HIGH	0.10	0.20	0.70
SPA	757	MEDIUM	0.15	0.25	0.60

Source: Authors based on ECB data

Figure 1: Summarised balance sheet structure for the banks in the network.



Source: Authors based on data from BIS International Financial Statistics

We calculated the estimated structure of each national banking sector based on data available from the ECB (BCBS, 2009; BCBS, 2013). For example, Table 4 presents an aggregated balance sheet of the German banking sector with total assets worth EUR 7.6 trillion as of 31 December 2013. The banking sector balance sheet for each country and bank type (Table 2) can be used to simply calculate the aggregate balance sheets for large, middle and small banks in each country. The assets of each size group are calculated based on the total assets for the country and estimated shares of each size group (Table 2). The assets are further split into assets of each individual bank, dependent on the bank number in each size group. The individual banks balance sheets are calculated based on the balance sheet prototypes (Figure 1). The total number of the banks in the network is 286. While we do not present balance sheets of all banking sectors due to size constraints for this paper; however, the complete data is available on request.

Table 4: An aggregated balance sheet of the Germany banking sector as of 31 December 2013 (EUR millions)

Share	**Value**	**TOTAL ASSETS**	**TOTAL LIABILITIES**	**Value**	**Share**
22.8%	1 728 323	sovereign debt	interbank liabilities	1 766 438	23.3%
27.0%	2 046 832	interbank assets	external liabilities (deposits)	5 366 262	70.7%
50.3%	3 814 082	external assets	equity (capital buffer)	456 537	6.0%
Total	7 589 237			7 589 237	

Source: Authors based on ECB and BIS data

Table 5: Illustrative balance sheets of a large. middle and small bank in Germany

LARGE BANK					
Share	**Value**	**TOTAL ASSETS**	**TOTAL LIABILITIES**	**Value**	**Share**
15.0%	75 892	sovereign debt	interbank liabilities	126 487	25.0%
25.0%	126 487	interbank assets	external liabilities (deposits)	354 164	70.0%
60.0%	303 569	external assets	equity (capital buffer)	25 297	5.0%
Total	505 949			505 949	

MEDIUM BANK					
Share		**TOTAL ASSETS**	**TOTAL LIABILITIES**		Share
20.0%	45 535	sovereign debt	interbank liabilities	22 768	10.0%
10.0%	22 768	interbank assets	external liabilities (deposits)	182 142	80.0%
70.0%	159 374	external assets	equity (capital buffer)	22 768	10.0%
Total	**227 677**			**227 677**	

SMALL BANK					
Share		**TOTAL ASSETS**	**TOTAL LIABILITIES**		**Share**
30.0%	40 982	sovereign debt	interbank liabilities	6 830	5.0%
5.0%	6 830	interbank assets	external liabilities (deposits)	109 285	80.0%
65.0%	88 794	external assets	equity (capital buffer)	20 491	15.0%
Total	**136 606**			**136 606**	

Source: Authors based on ECB and BIS

3.2 INTERBANK DEBT STRUCTURE ESTIMATION

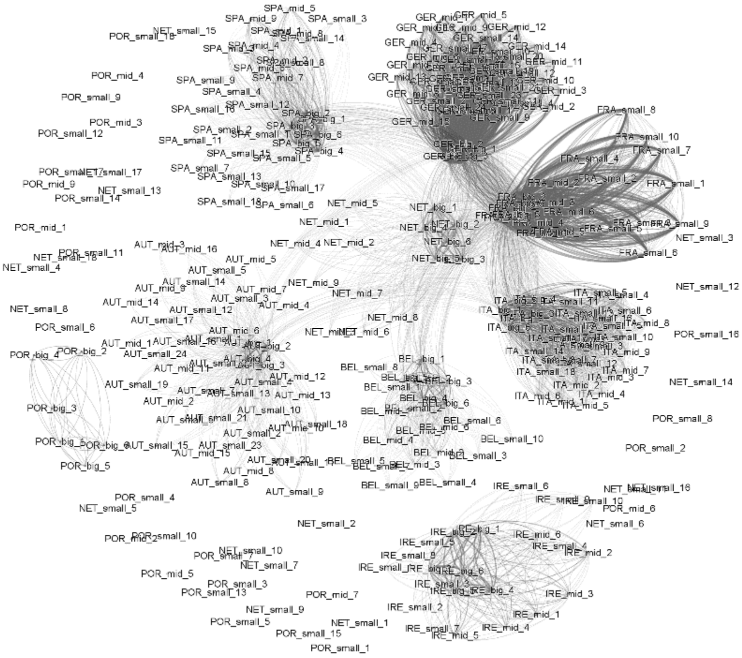
To estimate the structures of dependencies that connect the banks into a network, we explore the interbank exposure datasets from the BIS International Financial Statistics (BCBS, 2013). In these datasets, the central banks compile national aggregate data for the banks in their jurisdictions. The interbank exposure matrix is inferred from the consolidated statistics of foreign claims on an immediate borrower basis. The aforementioned data provides insight into the exposures of domestically-owned parent banks on the highest consolidation level. Therefore, they include banks' external exposures of foreign offices and exclude all internal inter-office positions in the consolidation group (BCBS, 2009).

Nevertheless, to the best of our knowledge, there are no publicly available data on pure bank-to-bank exposures between the banking sectors in the individual countries. Therefore, a certain level of approximation is inevitable. We ground our estimates in the BIS total claims dataset that contains information about total exposures among pairs of countries from our model. However, as it is not possible to obtain directly the pure bank-to-bank exposures between the individual countries' banking sectors, some level of approximation is inevitable. To estimate the bank-to-bank exposures from the reporting banking sectors' pool of total claims, we employ another dataset of the BIS statistics, which is the total claims on each country's banking sector by all the reporting sectors, grouped by the type of the debtor institution (i.e. whether it is a bank, public sector or a non-bank private sector.

Combining the two datasets and calculating the banking sector percentage in the known total exposure, it is possible to obtain proxy variables for pairs of banking sectors in the model we are calibrating. The interbank exposures for individual banks are calculated by distributing the exposures of the sector interdependencies, proportional to the individual bank exposures as defined in the large/medium/small structures. When the network is created, it can be plotted as shown in

Figure 2.

Figure 2*: Interbank network of the selected countries as of Q4 2011*



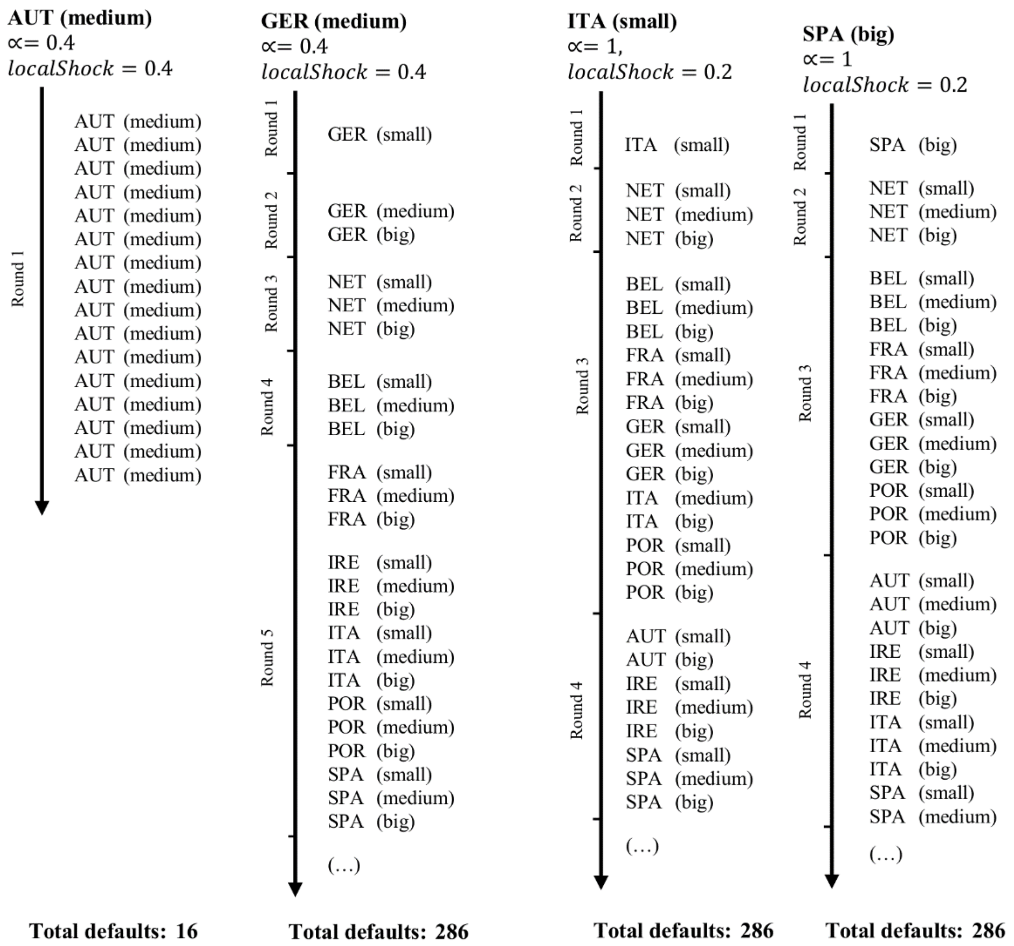
Source: Authors based on data from BIS International Financial Statistic

4 RESULTS

We run a number of experiments based on the model developed. The behaviour of the system was tested under various conditions – we wanted to investigate the influence of the shock size and market illiquidity factor α. For example, if $\alpha = 1$, it means that 10% of external assets sold by the defaulting banks impose a 10% price shock at the external assets on the balance sheets of other banks. In a perfectly liquid market, this parameter equals to zero. With our analysis, we focus on the range $\alpha \in [0,2]$ as increasing the parameter even further leads too often to total collapse of the system. The range used is in line with Nier, et al., 2007, who uses a range of $\alpha \in [0,3]$. In the examples below, we focus on values where there are interesting breakpoints for different countries (partially illustrated in Figure 10).

A series of experiments was performed to investigate different combinations of these parameters in order to assess their mutual influence on systemic risk. Additionally, the effects of failures originating from different countries were analysed. This way, unique local market features can be considered. The results have shown that the system behaviour is significantly influenced by the investigated parameters. Furthermore, their interpretation might provide insights into the influence of interconnectedness and size on the systemic stability in the present banking system. Figure 3 presents a detailed timeline of the simulation events under various settings and when starting with a shock in different countries. It is clear that shocking the midsize Austrian banks does not cause much distress in the entire system, in that manner pointing out the robustness and the low systemic risk of the Austrian sector. While 16 Austrian banks fail, causing a damage to the system, the contagion does not spread further and the banks outside Austria remain stable. In other examples, we present setups that have caused a total banking system collapse, causing all 286 banks in the network to shut down. Such cases are large shocks to the medium German banks under relatively liquid market as well as moderate shocks to small Italian and large Spanish banks under higher illiquidity.

Figure 3: Detailed timeline of bank failures after a shock in diffferent countries under various settings



The issue of interconnectedness is a widely-studied area that is especially interesting to investigate using the model devised in our work. We provide confirmations that the notion of "too connected to fail" and measures such as node degree and feedback centrality provide valuable metrics for estimating the systemic risk. Imposing a shock - a share of external assets is deducted from a random bank's balance sheet- on highly interconnected banks is highly risky for the entire system as they propagate the shock to a large number of other banks. A good example of this are the experiments in shocking the large French banks.

Figures 4-9 show the results of the experiments where a group of banks from a certain country receives the shock. On the x-axis, the banking sectors in each country are placed in the same order across all charts. The y-axis displays the intensity of a shock, as a part of the bank assets. The value of the losses and number of failing banks are represented as heat maps so that the lowest value and the best possible outcome correspond to white. The highest losses and the highest number of failing banks are the worst possible outcome and are drawn in black. It is clear that even with low illiquidity levels, shocks larger than 0.4 have the potential to lead to a total collapse of the entire system. With moderate illiquidity level, this effect happens regardless of the shock size and even the lowest tested shock size (0.2) causes all the capital to be wiped out of the system. From the point of view of the depositor loss, this scenario is nevertheless relatively mild compared with shocks to other large banking systems. This can be explained by the fact that the collapse happens very quickly due to the high level of interconnectedness. However, the asset losses are not high as the liquidity channel is not as intense in this case.

With alpha equal to 0.4 and 40% of external assets liquidated, the large French banks are unable to absorb the shock and fail in the first lap. In the second lap, the shock is transferred to all the other French banks. This is due to the fact that the interbank connections are the strongest among banks in the same country and in this case, the shock propagates almost entirely by the interbank transmission channel. In the subsequent rounds, both channels are active and cause the Dutch banks to fail in the third lap, Belgian in the fourth and all others except the Austrian banks in the fifth. The Austrian banking system is the most resilient thanks to its high capital buffers and fails last, in the sixth lap.[3] In this scenario, the simulation ends with all the banks in the system closing. This is clearly evident in the case when alpha is equal to 1 as well, as shown in Figure 4 and Figure 8.

Great turmoil is produced when small German banks are affected by a shock. In this case, the liquidity channel is comparatively stronger, as can be seen in Figure 5. While the system

[3] We should note that the Austrian banking system has not been reporting strong capital positions in the last years, though improving recently. However, its weak capital position was primarily due to poor performance of the sector´s subsidiaries in Central and Eastern Europe (including higher credit risk in Ukraine and bank taxes in Hungary) rather than due to losses stemming from the interbank market.

doesn't fail completely for $\alpha = 0.2$, it is enough to increase it to $\alpha = 0.4$ and create an impact of 40% of the assets for the entire system to collapse. Counterintuitively, with $\alpha = 0.4$, the system is more stable when stronger shocks are imposed on the small German banks. In this case, only the German banking system shuts down while the remainder of the European system is able to handle the crisis. Similar results, when a higher intensity of the simulated shock causes fewer banks to fail and less capital loss is evident occur for the small Italian, Spanish and French banks, as seen in Figure 5. This is explained by the fact that the small banks have fewer external assets to fire-sale, therefore putting less influence on the entire system. Conversely, in the cases of high illiquidity, the entire system can quickly collapse when similar disturbances are imposed on banks which have a lot of external assets. As the initial group gets a certain part of their external assets wiped out, if the losses are large enough, the failing banks are forced to sell the rest of their external assets. As the price of the overall external assets depends on the amount of those sold in each simulation round, intense selling has the potential to decrease the asset value and therefore produce indirect pricing shocks to all banks in the system. Therefore, it appears that it might be better if failing banks quickly default due to large shocks than if they keep failing for a considerable time. If the bank defaults right away, aside from the first level of immediate losses, the system recovers as the system – wide shocks transmitted by the liquidity channel do not appear. This is because the assets immediately written off as the part of the initial shock do not have to be sold on the market. However, indeed, these create significant depositor loss which in reality has to be covered up by state support or deposit insurance. The subsequent effect on financial stability when state support channels are accounted for and the transfer of the risk between the public support measures and financial system is discussed in detail in Klinger & Teply (2016).

Among the national banking systems we have identified that large Italian and Spanish banks comprise the highest risk to system stability. In Figure 5 and Figure 8, it can be seen that hitting a small portion of external assets of large Spanish banks results in total systemic collapse when the market is not deep enough to absorb the flood of assets being liquidated in fire sales. Additionally, the less liquid the system is, the fewer asset sales are needed to bring the system to collapse. In these cases when all the banks fail, the entire capital pool of the banking system is wiped out. The depositor losses are not as severe as in cases of larger shocks that propagate mainly through the interbank network.

With alpha equal to one and 20% of external assets liquidated, the large Spanish banks cannot absorb the shock and fail in the first simulation round. In the second round, the shock is transferred to all Dutch banks, which do not hold sufficient capital reserves to withstand even the lesser shocks initiated by the Spanish banks fire-selling their assets. In the following rounds, the Belgian, Portuguese, German and French banking systems fail, which finally leads to the failure of the rest of the system. As the chain reaction of decreasing asset prices is very strong, even the robust banking systems such as that in Austria cannot withstand the crisis. It is interesting to point out that the medium and small Spanish banks failed only in the last round, which provides additional evidence that this shock does not progress through the interbank network but externally via the liquidity channel. Increasing the shock intensity lowers the total losses in the entire system, as can be seen in Figure 4 and Figure 8. The progress is very similar to the case of shocking small Italian banks when wiping off 20% of their external assets and alpha set to 1.2.

Total capital losses further show the noticeable influence of illiquidity on the entire system. As shown in Figure 10, as the market is shallower, the capital loss increases, regardless of the country. For some of those capital losses, the dependence is linear as there are no propagations – aside from the initial shock in a group of banks. The losses are resulting from the fire-sale price adjustment on all books. For some of them, the shock is propagated further and with alpha high enough a total systemic collapse may easily happen. As can be seen in the following figures, this holds for large as well as small banks.

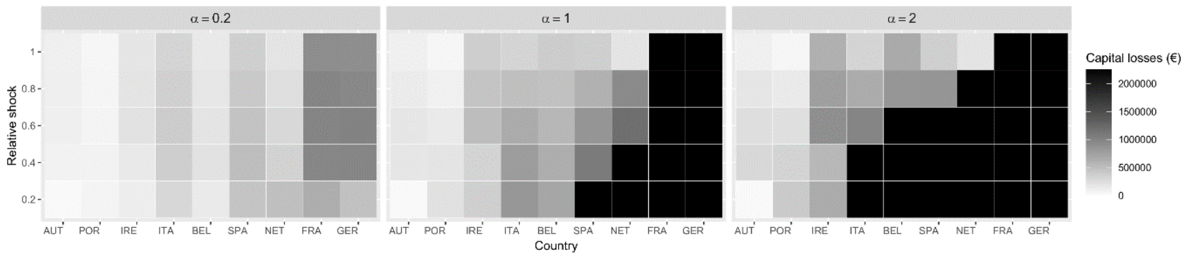


Figure 4 Capital losses in the network for initial shocks in large banks in various countries

Figure 5 Capital losses in the network for initial shocks in small banks in various countries

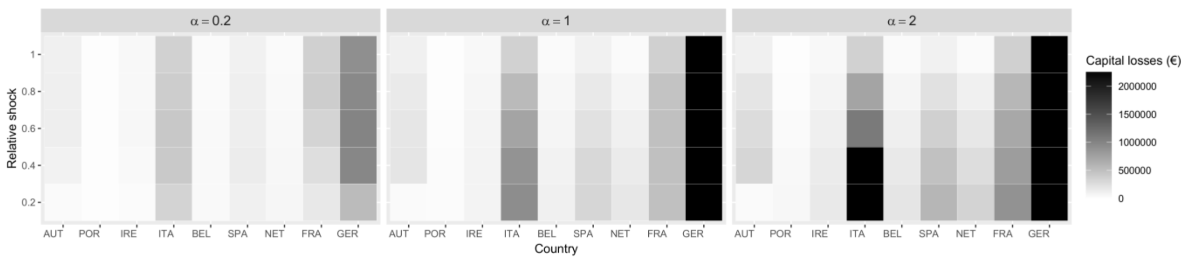


Figure 6 Depositor losses for initial shocks in large banks in various countries

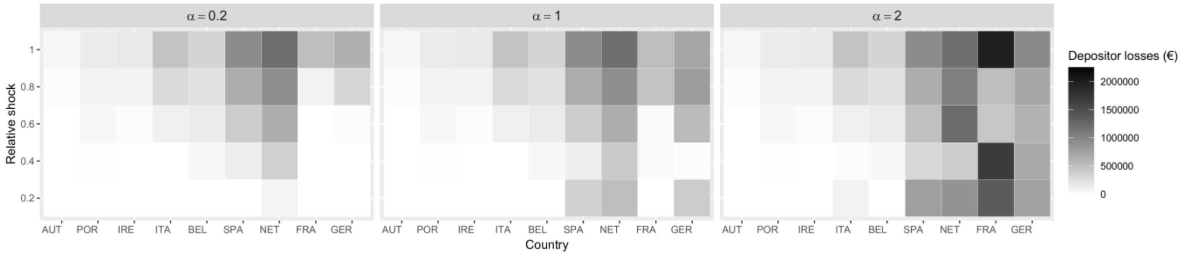


Figure 7 Depositor losses for initial shocks in small banks in various countries

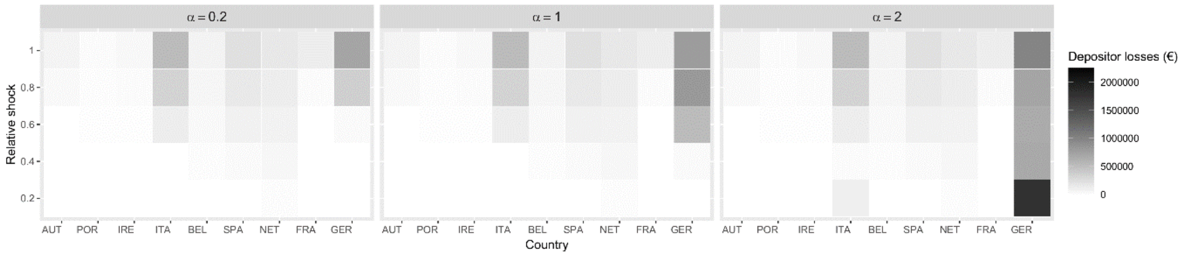


Figure 8 Number of failing banks after a shock in large banks across countries

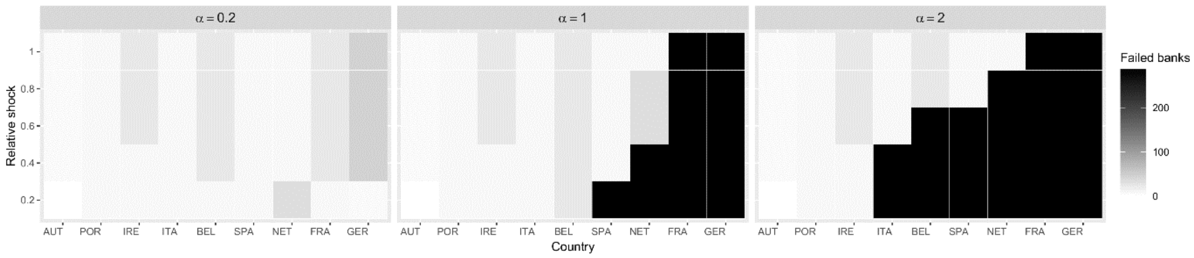


Figure 9 Number of failing banks after a shock in small banks across countries

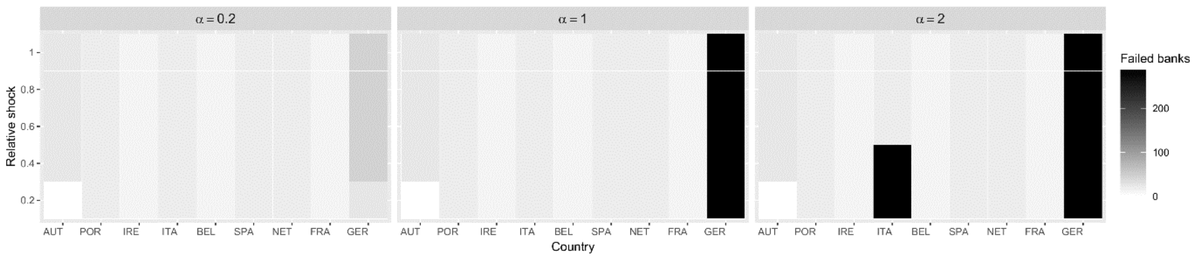
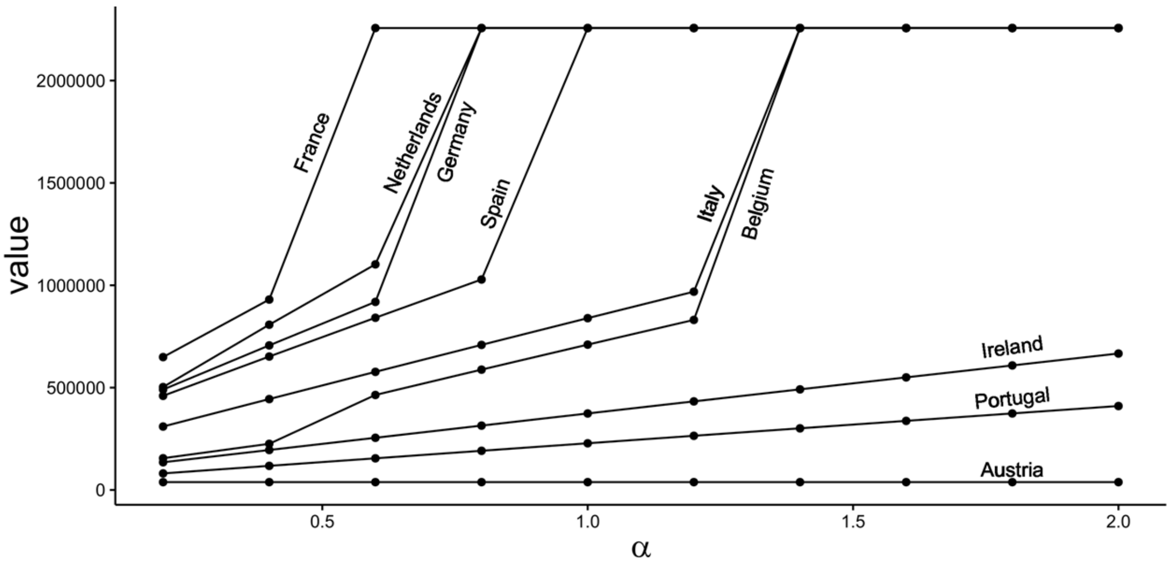


Figure 10 Capital losses per country for all the conducted experiments



5 Conclusion

In this paper, we use a unique approach based on agent-based simulation to assess the systemic risk in the present-day European banking system. The bank interdependencies are expressed in the form of balance sheets and modelled as an interconnected network. The model devised allows simulations of bank behaviour when hit by adverse shocks of various sizes and under various market conditions. Furthermore, the model is methodologically extended with methods for modelling banks of various sizes. In our simulations, the banks can operate in a diverse range of interdependence structures and market conditions. Two parameters are key factors that influence bank behaviour in our study: market illiquidity α and the size of the initial shock. We use the most realistic data available to us in order to calibrate the model to the real-world bank network and provide insights into the specifics of banking markets in each country in this study. In total, we simulate the behaviour of 286 banks from 9 countries: Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain. All the banks are divided into three categories: small, mid-sized and large.

We run the simulation of a shock hitting a set of banks in the network to study how the shock propagates and how the entire system responds to such disturbances. Various insights can be gained through investigation of the ways the banking systems in different countries respond to the crisis and the way they are connected to other banks in the system.

In France, it appears that the key factor contributing to the systemic risk is bank size, while the liquidity doesn’t matter as much. Failure of large French banks indeed poses a significant risk to the entire system as even mild shocks to the large banks in France have the potential to lead to a system-wide collapse, regardless of the α factor. The system is much more resilient to shocks in small and medium-sized banks since a system-wide collapse happens only in cases of large shocks to medium-sized banks under high illiquidity.

Similar results were observed in experiments involving German banks. However, the German bank network seems to be more susceptible to variations in liquidity. This effect is especially prominent for small banks, where no more than 44 banks fail in case of $\alpha = 0$ and the system collapse is complete for $\alpha = 2$ regardless of the shock intensity. In Germany, size matters as well, however not nearly as much as in France.

Interesting results are produced when performing simulations of shocks in the Italian banking sector. The Italian banks seem to have a much higher contribution to the systemic risk than the German and French banks. Despite the fact that the Italian banking sector is smaller than those in Germany and France, the effects of bank collapses in Italy are comparable to those in Germany and France. We believe these results are another contribution to the recent guidelines to the decision makers to handle the Italian banks with great care.

The agent-based modelling proposed has been shown to be a highly flexible methodology due to its ability to simulate both realistic and hypothetical cases on the market. It also provides means for researching complex interactions that are difficult to solve analytically. Regarding the further refinements to the study, we suggest another research direction regarding the lack of reliable data about the interbank relations. Instead of relying on indirect proxy datasets, finding more direct and more precise data could significantly improve the level of detail and the accuracy of the results. Moreover, the model still relies on several simplifications. Firstly, the simulations of the liquidity hoarding channel assume a very short time period. On the other hand, liquidating a bank or its loan portfolios can take up to several years (as well as writing off the losses). However, in such a time frame banks could already make profits and rebuild their capital positions. In general, all three channels are not likely to contribute to the contagion simultaneously. Secondly, the assumption integrated asset market and one asset price level across Europe is a simplification. The study of integration across the liquidity channel would deserve deeper investigation as another area of research.

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Abstrakt

Finanční krize v letech 2007-2009 odhalila slabiny globálního bankovního sektoru, což vyústilo k hlubšímu výzkumu systémového rizika. Multiagentní síťové modely začaly být užívány pro deskripci komplexních bankovních systémů, které je velmi obtížně analyticky popsat a následně modelovat. Náročnost na data a kalkulace v těchto modelech snižují jejich vypovídací hodnotu, neboť ne vždy zcela neodráží realitu. V tomto článku aplikujeme agentský model a jeho kalibraci na reálná data evropského bankovního sektoru. Dále rozšiřujeme obecný síťový model o jeho granularitu a analyzujeme různé typy bank podle velikosti. Rovněž analyzujeme a následně modelujeme vzájemné vztahy mezi jednotlivými bankami. Prezentovaný model obsahující 286 bank v 9 evropských zemí implikuje výsledky, které slouží k bližšímu pochopení systémového rizika, z čehož následně vyvozujeme doporučení pro tvůrce relevantních politik v tomto sektoru.

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