CoMap: Mapping Contagion in the Euro Area Banking Sector

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Abstract

This paper presents a novel approach to investigate and model the network of euro area banks' large exposures within the global banking system. Drawing on a unique dataset, the paper documents the degree of interconnectedness and systemic risk of the euro area banking system based on bilateral linkages. We then develop a Contagion Mapping (CoMap) methodology to study contagion potential of an exogenous default shock via counterparty credit and funding risks. We construct contagion and vulnerability indices measuring respectively the systemic importance of banks and their degree of fragility. Decomposing the results into the respective contributions of credit and funding shocks provides insights to the nature of contagion which can be used to calibrate bank-specific capital and liquidity requirements and large exposures limits. We find that tipping points shifting the euro area banking system from a less vulnerable state to a highly vulnerable state are a non-linear function of the combination of network structures and bank-specific characteristics.

Keywords: Systemic Risk, Network Analysis, Interconnectedness, Large Exposures, Stress Test, Macroprudential Policy.

JEL Codes: D85, G17, G33, L14.

Non-technical Summary

We develop a contagion mapping methodology (CoMap) to study systemic risk stemming from interconnectedness based on the euro area Significant Institutions' network of large exposures within the global banking system. On the basis of supervisory reporting of large bilateral exposures we construct the arguably most comprehensive to-date euro area network of bilateral linkages and combine it with bank balance sheet information to capture bank-specific characteristics and related (regulatory) solvency and liquidity constraints.

The CoMap methodology estimates contagion potential due to credit and funding risks via bilateral linkages. The main objective is to assess the amount of losses and number of defaults an exogenous shock to a bank (or a group of banks) induces to the system. In achieving this, the CoMap methodology evaluates first round effects (direct losses) and subsequent round effects (cascade losses) due to domino defaults and potential fire sale losses.

We then develop contagion and vulnerability indexes capturing counterparty credit and funding risks of an exogenous default shock so as to rank banks in terms of contribution to euro area systemic risk and their degree of fragility, respectively. The outcome is a practical and quarterly updatable policy tool to map contagion risks stemming from within and outside the euro area banking system. Overall, the paper provides unique insights on the interplay of banks' characteristics and the topology of the euro area interbank network.

Specifically, the methodology allows for taking a more granular, heterogeneous and holistic approach to the euro area banking system's study of contagion risk. Thus, we model 199 consolidated banking groups (of which 90 from the euro area) in Q3-2017 tracking among them debt, equity, derivative and off-balance sheet exposures larger than 10% of a bank's eligible capital. We then model banks' heterogeneity by calibrating the model's parameters using exposure-specific information on collateral pledged and maturity structure as well as bank-specific pool of HQLA and non-HQLA assets and capital requirements. Overall, the large exposures dataset covers on average 90% of euro

area banks' RWAs vis-à-vis credit institutions for a total amount of EUR 1.4 trillion and EUR 680 billion, respectively in gross and RWA terms.

We furthermore calculate the contribution of amplification effects (beyond the initial loss) to the overall losses induced by a bank's default or distress (amplification ratio), and we derive a sacrifice ratio indicator assessing the cost-return trade off of a bank-bailout. Finally, we illustrate how our framework can be used to run counterfactual simulations showing how contagion risk can be reduced by fine-tuning prudential capital and liquidity measures.

Key findings highlight that the degree of bank-specific contagion and vulnerability depends on network specific tipping points affecting directly the magnitude of amplification effects. It follows that the identification of such tipping points and their determinants is the essence of an effective micro and macro prudential supervision. Moreover, we bring evidence that in isolation and with linear variations, bank-specific characteristics seem to play a less relevant role than the network structure, whereas what really matters comes from their non-linear interaction, for which both are equally important. In a variety of tests, heterogeneity in the magnitude of bilateral exposures and of bank-specific parameters is detected as a key driver of the total number of defaults in the system. We also show that international spillovers (also coming from non-euro area banks) are an important channel of contagion for the euro area financial system.

Overall, we think that the CoMap methodology combined with the large exposures dataset may help enhance our understanding of how contagion within the euro area interbank network may propagate and be amplified by the actual heterogeneous characteristics of the agents and the topologic features of the network. It also provides a practical monitoring toolkit for the regular surveillance and assessment of contagion risk within the euro area interbank network.

"The financial crisis really was a stress test for the men and the women in the middle of it. We lived by moments of terror. We endured seemingly endless stretches when global finance was on the edge of collapse, when we had to make monumental decisions in a fog of uncertainty, when our options all looked dismal but we still had to choose" (Geithner, 2014: 19).

1. Introduction

The collapse of Lehman Brothers has been the defining event of the Great Financial Crisis of 2007-2008. While the size of its balance sheet alone did not foreshadow the sequence of events that followed, surely, the uncertainty stemming from its default left market participants in panic of a wide-spread contagion. Regulators with limited information about its degree of interconnectedness and bilateral exposures faced the true dilemma: let it fail or save it. Lehman was allowed to default and the counterfactual outcome would be debated for years to come. In the last decade, significant progress has been made in studying the growing interconnectedness of the global financial system and how shocks are amplified or mitigated depending on the network topology and the heterogeneity of the agents. However, up to now, uncertainty surrounding the network due to the lack of available information still represents the major challenge policy makers face in order to assess the potential cascading effects of such an event. This is the fundamental question, as highlighted in the incipit of this paper, policy makers and regulators must answer and be prepared for in case such an adverse event takes place.

Motivated by this question, the systemic risk literature has evolved along two tracks. The first group of studies try to get around the problem of limited information by relying on market data such as Acharya et al. (2012, 2017), Billio et al. (2012) and Diebold and Yilmaz (2014) among others. These market data-based studies allow for capturing financial institutions' interconnectedness and to build systemic risk indexes in real time by exploiting high frequency information on co-movements of stock prices or CDS spreads. Nevertheless, the interpretation and identification of the underlying mechanism generating the co-movements may be difficult (Glasserman and Young, 2016). Moreover, the VAR approaches used to estimate variance decomposition for the forecast errors suffer from high-dimensionality problems which limits the analysis to small samples of banks (Alter and Beyer, 2013; Diebold and Yilmaz (2009, 2012). Only recently, Demirer, et al. (2017), Basu et al. (2017), Moratis and Sakellaris (2017) manage to estimate a high-dimensional network using LASSO methods or Bayesian VARX models. Although recent innovations in estimation techniques has allowed to increase the sample of banks, these approaches still cover only a fraction of the banking system, as information on CDS and stock prices is limited to listed companies. Furthermore, this branch of the literature does not allow to directly model the interplay of prudential regulations and systemic risk since the former are only implicitly captured in the degree of co-movements of bank market prices.

Another stream of the interconnectedness literature hence exploits bilateral exposures and uses bank balance-sheet based methodologies[1]. This approach allows for studying the underlying mechanism of systemic risk formation and contagion stemming from concrete features of the network, the heterogeneity of the agents, the sources of risk, and their interplay. In general, balance sheet based studies have tended to focus on a few specific features so as to better disentangle the path of contagion and amplifications effects due to e.g. credit risk (Eisenberg and Noe, 2001; Rogers and Veraart, 2013), funding risks (Gai and Kapadia, 2010; Gai et al. 2011), cross-holdings of assets and fire sales (Espinoza-Sole 2010; Caballero and Simsek, 2013; Caccioli et al. 2014; Cont and Schaanning, 2017), as well as from multi-layer networks (Bargigli et al., 2015; Kok and Montagna, 2016). Overall, these approaches are more theory-based than empirical since they aim at providing insights on the properties of the network and their implications for financial stability than actually construct contagion and vulnerability indexes for a systemic risk assessment as in the market-based approaches.

This is due, among other things, to the lack of availability of a complete set of bilateral exposures which undermines the accuracy of such systemic risk indicators. In this respect, most of the empirical literature tends to focus on specific market segment, overnight or repo markets, or they are country-specific such as studies on the Austrian, German, Dutch and Italian interbank market (Purh et al. 2012; Craig and von Peter, 2014; Craig et al. 2014; Veld and Van Lelyveld, 2014; Bargigli et al., 2015). Other studies try to compensate for the lack of complete network data by imputing missing bilateral

[1] See Hüser (2015) for a summary of the literature.

linkages based on maximum entropy solution as in Sheldon and Maurer (1998), on minimum entropy methods (Degryse and Nyguyen, 2007; Elsinger et al. 2006; Upper, 2011), on relative entropy (Van Lelyveld and Liedorp, 2006), or by generating random networks consistent with partial information (Halaj and Kok, 2013; Anand et al., 2014). Overall, as emphasized by Glasserman and Young (2016) empirical work in this field was limited by the confidentiality of interbank transactions and the incomplete set of information on bilateral exposures. Moreover, these studies focused on rather standard network measures such as degree centrality, eigenvector centrality and pagerank algorithms to assess financial system vulnerabilities and systemic importance of banks

Additionally, as access to confidential supervisory data is granted at national level, most empirical analyses tend to be country-specific. This resulted in the lack of a comprehensive analysis of cross-border financial exposures, thereby missing bi-directional linkages with institutions outside a country's jurisdiction. To a certain extent, Garratt et al. (2011) and Espinoza-Vega and Sole (2010) overcame this challenge by using aggregate-level International Consolidated Banking Statistics database from BIS to assess the cross-border credit and funding risks of a banking system's default on another country's banking system. However, neither study includes bank and exposure level information thereby ignoring the added value that a specific distribution of exposures and bank-specific characteristics may bring to the overall stability of the system.

Against this background, this paper aims at overcoming some of the data and modelling gaps in the interconnectedness literature by studying the degree of contagion and vulnerability of euro area significant institutions within the global banking system. In overcoming this challenge, we exploit the actual topology of the euro area interbank network of large exposures and account for the heterogeneous characteristics of individual banks via a set of bank and exposure-specific parameters retrieved and calibrated on ECB supervisory data. This comprehensive data infrastructure allows us to build a detailed modelling framework capturing the specificities of prudential regulations such as minimum capital requirements, macroprudential capital buffers, the liquidity coverage ratio and large exposure limits and their interplay with credit, funding and fire sales risks.

We contribute to the literature in various directions. First, we construct contagion and vulnerability indexes assessing the systemic footprints of banks. These model-based estimates allow us to conduct welfare analysis trading off systemic losses due to bank failures and the cost of policy interventions. Second, we provide a calibration benchmark for parameters capturing three types of risks: credit, liquidity and fire sales. Third, we bring evidence that liquidity risk is a major source of default in the interbank network of large exposures. Fourth, we perform stress test scenarios to assess resilience of the network structure to wide macro shocks. Fifth, we perform sensitivity analyses to changes in model parameters so as to assess the non-linear effects derived by the interplay of network structure and banks' characteristics. Finally, we provide counterfactual exercises of prudential measures and their possible usages in reducing the vulnerability of the network.

We find that tipping points shifting the euro area banking system from a less vulnerable state to a highly vulnerable state are a non-linear function of the combination of network structures and bank-specific characteristics. Hence, policies aiming at reducing systemic risk externalities related to interconnectedness should focus on increasing the resilience of weak nodes in the system, thereby curbing potential amplification effects due to cascade defaults, and on reshaping the network structure in order to set a ceiling to potential losses. Unless systemic risk externalities are internalized by each bank in the network, bank recapitalizations may be still convenient from a cost-return trade-off of a global or European central planner. It follows that international cooperation is essential to limit the ex-ante risk and reduce the ex-post system-wide losses.

The remainder of the paper is organized as follows. Section 2 presents the data infrastructure and illustrates the topology of the euro area interbank network of large exposures. Section 3 details the Contagion Mapping (CoMap) methodology and provides insights on the calibration of the model parameters. Section 4 discusses the results based on the contagion and vulnerability indicators and performs sensitivity analysis to assess the interplay of bank-specific characteristics and the network structure. Section 5 derives policy implications from a macroprudential supervisor's perspective via fine-tuning prudential measures based on counterfactual exercises. The last section concludes.

2. Data

The Great Financial Crisis (GFC) of 2008 has led to a rethinking and strengthening of banking and financial regulation worldwide. The result was the Basel III standards, the new legal framework aiming at shaping a safer financial system. Macro and micro prudential regulatory requirements enhancing banks' capital and liquidity standards as well as defining leverage and large exposure limits were the actual outcome of this process.[2] In this regard, the large exposures regulation has been developed as a tool for limiting the maximum loss a bank could incur in the event of a sudden counterparty failure so as to complement the existing risk-based capital framework (pillar 2) and better deal with micro-prudential and concentration risks (BIS, 2014).[3] Accordingly, banks are required to report to prudential authorities detailed information about their largest exposures.

The focus and novelty of this paper is to exploit the microprudential supervisory framework of large exposures with the aim of constructing the euro area interbank network to enable us to track the systemic (contagion) risk embedded in the euro area banking system. The large exposure reporting represents, to our knowledge, the most comprehensive and up-to-date (on a quarterly basis) dataset capturing granular bank and exposure level-information of the euro area banking system vis-à-vis entities located worldwide covering all economic sectors: credit institutions (CIs), financial corporation (FCs), non-financial corporations (NFCs), general governments (GGs), central banks (CBs) and households (HHs). In this paper, however, we focus primarily on the exposures vis-à-vis other credit institutions i.e. the interbank network of large exposures.

Nevertheless, there exist several barriers to utilizing these supervisory data in network analysis. Because of the confidential nature of this data, the access is generally restricted to banking supervisors and central banks. However, even for those with access to these reports, transforming raw data into a suitable format for network analysis is a laborious task with many challenges. ECB is in a unique position where the supervisory data from

[2] This new set of rules was incorporated with the Capital Requirement Regulation (CRR) into EU law, which from January 2014 applies. This date also coincides with banks' reporting requirements to National Central Authorities (NCAs) and to the European Banking Authority (EBA), which ultimately transmits these large exposures data for monitoring purposes to the Single Supervisory Mechanism (SSM).
[3] The large exposure limit is set at 25% of a bank's eligible capital or 15% for exposures among GSIBs.

member states are centrally accessible for monitoring purposes. While this wealth of information promises high potential, it is a colossal undertaking to reconcile this data across many jurisdictions and set-up a euro area banking network of large exposures for a comprehensive systemic risk assessment.

2.1 Large Exposures

An exposure is considered a "large exposure" when, before applying credit risk mitigations and exemptions, it is equal or higher than 10% of an institution's eligible capital vis-à-vis a single client or a group of connected clients (CRR, art. 392).[4] Moreover, institutions that report FINREP supervisory data are also requested to report large exposures information with a value above or equal to EUR 300 million. Therefore the data sample coverage is very comprehensive and captures almost EUR 13.5 trillion of gross exposures in Q3 2017 (our reference date), more than 50% of euro area credit institutions' total assets. In risk-weighted terms the coverage is smaller but still comprehensive, capturing almost 40% of the total RWAs of euro area banks. However, in terms of studying the euro area interbank network, which is the subject of our paper, the large exposures sample captures 90% of euro area banks' RWAs vis-à-vis credit institutions. This extensive coverage provides us with confidence that we can reliably model euro area banks' degree of interconnectedness and their contribution to cross-sectional systemic risk.

It is also notable that the large exposure data go well beyond the standard unsecured interbank transactions typically covered in many interbank network studies. In fact, in the supervisory reporting a large exposure is defined as any direct and indirect debt, derivative, equity, and off-balance sheet exposure that complies with the reporting threshold.[5] In this regard, a key feature of the regulation is that the counterparty may be identified not only as an individual client, but also as a group of connected clients (CRR,

[4] Eligible capital is defined as the sum of tier 1 capital plus one-third or less of tier 2 capital (CRR, art. 4: 71).

[5] Direct exposures refer to exposures on "immediate borrower" basis, while an indirect exposure, according to article 403 of CRR, is an exposure to a client guaranteed by a third party, or secured by collateral issued by a third party. Moreover, according to article 399 of CRR exposures arising from credit-linked notes shall also be reported as indirect exposures.

art. 4:1:39).[6] The latter refers to the fact that the reporting institution needs to assess and take into account - not only direct and indirect risks - but also possible domino effects and negative externalities from funding shortfalls due to control relationships and economic interdependencies (EBA/GL/2017/15). This is a highly relevant feature and an added value of the data because large exposures allow us to capture the full risk spectrum and not only the actual amount of exposures at risk. Moreover, in achieving this, a standardized evaluation method is applied so that the totaling final exposure amount is reliably comparable across countries and reporting institutions[7].

2.2 Dataset

This subset of large exposures data captures almost completely credit and funding risks of euro area SIs among themselves, and credit risks of EA SIs vis-à-vis non-euro area banks. However, the large exposures dataset does not capture euro area SIs' funding risks from non-euro area banks. In order to tackle this information gap, we retrieve data on the 10 largest funding sources of euro area SIs by using another COREP supervisory template defined as concentration of funding by counterparty or C.67.[8] These 10 largest funding sources may come from central banks, governments, credit institutions, and corporates. Regarding, our sample of counterparties we find 41 funding exposures from non-euro area banks towards euro area SIs. We incorporate them into the large exposures dataset matching them with the gross exposures before exemptions and credit risk mitigations. Next, we consolidate the large exposures data from euro area SIs that are euro area-based subsidiaries of non-euro area banks with these 41 funding sources from non-euro area banks. We then drop intra-group exposures and set a 50 million threshold for exposure before credit risk mitigations (but after exemptions) to clean-up the network from negligible edges.

[6] EBA's guidelines on connected clients - final report - further detail Art. 4(1)(39) emphasizing that whether financial difficulties or a failure of a client would not lead to funding or repayment difficulties for another client, these clients do not need to be considered a single risk (e.g. where the client can easily find a replacement for the other client). Moreover, these guidelines point out that a reporting institution should investigate all economic dependencies for which the sum of all exposures to one individual client exceeds 5% of Tier 1 capital.

[7] Details on the construction of the dataset are provided in the appendix.

[8] A minimum threshold of 1 percent of total liabilities applies either as a single creditor or a group of connected clients.

On top of this, for modelling purposes, we retrieve from other COREP supervisory templates euro area SI's RWAs (C.02.10), the total capital base (C.01.10), Tier 1 (C.01.15), CET1 (C.01.20), pillar 2 capital requirements (C.03.00), and capital buffers (C.06.01, and ECB website).[9] In this respect, bank-specific combined capital buffers were constructed following regulatory capital requirements: banks' minimum capital requirement (MC), pillar 2 requirements (P2R), the capital conservation buffer (CCoB), the OSII, GSII and the systemic risk buffers (SRB), as well as the prevailing countercyclical capital buffer requirements (CCyB).[10] Regarding the international Globally Systemic Important Institutions, the GSII buffers were retrieved from the Financial Stability Board 2017 list.[11] Moreover, in order to calibrate the model we also retrieve from COREP templates the maturity buckets of large exposures (template C.30), banks' HQLAs (C.72.00.a.10), the liquidity buffer and net liquidity outflow, respectively numerator and denominator of the liquidity coverage ratio (template C.76.00.a.10/20) as well as from FINREP templates banks' total assets and their components (F.1.1.380).[12] Whereas, for the international banks we match our data set to Bankscope for bank characteristics, and when missing, we use the most recent annual consolidated financial report.[13] In the end, we limit our data set to banks that has a complete set of information on the above described metrics. This yields our main dataset of 199 consolidated banking groups or nodes, whose total assets amount up to EUR 74 trillion, approximately 6.6 times the GDP of the euro area.

Overall, this brings us to a total number of large exposures equal to 1.734, and a total gross amount of EUR 1.38 trillion, or EUR 675 billion of risk-weighted assets. This sub-set of SIs' large exposures to credit institutions cover almost 80% of the total gross

[9] ECB Website: http://www.ecb.europa.eu/pub/fsr/html/measures.en.html

[10] Minimum capital requirements are defined as follows: 4.5% of CET1, 6% of TIER1, and 8.0% of own funds that is the sum of 4.5% CET1 + 1.5% AT1 + 2% T2. Pillar 2 measures are included on top of minimum capital requirements and are mandatory only within the EU. CCoB may take value of 1.875% CET1 if the country is still in a transitional period, or 2.5% CET1 if fully-loaded.

[11] Financial Stability Board's 2017 list of global systemically important banks: http://www.fsb.org/wp-content/uploads/P211117-1.pdf

[12] Tangible assets are calculated as total assets minus intangible assets (300), tax assets (330), other assets (360), and non-current assets and disposal groups classified as held for sale (370).

[13] In few cases for international banks, variables were approximated using a balance sheet-based methodology (discussed in the calibration section) using as reference value the average of the sample.

amount. Furthermore, the selected sample of counterparties guarantees a complete coverage of LEI codes, country of domicile and sector of belonging.

Table 1 presents the summary statistics of the interbank network of large exposures in Q3 2017. It consists of 179 counterparties and 101 reporting institutions, for a total of 1264 exposures (or edges), of which, almost 90% (1185) is reported by euro area-based banking groups, and the remaining 10% (79) from international banks. The latter provides a partial picture of the euro area banks' funding risk related to non-euro area creditors. On the contrary, euro area banks' credit risk is captured in its entirety, and it is distributed almost equally between euro area and extra-euro area counterparties, amounting to respectively 613 and 651 in terms of number of exposures (edges) or EUR 431 billion and EUR 432 billion (gross amount minus exemptions). In comparison, gross exposures before exemptions and CRM (gross amount) amount to EUR 1.13 trillion, while after exemptions and CRM, exposures amount up to EUR 623 billion (net amount). No bilateral-linkages among extra-euro area banks are captured in this study. Therefore, to the best of our knowledge, in terms of coverage this dataset represents one of the most comprehensive attempts to study euro area systemic risks by means of granular bank and exposure level-information.

Table 1: Interbank Network of Large Exposures

Data Sample	**Total**	**Euro Area**	**non-Euro Area**
Entities			
Consolidated Banking Groups	199	90	109
Counterparties	179	69	110
Reporting	101	84	17
Number of Exposures			
From	1264	1185	79
To	1264	613	651
Total Exposures Amount			
Gross Amount	1126	639	487
- Exemptions	263	208	55
Gross Amount minus Exemptions	863	431	432
- Credit Risk Mitigations	240	165	75
Net Amount	623	266	357

Note: Amounts are expressed in billions of euros. Outstanding amounts as of Q3 2017. Gross amount minus exemptions is the reference metrics of this study. A 50 million threshold to exposures before credit risk mitigation was applied. Exemptions are those amounts which are exempted from the large exposure calculation, whereas credit risk mitigations refer to the amounts adjusted for risk weights.

2.3 Network Topology

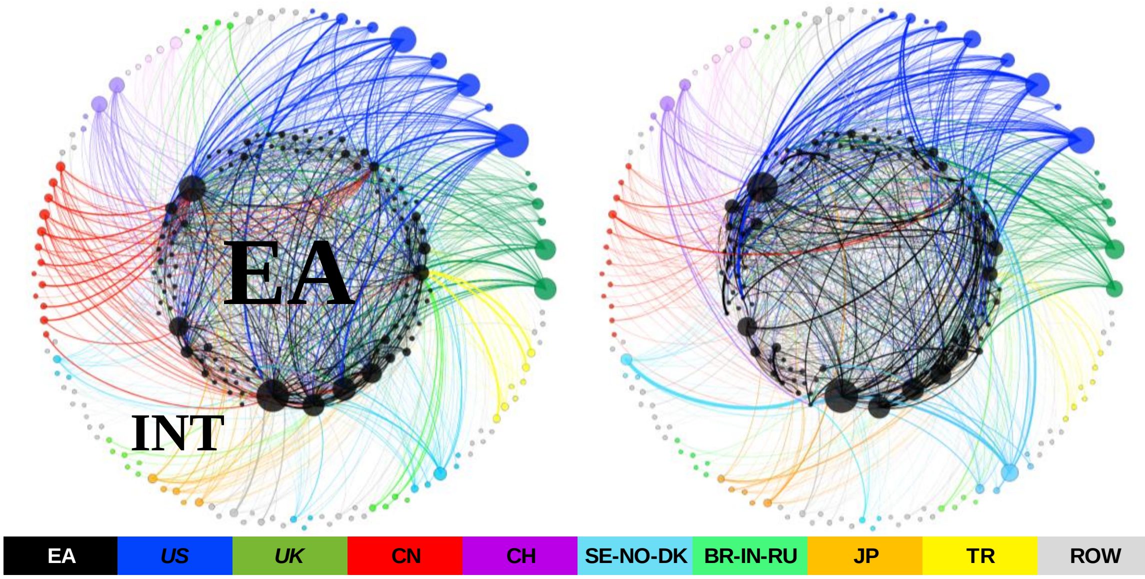
We are now in the position to plot the euro area interbank network of large exposures. For a graphical interpretation of the edges' directionality, we drop from the interbank network the 79 funding linkages from international banks. This allows us to split each chart into two concentric circles. An inner-circle composed only of euro area banks' credit and funding exposures among themselves (EA), and an outer-circle reflecting the international dimension of euro area banks' credit exposures towards non-euro area banks (INT). Therefore all edges linking the inner circle to the outer circle are outward oriented.

Figure 1 displays the network according to two mirror images, capturing respectively the size of exposures in Euro Billions - panel (a) - and in % of lender's capital - panel (b). In both panels the edges take the color from the node borrowing the fund, i.e. the amount international banks are borrowing from euro area banks. Given the lack of credit exposures from international banks to euro area banks, for comparative purposes, we assign as a node's size the weighted in-degree, that is, the sum of incoming exposures. Therefore, the node's size captures the relative size of each bank's funding exposure.

On the one hand, panel (a) identifies which international banking system is the most interconnected with the euro area banking system. For instance, euro area banks appear to have few exposures but sizeable (thick) towards Chinese banks, many but relatively small exposures to Swiss banks, and many and sizeable exposures to US and UK banks. Overall, international spillovers seem to be an important channel of contagion to the euro area banking system. On the other hand, panel (b) of figure 1, which presents the interlinkages in percentage of the lenders' capital shows that the node size of international banks becomes slightly smaller due to the fact that euro area medium and large-sized banks tend to lend more to international banks than small domestic banks, which by comparison tend to lend more to banks within the euro area. In this respect, even if not clearly visible, small-medium banks tend to have relatively fewer cross-border large exposures both within the inner circle and with the outer circle, implying that the potential for cross-country spillovers is likely to mostly pass-through the major country hubs. Overall, the euro area interbank network of large exposures can be characterized by a core-periphery network structure. This feature also results in a relatively sparse network. In fact, only 6.3% of all possible links are present.

Figure 1. Euro Area Interbank Network of Large Exposures - Borrower Perspective

Euro Billions - Panel (a) % of Capital - Panel (b)



Source: COREP C.27-C.28.
Note: The size of the nodes captures the weighted in-degree of interconnectedness. The colours of nodes are clustered by country of origin, the thickness of the flows summarizes the value of the exposures in EUR billions and percentage of eligible capital, respectively. The colour of the flows refers to the target of the node's colour capturing respectively the borrower perspective.

3. Contagion Mapping (CoMap) Methodology

This paper relies primarily on a balance sheet simulation approach to map contagion. In addition to demonstrating the architecture of banking networks through bilateral linkages, such an approach also allows us to quantify systemic losses and determine channels of contagion by assuming hypothetical failures in the network. The emphasis on granularity in establishing bilateral connections applies equally in modeling contagion. By incorporating model parameters which are calibrated based on bank-specific - and to the extent possible exposure-specific - data allows us to simulate a contagion model that provides a fairly accurate picture of the reality.

3.1 Modelling Framework

Our Contagion Mapping model (CoMap) is essentially a variant of the Eisenberg and Noe (2001) framework. This framework has been at the center of many studies in the financial networks literature. Our starting point is a simple interbank exposure model with both credit and funding shocks.[14] Credit shocks capture the impact of a bank defaulting on its liabilities to other banks. Funding shocks, on the other hand, represent how a bank's withdrawal of funding from other banks forces them to deleverage by selling assets at a discount (fire sale). Triggering a distress event (single or multiple bank failures) reveals the cascade effects and propagation channels transmitted through these solvency and liquidity channels. In order to achieve a more realistic setting, we enrich this simple framework with a series of new features that reflect heterogeneity across banks, one of the novelties of this paper. Specifically, we model the effects of: (i) bank-specific default thresholds, such as minimum capital requirements and capital buffers; (ii) changes to the network structure via large exposure limits; (iii) variations in exposures at risk (loss-given-default); (iv) maturity structure of bank funding; (v) market risk linked to a bank's business model captured by the amount of financial and HQLA assets on a bank's balance sheet; (vi) changes in bank-specific LCR ratio due to adjustments in the liquidity buffer and/or the net liquidity outflows. As a result, this comprehensive modelling framework is able to capture the risk-return trade-off a bank faces between holding HQLA and non-HQLA financial assets and allows for assessing both solvency and liquidity risk while accounting for bank-specific parameters. Hence, it incorporates (vii) liquidity constraint on the amount of assets available for sale allowing a bank to default because of being illiquid. These seven distinctive features are jointly modelled in our framework.

The initial set-up of our model, while closely following Espinosa-Vega and Sole (2010), expands the scope beyond interbank loans to capture all interbank claims. This is reflected in the stylized balance sheet identity of *bank i* as follows:

$$\sum_j \sum_k x_{ij}^k + a_i = c_i + d_i + b_i + \sum_j x_{ji} \tag{1}$$

where x_{ij}^k stands for *bank i*'s claims of type k on *bank j*, a_i stands for other assets, c_i stands for capital, b_i are wholesale funding (excluding interbank transactions), d_i stands for deposits, and x_{ji}^k stands for *bank i*'s total obligations vis-à-vis *bank j*, or conversely,

[14] Espinosa-Vega and Sole (2010) illustrate the workings of such a model with the use of aggregated data.

bank j's claims on *bank i*. $\mathcal{Z}$ is the complete set of all banks in the network with a total of N number of banks.

Next, we introduce the key elements of our baseline model that will be used as a reference framework in the remainder of this paper.

3.1.1 Credit Shock

Credit shock captures the impact of a bank or a group of banks defaulting on their obligations to other banks. As a result, a bank incurs losses on a share of its claims depending on the nature and counterparty of its exposures. Other studies have assumed uniform loss-given default rates, be it at entity level or for the entire network.[15] In practice, different claims may have different recovery rates. For example, the recovery rates from equity stakes and debt claims can vary. We introduce exposure-specific loss-given default rates to reflect the precise risk mitigation and collateralization a bank has accounted for its claims vis-à-vis each counterparty. In response to a subset of banks, $\mathcal{Y} \subset \mathcal{Z}$, defaulting on their obligations, *bank i*'s losses are summed across all banks $j \in \mathcal{Y}$ and claim types k using exposure-specific loss-given default rates, λ_{ij}^k, corresponding to its claim of type k on *bank j*, x_{ij}^k:

$$\sum_{j\in\mathcal{Y}}\sum_{k}\lambda_{ij}^k x_{ij}^k, \qquad where\ \lambda_{ij}^k \in [0,1]\ and\ i \notin \mathcal{Y} \tag{2}$$

The total losses are absorbed by *bank i*'s capital while the size of its assets is reduced by the same amount.

$$\sum_{j\in\mathcal{Z}\setminus\mathcal{Y}}\sum_{k}x_{ij}^k + \left[a_i + \sum_{j\in\mathcal{Y}}\sum_{k}\left(1-\lambda_{ij}^k\right)x_{ij}^k\right] = \left[c_i - \sum_{j\in\mathcal{Y}}\sum_{k}\lambda_{ij}^k x_{ij}^k\right] + d_i + b_i + \sum_{j}x_{ji} \tag{3}$$

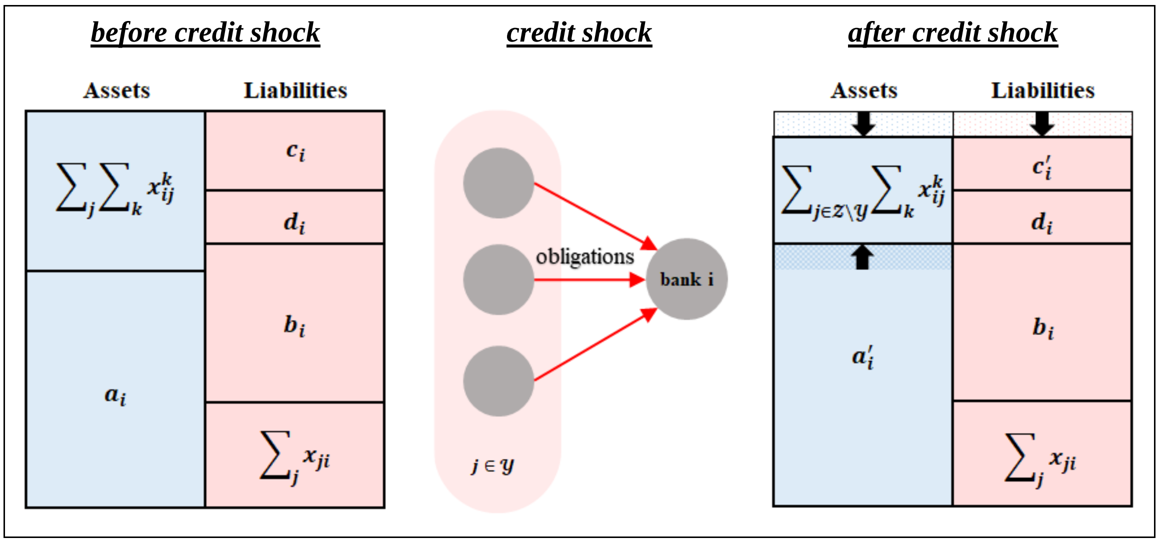
As a result, *bank i*'s balance sheet shrinks, with lower capital, c_i', reflecting the losses. The recouped portion of its claims are commingled with other assets, a_i'.

[15] See for instance: Battiston et al. (2012), Cifuentes et al. (2005), Cont et al. (2010), Espinosa-Vega and Sole (2010) and Rogers and Veraart (2013).

$$\sum_{j \in \mathcal{Z} \setminus \mathcal{Y}} \sum_k x_{ij}^k + a_i' = c_i' + d_i + b_i + \sum_j x_{ji} \quad (4)$$

Figure 2 illustrates the transmission of credit shock via bilateral linkages on *bank i*'s balance sheet.

Figure 2. Impact of Credit Shock on *Bank i*'s Balance Sheet



3.1.2 Funding Shock

Funding shock represents how a bank's withdrawal of funding from other banks forces them to deleverage by selling assets at a discount (fire sale). Typically, an assumption is made about the share of short-term funding that cannot be rolled over and the haircut rate that must be applied to fire sale of assets to meet the immediate liquidity needs. This would result in losses on the trading book, which would then be absorbed by the capital base. We introduce bank-specific funding shortfall rate, ρ_i, reflecting precisely the maturity structure of bank i's wholesale funding. In response to a subset of banks defaulting (getting into distress), $\mathcal{Y} \subset \mathcal{Z}$, and thereby withdrawing funding from other counterparties, *bank i* faces funding shortfall summed across all banks $j \in \mathcal{Y}$ using its specific funding shortfall rate, ρ_i:

$$\sum_{j \in \mathcal{Y}} \rho_i x_{ji}, \qquad where\ \rho_i \in [0,1] \quad (5)$$

We introduce to the model banks' ability to hold liquidity surplus, which can be used to absorb these shortfalls, at least partially. In order to mitigate banks' short-term funding risk, regulators have imposed liquidity coverage ratios (LCR) to ensure that banks have sufficient high-quality liquid assets (HQLA) to cover liquidity shortages. In practice, for immediate liquidity needs, banks can pledge HQLA as collateral to the central bank for overnight borrowing. From a modeling perspective, this implies that *bank i* can offset funding shortfall with the new credit line up to its liquidity surplus, γ_i:

$$min\left\{\gamma_i, \sum\nolimits_{j\in\mathcal{Y}} \rho_i x_{ji}\right\} \tag{6}$$

with the remaining liquidity shortage computed as:

$$max\left\{0, \sum\nolimits_{j\in\mathcal{Y}} \rho_i x_{ji} - \gamma_i\right\} \tag{7}$$

In our model, a bank is pushed toward a fire sale when it has exhausted emergency credit lines from the central bank, that is, if the remaining liquidity shortage (7) emanating from the funding shock is strictly positive. At this point, we introduce a constraint, θ_i, on the amount of remaining assets available to the bank to sell. This constraint sets an upper threshold to how much of the remaining liquidity shortage can be sustained with the fire sale proceeds after accounting for haircuts proportional to a discount rate, δ_i. As a result, the deleveraging amounts to the sale of assets is equivalent to:

$$min\left\{\frac{1}{1-\delta_i} max\left\{0, \sum\nolimits_{j\in\mathcal{Y}} \rho_i x_{ji} - \gamma_i\right\}, \theta_i\right\} \qquad , where\ \delta_i \in [0,1] \tag{8}$$

As in credit shock, the losses due to the fire sale are absorbed fully by *bank i*'s capital. The other liabilities of the bank decline by the amount of funding shortfall that couldn't be replenished by central bank loans. The sum of the two declines are matched by the contraction on bank's assets due to fire sales.

$$\sum_j \sum_k x_{ij}^k + \left[a_i - min\left\{\frac{1}{1-\delta_i} max\left\{0, \sum_{j \in \mathcal{Y}} \rho_i x_{ji} - \gamma_i\right\}, \theta_i\right\}\right]$$
$$= \left[c_i - \delta_i min\left\{\frac{1}{1-\delta_i} max\left\{0, \sum_{j \in \mathcal{Y}} \rho_i x_{ji} - \gamma_i\right\}, \theta_i\right\}\right] + d_i$$
$$+ \left[b_i + min\left\{\gamma_i, \sum_{j \in \mathcal{Y}} \rho_i x_{ji}\right\}\right] + \left[\sum_{j \in \mathcal{Z} \setminus \mathcal{Y}} x_{ji} + \sum_{j \in \mathcal{Y}} (1-\rho_i) x_{ji}\right] \quad (9)$$

Overall, the balance sheet of the bank can potentially shrink by a larger factor than the associated capital losses in contrast with the credit shock. On the liabilities side, there is a shift in wholesale funding from other banks to the central bank, as well as an overall decline.

$$\sum_j \sum_k x_{ij}^k + a_i'' = c_i'' + d_i + b_i'' + \left[\sum_{j \in \mathcal{Z} \setminus \mathcal{Y}} x_{ji} + \sum_{j \in \mathcal{Y}} (1-\rho_i) x_{ji}\right] \quad (10)$$

Figures 3 and 4 illustrate the transmission of funding shock via bilateral linkages on *bank i*'s balance sheet, when the liquidity surplus is sufficient to meet funding shortfall and when it is insufficient, respectively.

Figure 3. Impact of funding shock on *bank i*'s balance sheet with sufficient buffer

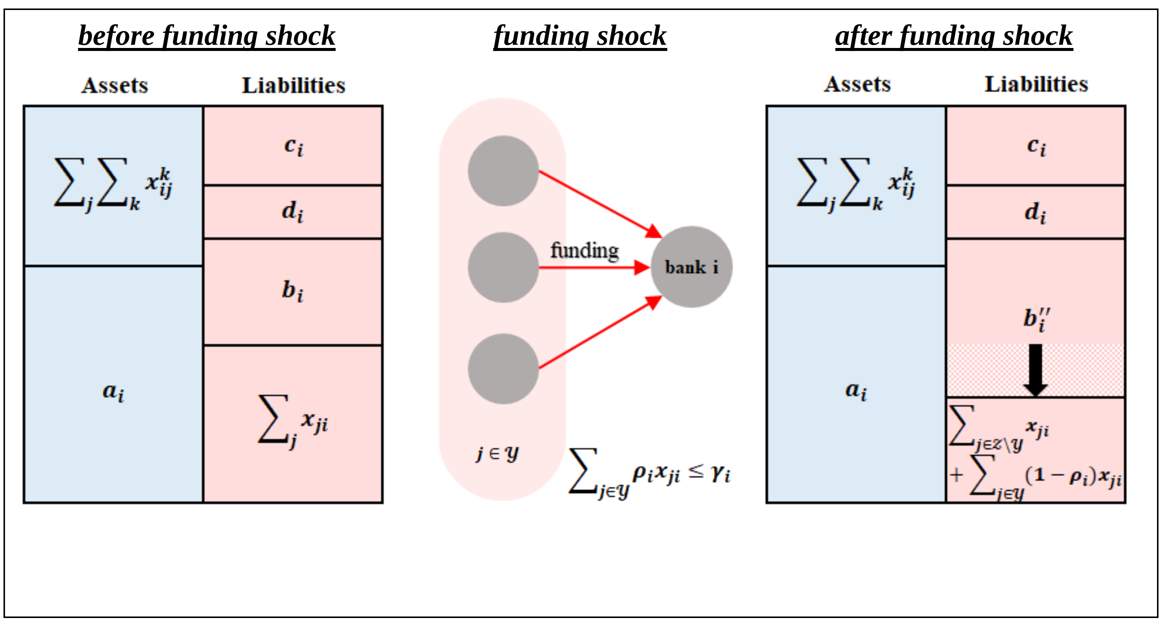
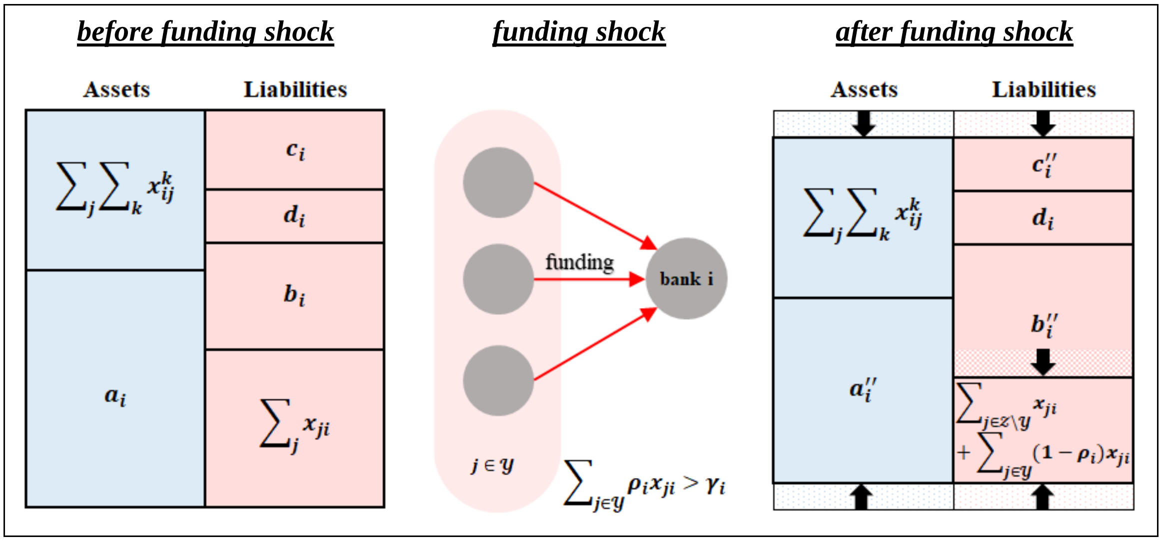


Figure 4. Impact of funding shock on *bank i*'s balance sheet with insufficient buffer



3.1.3 Simultaneous Credit and Funding Shocks

While it is helpful to consider credit and funding shocks in isolation, when a bank or a group of banks are in distress, they are likely to default on their obligations and shore up liquidity by withdrawing funding simultaneously. Therefore, we combine the impact of both shocks on *bank i*'s balance sheet to capture the full impact of a distress event.

$$\begin{aligned}
&\left[a_i + \sum\nolimits_{j\in\mathcal{Y}}\sum\nolimits_{k}(1-\lambda_{ij}^k)x_{ij}^k - min\left\{\frac{1}{1-\delta_i}max\left\{0,\sum\nolimits_{j\in\mathcal{Y}}\rho_i x_{ji} - \gamma_i\right\},\theta_i\right\}\right] \\
&\quad + \sum\nolimits_{j\in\mathcal{Z}\setminus\mathcal{Y}}\sum\nolimits_{k} x_{ij}^k \\
&\quad = \left[c_i - \sum\nolimits_{j\in\mathcal{Y}}\sum\nolimits_{k}\lambda_{ij}^k x_{ij}^k - \delta_i min\left\{\frac{1}{1-\delta_i}max\left\{0,\sum\nolimits_{j\in\mathcal{Y}}\rho_i x_{ji} - \gamma_i\right\},\theta_i\right\}\right] + d_i \\
&\quad + \left[b_i + min\left\{\gamma_i,\sum\nolimits_{j\in\mathcal{Y}}\rho_i x_{ji}\right\}\right] \\
&\quad + \left[\sum\nolimits_{j\in\mathcal{Z}\setminus\mathcal{Y}} x_{ji} + \sum\nolimits_{j\in\mathcal{Y}}(1-\rho_i)x_{ji}\right] \qquad (11)
\end{aligned}$$

3.1.4 Default Mechanisms

Up to this point, we focused on how credit and funding shocks are transmitted to a bank's balance sheet. While credit shocks translate directly to weakening of a bank's capital, funding shocks lead to depletion of its liquidity and via fire sales to capital losses. Now, we define at what level these losses result in a severe distress for a bank triggering its default.

In a distress event, the capital of exposed counterparties, such as *bank i*, must absorb the losses on impact. Then, *bank i* becomes insolvent if its capital falls below a certain threshold c_i^d, which may be defined as the bank's minimum capital requirements with or without capital buffers. In other words, *bank i* is said to fail if its capital surplus $(c_i - c_i^d)$ is insufficient to fully cover the losses:

$$c_i - c_i^d < \sum_{j \in \mathcal{Y}} \sum_k \lambda_{ij}^k x_{ij}^k + \delta_i min \left\{ \frac{1}{1-\delta_i} max \left\{ 0, \sum_{j \in \mathcal{Y}} \rho_i x_{ji} - \gamma_i \right\}, \theta_i \right\} \tag{12}$$

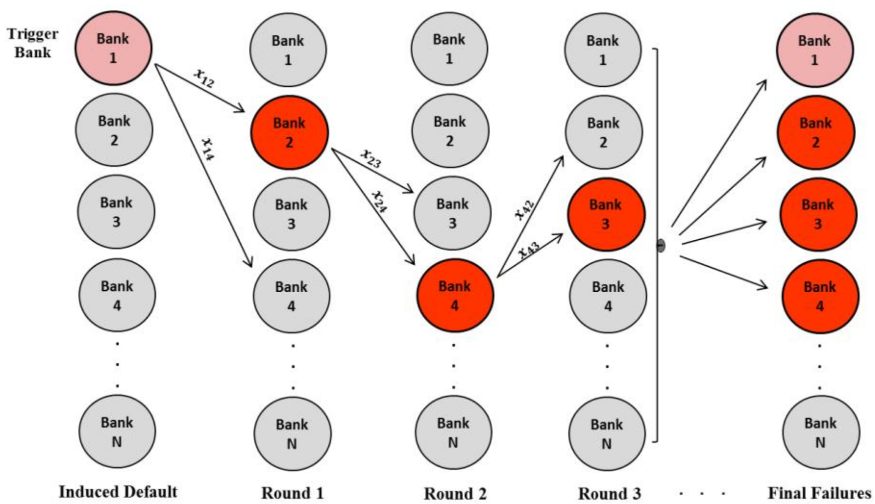
In terms of the impact through the liquidity channel, *bank i*'s liquidity surplus serves as the first line of defense. However, the remaining liquidity shortages might require a large-scale fire sale operation relative to its financial assets. Having already exhausted its liquidity surplus, *bank i* becomes illiquid if its remaining assets are insufficient to match the liquidity shortage:

$$\theta_i < \frac{1}{1-\delta_i} max \left\{ 0, \sum_{j \in \mathcal{Y}} \rho_i x_{ji} - \gamma_i \right\} \tag{13}$$

Notably, in our framework, a bank may default contemporaneously via solvency and liquidity when inequalities (12) and (13) are jointly satisfied. This implies that the funding shortfall is larger than the funds retrieved from the liquidity surplus and the fire sale operations, and, at the same time, the cumulated losses incurred via credit losses and fire sales are larger than the capital surplus.

Bringing the full network of banks into picture, in each simulation the exercise tests the system for a given bank's default as depicted in Figure 5. The initial default of *bank 1* is triggered by design in order to study the cascade effects and contagion path it causes through the interbank network. According to this example, the trigger bank is linked to bank 2 and bank 4 via large exposures, respectively x_{12} and $x_{14.}$ The initial shock determines the subsequent bank 2's default and losses to bank 4 via credit and funding risks. Hence, the exercise continues to the second round since there is at least one additional failure in response to the initial exogenous shock. In this round, banks' losses are cumulated in calculation of their distress conditions. Therefore, bank 4's losses experienced by bank 2's default ($x_{24.}$) in round 2 are summed up with bank 1's induced losses in round 1 ($x_{14.}$). Although, the initial default of bank 1 does not directly induce bank 4's default, due to contagion and amplification effects, in round 2 bank 4's default realizes. In turn, bank 4 triggers the default of bank 3 (x_{43}) and produces additional losses to bank 2 (x_{42}) which already defaulted in round 2. In this respect, the losses experienced by bank 2 via the large exposure (x_{42}) will not further affect bank 2 since its surplus of capital above the minimum has been already depleted given bank 1 shock.[16] The exercise moves to subsequent rounds if there are additional failures in the system and stops when there are no other failures.

Figure 5: Contagion Path and Rounds to Defaults



Note: The trigger bank initializes the algorithm, rounds track the path of contagion via internal loops, while final failures define the convergence of the algorithm.
Source: Inspired by Espinoza-Sole (2010).

[16] This is an assumption of the model that may be relaxed depending on whether we want to model the entire distress induced to the capital base or simply to the capital base above the minimum capital requirements.

3.2 Calibration

The typical approach in the application of balance sheet simulation exercises has been to use benchmark parameters based on cross-country studies or sectoral averages. Few studies introduced some improvement by using random drawings from a distribution of observed values. One of the main contributions of this paper is to model bank-level heterogeneity with granular exposure and other balance sheet information. In the following, we describe in detail how we calibrate the bank-specific parameters for the set-up of our benchmark model.

3.2.1 Loss Given Default

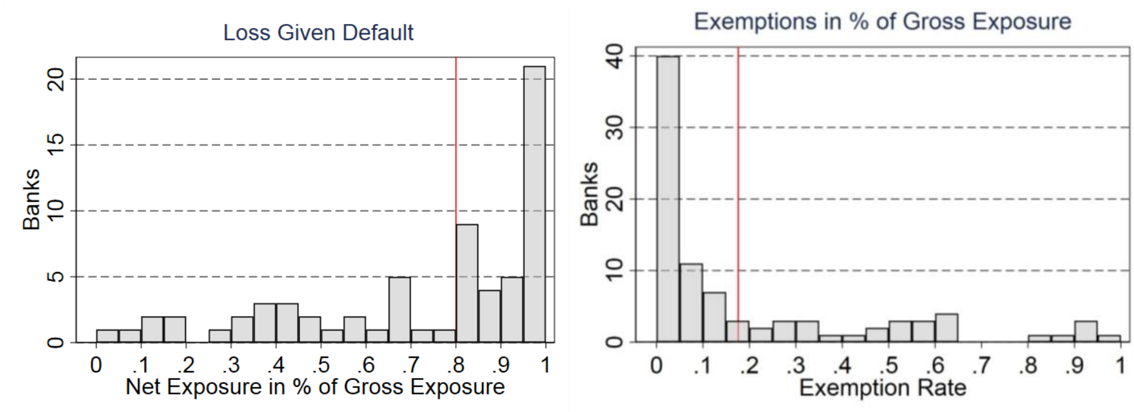
The loss given default (LGD) parameter is calibrated for each bank at exposure level by calculating the ratio of net exposures to gross exposures. Gross exposures (GE) are defined as those after deducting defaulted amounts and exemptions from original gross exposures. Net exposures (NE) refer to the remaining exposures after adjusting gross exposures for credit risk mitigation measures. In other words, if *bank i* is lending to counterparty j, the exposure-specific LGD is defined as in equation (14). Non-reporting banks in the sample are assumed to have a uniform LGD equal to the average $\bar{\lambda}$ across all reporting banks.

$$\lambda_{i,j} = \frac{NE_{i,j}}{GE_{i,j}} = LGD_{i,j} \tag{14}$$

On the one hand, panel (a) of Figure 6 presents the distribution of the exposure-specific loss given default parameters ($\lambda_{i,j}$). The red line shows the average of the sample ($\bar{\lambda}$) upon which is based the calibration for the non-reporting banks. The average net exposure amount is 80% of the gross amount after deducting exemptions. Panel (b) reports the distribution of exemptions across exposures. Both samples are concentrated respectively on the right and left side of the distribution, though cross-exposure heterogeneity is visible.

Figure 6: Exposure-Specific Loss Given Default Parameter

Panel (a) Panel (b)



Source: COREP Supervisory Data, Template C.28.00.

Note: The LGD parameter is calculated on an exposure basis as the share of the net exposure (after CRM and exemptions) over the gross exposure amount before taking into account CRM, but after exemptions. The exemption rate shows the share of exempted amount over the original gross amount before deducting exemptions and CRM.

3.2.2 Funding Shortfall

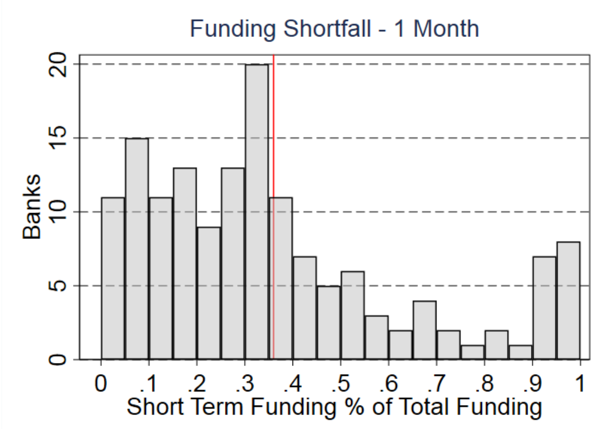
Funding shortfall refers to the portion of withdrawn funding that is assumed not to be rolled over when the bank providing the funding defaults (or gets into distress). It is calibrated at bank-level using the share of short-term liabilities shorter than 30 days (1 month maturity). The choice of this maturity threshold as baseline calculation is to allow the funding shortfall to be consistent with the Liquidity Coverage Ratio (LCR) which assumes a 30-day liquidity distress scenario. However, this assumption may be relaxed and ρ_i can be calibrated on a shorter or longer period depending on the scenario we want to test.

For each bank, we use exposure level information retrieved from the concentration of funding template (C.67.00.a) and the large exposure maturity breakdown template (C.30). The former template allows us to retrieve information on the exposures' amount and maturity breakdown on international banks lending to euro area banks. Therefore, as reported in equation (15), the funding shortfall is calibrated based on the share of exposures in buckets with maturities of less than 30 days over the total amount of funding, aggregated across all reporting banks for whom bank i is a large exposure counterpart (F_i).[17]

$$\rho_i = \frac{\sum_{j\epsilon F_i} x_{i,j<30days}}{\sum_{j\epsilon F_i} x_{i,j}} = \frac{Short\ Term\ Funding}{Total\ Funding} \tag{15}$$

When no maturity information is available, we use the average maturity to which the reporting banks having an exposure to bank i are lending at to other banks. Therefore, we assume that the maturity information of the reporting bank is more accurate than setting ρ_i equal to the average of the sample. This approach allows us to increase heterogeneity in the distribution of the funding shortfall parameter.

Figure 7: Bank-Specific Funding Shortfall Parameter



Source: COREP Supervisory Data, Template C.30 and Template C.67.00.a
Note: Funding shortfall is constructed as short-term funding divided by total funding.

As we see in figure 7, banks' short term funding as share of total funding is distributed on the whole range of the maturity breakdown, with banks experiencing an average of 35% of short term funding over total funding.

3.2.3 Liquidity Surplus

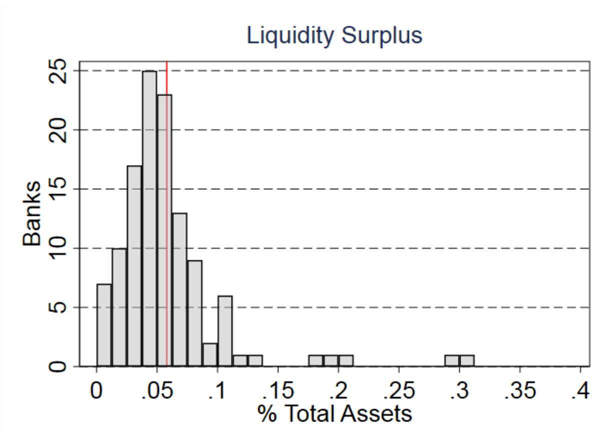
The liquidity surplus is directly derived from the liquidity coverage ratio template C.72.00a. It consists of the difference between the LCR's numerator and denominator since the former, as of 2018, needs to be larger than 100% of the latter (equation 16). Hence, the liquidity surplus (γ_i) refers to the stock of HQLAs (LB_i) above the net

[17] Bank i's large exposure vis-à-vis bank j can be equally thought of as the amount of funding provided by bank i to bank j.

funding outflows (NLO_i) over a 30-day liquidity distress scenario. Figure 8 reports the surplus as share of banks' total assets. The average of the sample is close to 5.8% which is used for approximating the missing (γ_i) for some international banks. Furthermore, if a bank is currently facing a transition period to achieve the 100% LCR ratio, whenever $NLO_i > LB_i$, to be conservative, we set $\gamma_i = 0$.

$$LCR\colon \frac{LB_i}{NLO_i} > 1 \xrightarrow{yields} LB_i > NLO_i \xrightarrow{yields} \gamma_i \equiv LB_i - NLO_i > 0 \tag{16}$$

Figure 8: Bank-Specific Liquidity Surplus



Source: COREP Supervisory Data, Template C.72.00.a and Bankscope.

Note: Liquidity Surplus ($\boldsymbol{\gamma}$) is constructed as the difference between the numerator and the denominator of the liquidity coverage ratio (LCR), i.e. the difference between the stock of HQLAs (LB) and the net funding Outflows (NFO).

3.2.4 Fire Sale Discount Rate and Pool of Assets

The additional parameters required to simulate the contagion impact of a funding shock is the rate at which banks are forced to discount their assets as they react to a funding shortfall by deleveraging. Since, as the described in the previous section, we assume that the set of HQLA assets is used to cover the liquidity shortfall, and the fire sale stage is triggered only when it is exhausted, the set of assets available for sale is defined as the amount of unencumbered non-HQLA assets. This category of assets is retrieved from the asset encumbrance template F.32.01 which is further broken-down into different asset classes. In this respect, Equation (17) approximates the discount rate (δ_i) as the ratio between the discounted amount of unencumbered non-central bank eligible assets (D_UNCBEA_i) over the total amount of unencumbered non-central bank eligible assets

($UNCBEA_i$), which captures the pool of assets available for sale (θ_i). Therefore the δ_i coefficient for euro area banks is derived as the weighted average haircut ($\bar{\delta}_J$) of each asset classes A_j: respectively covered bonds ($\bar{\delta}_{CB}$), asset backed securities ($\bar{\delta}_{ABS}$), debt securities issued by general governments ($\bar{\delta}_{GG}$), debt securities issued by financial corporations ($\bar{\delta}_{FC}$), debt securities issued by non-financial corporations ($\bar{\delta}_{NFC}$), and equity instruments $\overline{(\delta_E}$). The average haircut ($\bar{\delta}_J$) for each asset class is based on the latest ECB's guidelines on haircuts.[18] Moreover, in order to take into account that the instruments we are dealing with are non-central bank eligible, we assume that the bottom threshold for haircuts is the highest haircut for central bank eligible instrument, i.e. 38%.

$$\delta_i = \sum_{j}^{N} \frac{\bar{\delta}_J A_j}{A_j} = \frac{\bar{\delta}_{CB} CB_i + \bar{\delta}_{ABS} ABS_i + \bar{\delta}_{GG} GG_i + \bar{\delta}_{FC} FC_i + \bar{\delta}_{NFC} NFC_i + \bar{\delta}_E E_i}{UNCBEA_i} \qquad (17)$$

For international banks for which we lack FINREP template F.32.01, we derive the discount rate δ_i and the pool of assets available for sale (θ_i) with a two-step procedure. First, we regress the balance sheet categories i) assets available for sales, ii) assets held for trading and iii) HQLA assets for the euro area banks sample as reported in equation (18) on the numerator and denominator of equation (17).

$$\sum_{j}^{N} \overline{\delta_{\iota,J}} A_{i,j} = a_1 FAAS_i + a_2 FAHT_i + a_3 HQLA_i + e_i \qquad (18)$$

In this way we obtain three coefficients a_1, a_2, a_3 explaining the contribution of each asset class for both dependent variables. As we can see from Table 2, the first two coefficients are statistically significant at 1% and the model shows a reliable goodness of fit, respectively 89% and 86% for the numerator and denominator of equation (17). Next, we retrieve from Bankscope the very same balance sheet categories for which we have a statistically significant coefficient, i.e., financial assets available for sale and financial assets held for trading. Hence, the second step consists in multiplying each balance sheet

[18] The haircut used for each asset class is the average across maturities. Calculations can be provided upon request. See: https://www.ecb.europa.eu/ecb/legal/pdf/celex_32018o0004_en_txt.pdf
https://www.ecb.europa.eu/mopo/assets/risk/liquidity/html/index.en.html

category for the relative estimated coefficients to derive the numerator and denominator of equation (17) for the sample of international banks and so obtaining the discount rate (δ_i) and the pool of assets (θ_i).

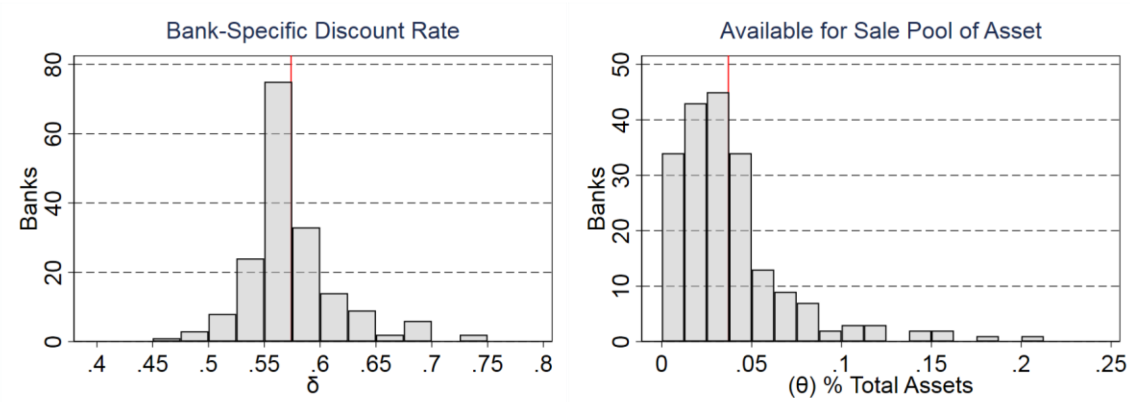
Table 2: Step 1 - Regression Results for Euro Area Banks Sample

VARIABLES	Coefficients	EA Banks Numerator Eq. 12	EA Banks Denominator Eq. 12
Financial Assets Available for Sale (FAAS)	(a1)	0.169***	0.309***
		-0.044	(0.0879)
Financial Assets Held for Trading (FAHT)	(a2)	0.0641***	0.108***
		(0.00973)	(0.0194)
High Quality Liquid Assets (HQLA)	(a3)	-0.0205	-0.0373
		(0.0327)	(0.0652)
Observations	/	85	85
Adj.R-squared	/	0.89	0.86

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 9 depicts respectively the bank-specific discount rate (δ_i) and the pool of assets available for sale (θ_i), the latter as share of total assets. As can be noticed, the bank-specific discount rate (δ_i) is centered around 57.5% and resembles a normal distribution, whereas the pool of non-central bank eligible assets is left skewed, with a mean centered around 4% of total assets and outliers reaching an amount higher than 20%.

Figure 9: Bank-Specific Discount Factor - Fire Sale Parameter

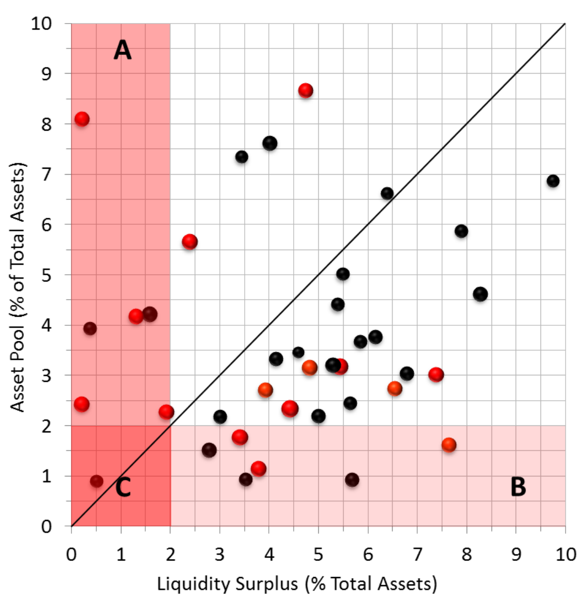


Source: COREP and FINREP Supervisory Data, Template F32.01 and bankscope.

Note: the $\boldsymbol{\delta}$ coefficient reflects a weighted average haircut of the portfolio $\boldsymbol{\theta}$ for non-central bank eligible instruments.

Overall, the nested set of liquidity and fire sale parameters $(\gamma_i, \theta_i, \delta_i)$, depicted in Figure 10, captures the degree of heterogeneity characterizing the liquidity strategies of banks in our sample. For instance, a bank may choose to hold a larger amount of HQLAs as a share of total assets (γ_i) - the area below the 45 degree line - than the pool of unencumbered non-HQLA financial assets (θ_i) - the area above the 45 degree line. Banks belonging to area (A) are those that may most likely suffer capital losses by liquidity shocks since the liquidity surplus may easily become binding, and in turn may trigger fire sales. On the contrary, banks belonging to area (B) are those that may most likely experience a liquidity defaultwhen the liquidity surplus (γ_i) is depleted. In this case, the pool of assets θ_i is likely to be insufficient to cover the remaining liquidity needs. In the end, the quadrant (C) captures those banks that are short of both buffers and are clear candidates for the realization of the liquidity default. Furthermore, the above mentioned effects are far more pronounced when the size of the nodes are large (red nodes), since it implies that they will face a harsher discount rate via fire sales. The realization of these dynamics (A, B, C) is conditional to the amount of short-term bilateral exposures $\rho_i x_{ih}$, which, in the end, determines the spread of contagion within the interbank market.

Figure 10: Liquidity Default Dynamics



Note: nodes' size is proportional to a bank's discount rate (δ). Red nodes highlight the 75th percentile of the discount factor. For confidentiality reasons, the chart shows statistics as average among three banks.

3.2.5 Distress-Default Threshold

A key assumption of the model is to define when counterparty *bank i* is not able to meet its payment obligations, i.e. a default or distress threshold (c_i^d). Accordingly, a bank can be considered in default/distress when the surplus of capital above the capital requirements a bank needs to meet at any time is depleted.

For our simulations we distinguish between two types of capital requirements: (i) minimum capital requirements and (ii) capital buffers. The former requires banks to hold 4.5% RWAs of minimum capital (MC). This minimum requirement might be higher depending on the bank-specific Pillar 2 requirement (P2R) set by the supervisor. In addition to this, a bank is required to keep a capital conservation buffer (CCoB) of between 1.875% and 2.5% CET1 capital as of 2018 (depending on the extent to which the jurisdiction where the bank is located has fully or only partially phased in the end-2019 requirement[19]), and a bank-specific buffer, which is the higher among the Systemic Risk Buffer (SRB), GSII and OSII buffers. Furthermore, some jurisdictions also apply a positive counter-cyclical capital buffer requirement (CCyB). In this regard, we retrieved bank-specific information on minimum capital requirements (CET1, TIER1, Own Funds) and capital buffers from COREP supervisory templates C.01, C.03 and C.06.01 and the bank-specific risk weighted assets (RWAs) from C.02. For international banks our data source is Bankscope.

Therefore, the capital surplus (k_i) can be defined in two ways: a capital surplus (k_i^{DF}) above the minimum capital requirements defined as a default threshold (c_i^{DF}) reported in equation (19a), or a capital surplus (k_i^{DS}) above the sum of the minimum capital requirements and the capital buffers defined as a distress threshold (c_i^{DS}) presented in equation (19b). When the bank breaches the minimum capital requirement (c_i^{DF}) it is assumed that the supervisor would declare the bank for "failing or likely to fail" (which is the official trigger for putting the bank into resolution).[20] When the bank breaches the

[19] In 2019 it will amount up to 2.5%.

[20] As stated in the Bank Recovery and Resolution Directive (BBRD), the resolution authority should trigger the resolution framework before a financial institution is balance sheet insolvent and before all equity has been fully wiped out (Title IV, Chapter I, Art. 32, Point 41). Thus, our calibration method is consistent with the Bank Recovery and Resolution Directive's (BRRD) guidelines on fail or likely to fail: "An institution shall be deemed to be failing or likely to fail in one or more of the following circumstances: … because the

buffer requirement (c_i^{DS}) while not yet breaching the minimum capital requirement, it is assumed that it will not be declared failing but that it would rather be constrained in its ability to pay out dividends. This, itself, could be a trigger for bank distress and is thus considered as an alternative trigger threshold.

$$\begin{aligned} k_i^{DF} &= c_i - c_i^{DF} \\ &= c_i - (MC_i + CCoB_i + P2R_i) \end{aligned} \tag{19a}$$

$$\begin{aligned} k_i^{DS} &= c_i - c_i^{DS} \\ &= c_i - [(MC_i + CCoB_i + P2R_i) + \max(SRB_i, GSII_i, OSII_i) + CCyB_i] \end{aligned} \tag{19b}$$

Hence, this calibration method allows for some flexibility on the determination of a bank's default depending on the purpose of the exercise. While from a resolution authority and supervisory perspective the capital surplus (k_i^{DF}) based on the default threshold (c_i^{DF}) may be the more relevant reference point, the distress threshold (c_i^{DS}) may be of interest to macroprudential supervisors. As this paper has a systemic risk focus, we will provide results based on the latter approach. This is further motivated by the fact that the inclusion of the macroprudential buffers ($SRB_i, GSII_i\ OSII_i, CCyB_i$) allows to take into account the impact of macroprudential policy actions.[21] Nevertheless, we discuss the differences in the two approaches in the sensitivity analysis section.

Finally, an additional feature that needs to be taken into consideration in order to accurately handle heterogeneity in the bank-specific capital surplus concerns the type of capital used in the calculation. In fact, both the capital base (c_i) and the minimum capital (MC_i) and pillar 2 requirements ($P2R_i$) may vary whether the capital considered is CET1, TIER1, or own funds calculated as the sum of TIER1 and TIER2 instruments. For instance, MC_i are respectively 4.5% of RWAs for CET1 capital, 6% of RWAs for TIER1 capital, and 8% of RWAs for own funds. In turn, these differences are also reflected in the capital base (c_i). Hence, this implies that the very same bank may face a capital surplus ($k_i^{CET1} \gtrless k_i^{TIER1} \gtrless k_i^{OF}$) larger or smaller depending on the capital considered.

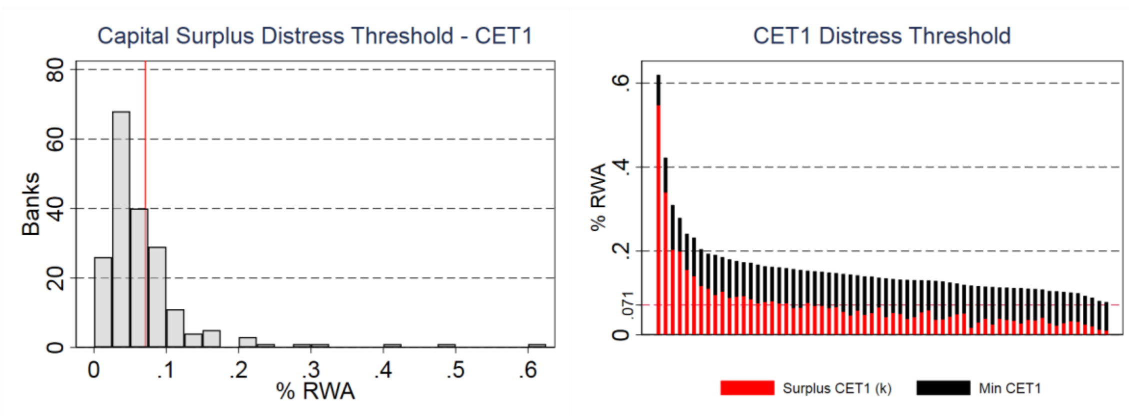
institution has incurred or is likely to incur losses that will deplete all or a significant amount of its own funds" (Title IV, Chapter I, Art. 32, Point 4).

[21] Potentially also the Pillar 2 Guidance (P2G) may be included into the distress threshold calculation.

In this study, we use as benchmark the CET1 ratio, although we provide in the results section evidence for the robustness of our findings to this calibration feature.

Figure 11: Bank-Specific Distress Threshold

Panel (a) Panel (b)



Source: COREP Supervisory Data Templates C.01-C.03, and Bankscope.

Note: The sum of minimum capital and capital surplus gives total capital (c). The decreasing ordering is based on total capital. For confidentiality reasons, panel (b) shows surplus and minimum CET1 as average among three banks following total capital decreasing ordering.

Panel (a) of Figure 11 depicts the distribution of the CET1 capital surplus based on a distress threshold, while panel (b) presents the contribution of the capital surplus (distress threshold) and the distress threshold to the capital base.[22]

Overall, the advantage of this methodology is twofold. It allows us to tailor a realistic distress-default threshold and put it in relation to the bank's voluntary buffer (here defined as 'capital surplus') as well as to perform scenario analysis and counterfactual analysis by imposing higher bank-specific capital requirements or by reducing the capital surplus under an adverse scenario.

3.3 Model Outputs

This exercise is tailored to rank banks for their systemic risk contribution to financial stability in terms of potential contagion and degree of vulnerability of the euro area

[22] Although the average capital surplus varies little among the different capital classes (close to 7-8% of RWAs). The number of banks close to the distress threshold moves from 24 for the CET1 capital threshold to 22 for TIER1, and to 18 for Total Capital (Own Funds). Bank-specific distress threshold for Tier 1 and total capital are available upon request.

banking system. Considering, a policy maker's perspective, each bank is evaluated upon four main model-based outputs, as follows:

i. *Contagion index (CI):* system-wide losses induced by *bank i* in percent of total capital in the system (excluding *bank i*);

$$CI_i = 100 \frac{\sum_{j \neq i} L_{ji}}{\sum_{j \neq i} k_j},$$

where L_{ji} is the loss experienced by *bank j* due to the triggered default of *bank i*.

ii. *Vulnerability index (VI):* average loss experienced by *bank i* across all simulations in percent of its own capital.

$$VI_i = 100 \frac{\sum_{j \neq i} L_{ij}}{\sum_{j \neq i} k_i},$$

iii. *Contagion level:* the number of banks that experience severe distress associated with a default induced by the initial hypothetical failure of *bank i*;

iv. *Vulnerability level:* the total number of simulations under which *bank i* fails;

where L_{ij} is the loss experienced by *bank i* due to the triggered default of *bank j*.

Essentially, losses experienced by each bank (L_{ji}) is the sum of losses associated with credit risk shock (LCr_{ji}) and losses associated with a funding risk shock (LFu_{ji}). Hence, each index can be broken down to the respective contributions by credit risk (CI_Cr and VI_Cr) and funding risk (CI_Fu and VI_Fu) shocks providing insights to the nature of contagion.

$$CI\_Cr_i = 100 \frac{\sum_{j \neq i} LCr_{ji}}{\sum_{j \neq i} k_j}, and\ CI\_Fu_i = 100 \frac{\sum_{j \neq i} LFu_{ji}}{\sum_{j \neq i} k_j},$$

$$VI\_Cr_i = 100 \frac{\sum_{j \neq i} LCr_{ij}}{\sum_{j \neq i} k_i}, and\ VI\_Fu_i = 100 \frac{\sum_{j \neq i} LFu_{ij}}{\sum_{j \neq i} k_i},$$

The indices can be further decomposed based on banks' geographical origins. For example, CI_EA_i is a sub-index based on the total induced losses by bank i to the subset of banks that are in the euro area. Similarly, VI_EA_i is a sub-index based on the average losses experienced by bank i across the subset of simulations where the triggered banks are in the euro area. Essentially, these two indices capture a given bank's contagion and vulnerability to euro area banks.

$$CI\_EA_i = 100\frac{\sum_{j\neq i} L_{ji}}{\sum_{j\neq i} k_j}\ , i \in \mathbb{S}_{EA}\ , and\ VI\_EA_i = 100\frac{\sum_{j\neq i} L_{ij}}{\sum_{j\neq i} k_i}\ , j \in \mathbb{S}_{EA}$$

where $\mathbb{S}_{EA}$ is the subsample of banks in the euro area.

The geographical focus can be based on distinguishing between euro area and non-euro area banks as well as between individual countries where banks are domesticated. Moreover, based on these outputs, we develop two additional indicators to deepen both analytical assessment and policy implications of contagion analysis and in turn facilitate the impact assessment of regulatory actions.

v. *Amplification ratio (cascade effect):* this metric compares the losses induced by a bank's simulated default in the initial round vis-à-vis those occurring in all successive rounds. From the perspective of a bank, *bank i,* triggering system-wide contagion:

$$AMP(C)_i = \frac{\sum_{j\neq i} L_{ji\, r_{0+t}}}{\sum_{j\neq i} L_{ji\, r_0}}$$

$$Where\ r_0 = initial\ round\ ;\ r_{0+t} = successive\ rounds.$$

This index measures how much of the system-wide impact from the failure of *bank i* is caused by cascading of defaults rather than direct and immediate losses from *bank i*. Hence, the higher the ratio, the larger the amplification through the network, and a ratio greater than 1 indicates that losses due to cascade effects dominate direct losses.

Conversely, banks' susceptibility to systemic events can be split into two similar components to distinguish how much of the losses experienced by bank i across all simulations were immediate losses as opposed to losses in successive rounds:

$$AMP(V)_i = \frac{\sum_{j\neq i} L_{ij\, r_{0+t}}}{\sum_{j\neq i} L_{ij\, r_0}}$$

Amplification effect quantifies the degree to which cascading behavior impacts the banks both at system-wide and entity level. These are the losses associated with contagion spread through indirect linkages. Amplification effect is an important metric of the financial system architecture in the sense that it captures what portion of systemic risk is not directly observable to banks and, possibly, to the regulators in the absence of granular data.

vi. *Sacrifice ratio:* One of the most important policy questions during financial crises or near-crisis episodes concerns bank recapitalization or emergency liquidity assistance. The concept of "too big to fail" does not solely depend on a bank's size and portfolio compared to the domestic system but also on whether a single failure would induce a larger collapse in the financial system. With respect to the latter, we construct a sacrifice ratio, which measures the ratio of system-wide losses due to the failure of a bank over the cost of a rescue package, tax-payer sacrifice, equal to the capital requirements of the bank.[23]

$$SR_i = \frac{\sum_{j \neq i} L_{ji}}{c_i^{DS}}$$

Therefore, ratios above 1 are associated with system-wide losses that could be avoided with relatively smaller cost to the tax payer. In contrast, ratios smaller than 1 would imply that potential system-wide losses are not sufficiently large to justify the government assistance to the bank. We provide three types of sacrifice ratios from the perspectives of: (i) a global central planner; (ii) a euro area authority; and (iii) a national authority. These three measures take into account system-wide losses respectively induced to all banks in the system (global central planner) or to those banks belonging to each jurisdiction, whether it is euro area based, or national. It is important to underline that our modelling strategy does not take into account the mitigation and amplification effects induced by a bail-in mechanism, neither for the triggering bank nor for the subsequent failing banks.[24] Once the magnitude of system-wide losses associated with bank failures are understood, a critical policy question is how the regulators respond to the pending default of an entity. In other words, the regulators would need to know whether the public cost of making the entity whole again justifies the potential damages to the system when no action is taken.

[23] Capital requirements are defined as for the distress threshold as follows: $(MC_i + CCoB_i + P2R_i) + \max(SRB_i, GSII_i, OSII_i) + CCyB_i$.

[24] Introducing a bail-in mechanism into the model would tend to reduce the cost of a bank-recapitalization since bailinable liabilities would be transformed into new equity of the bank considered for resolution thus shielding taxpayers. At the same time, it could increase the amount of losses experienced by the other banks in the network since creditors' assets such as additional tier 1 and tier 2 instruments, other subordinated debts, senior unsecured debt and non-eligible deposits, and non-covered eligible deposits may face a partial or complete written-off (see Hüser et al., 2017).

4 Results

4.1 Main Findings

This subsection delves in greater detail into main findings of the exercise across a broad range of interconnectedness attributes based upon our benchmark model with bank-specific calibration. For the sake of clarity, out of 199 worldwide consolidated banking groups, Table 3 reports the top-50 default events ranked in terms of contagion index (CI) to the euro area banking system.

The scale of losses follows a power-law distribution, with the top-10 banks inducing on average 2.5% of capital losses to the euro area banking system, around EUR 25 billion.[25] The CI index of the most contagious bank is larger by a factor of 12 than the average of the full sample, and even among the top-10 most contagious banks remarkable differences exist. International spillovers seem to be a key channel of contagion to the euro area banking system, with 27 banking groups out of the top-50 located outside the euro area. Therefore cross-border risks may propagate quickly via bilateral exposures to the euro area banking network, as evident during the Great Financial Crisis of 2008.

In terms of channels underlying contagion, losses due to credit risk dominate those due to funding/liquidity risk via fire sales. When it comes to the nature of defaults (contagion level), illiquidity-driven defaults outweigh by far those triggered due to insolvency matching the historical reality as emphasized by Aikman et al. (2018). Notably, solvency defaults are mostly concentrated in the top-10, underlying how contagion due to solvency risks may be highly concentrated on few players due to their central role in the network as borrowers; whereas liquidity risks may be triggered by a greater number of lenders in the network for which the intrinsic characteristics of the borrower play a more crucial role. In other words, funding risk relative to credit risk seems to be less diversifiable and more concentrated on few large exposures, whose defaults may trigger a liquidity default event. This finding may suggest that it may be prudent to impose limits on the concentration of funding since some small and medium-sized banks are exposed on the liability side to few large banks.

[25] Result for power-law distribution can be provided upon request. The capital of the triggering bank is not included in the CI index calculation.

Table 3: Contagion Measures

Contagion		EURO AREA			Defaults			Amplification		Sacrifice Ratio		
RANK	Country	CI	CI CR	CI FU	ToT	Solv.	Liq.	Rounds	Ratio	G	EA	N
1	EA	3.8	3.8	0.0	0	0	0	1	0.0	0.6	0.6	0.2
2	XEA	3.2	3.1	0.1	3	1	2	2	0.1	0.4	0.4	0.0
3	XEA	2.7	2.3	0.4	1	1	0	2	0.5	0.6	0.4	0.1
4	EA	2.4	2.4	0.0	2	2	0	2	0.0	0.7	0.7	0.3
5	EA	2.3	2.3	0.0	0	0	0	1	0.0	0.7	0.7	0.3
6	XEA	2.3	2.1	0.2	3	0	3	2	0.2	0.9	0.7	0.1
7	EA	2.2	2.1	0.1	1	0	1	2	0.0	0.4	0.4	0.2
8	XEA	1.9	1.9	0.0	0	0	0	1	0.0	0.3	0.3	0.0
9	XEA	1.9	1.9	0.0	0	0	0	1	0.0	0.5	0.5	0.0
10	EA	1.9	1.9	0.0	0	0	0	1	0.0	0.5	0.4	0.3
AVERAGE TOP 10		2.5	2.39	0.07	1.0	0.4	0.6	1.50	0.1	0.56	0.52	0.13
11	EA	1.8	1.8	0.0	1	1	0	2	0.0	0.3	0.3	0.1
12	XEA	1.4	1.2	0.2	1	0	1	2	0.1	0.3	0.2	0.0
13	XEA	1.4	1.3	0.1	2	0	2	2	0.3	0.9	0.7	0.0
14	EA	1.3	1.3	0.0	0	0	0	1	0.0	0.4	0.4	0.0
15	XEA	1.1	1.0	0.1	0	0	0	1	0.0	2.2	2.2	0.0
16	XEA	1.0	1.0	0.0	0	0	0	1	0.0	0.6	0.6	0.0
17	EA	1.0	1.0	0.0	0	0	0	1	0.0	0.5	0.4	0.2
18	EA	0.9	0.9	0.0	0	0	0	1	0.0	0.3	0.3	0.1
19	EA	0.8	0.8	0.0	1	0	1	2	0.1	0.4	0.4	0.3
20	XEA	0.8	0.8	0.0	0	0	0	1	0.0	0.3	0.3	0.0
21	XEA	0.8	0.8	0.0	0	0	0	1	0.0	0.5	0.5	0.0
22	EA	0.8	0.4	0.4	1	1	0	2	4.3	5.0	1.8	0.8
23	XEA	0.8	0.8	0.0	0	0	0	1	0.0	0.9	0.9	0.0
24	EA	0.8	0.8	0.0	0	0	0	1	0.0	0.5	0.5	0.2
25	XEA	0.7	0.7	0.0	0	0	0	1	0.0	0.3	0.3	0.0
26	EA	0.6	0.6	0.0	0	0	0	1	0.0	0.2	0.2	0.0
27	XEA	0.6	0.6	0.0	0	0	0	1	0.0	0.0	0.0	0.0
28	XEA	0.6	0.6	0.0	0	0	0	1	0.0	0.5	0.5	0.0
29	EA	0.5	0.5	0.0	0	0	0	1	0.0	1.2	1.2	1.2
30	EA	0.5	0.4	0.1	0	0	0	1	0.0	11.4	11.4	7.2
31	EA	0.5	0.5	0.0	0	0	0	1	0.0	1.2	1.1	1.1
32	XEA	0.5	0.5	0.0	0	0	0	1	0.0	0.1	0.1	0.0
33	XEA	0.5	0.5	0.0	0	0	0	1	0.0	0.0	0.0	0.0
34	XEA	0.5	0.4	0.1	3	0	3	2	1.4	1.3	0.5	0.0
35	EA	0.5	0.5	0.0	0	0	0	1	0.0	0.3	0.3	0.2
36	EA	0.4	0.4	0.0	0	0	0	1	0.0	0.2	0.2	0.0
37	XEA	0.4	0.4	0.0	0	0	0	1	0.0	0.3	0.3	0.0
38	XEA	0.4	0.4	0.0	0	0	0	1	0.0	0.0	0.0	0.0
39	EA	0.4	0.4	0.0	0	0	0	1	0.0	5.8	1.3	0.1
40	XEA	0.4	0.4	0.0	0	0	0	1	0.0	0.0	0.0	0.0
41	XEA	0.4	0.4	0.0	0	0	0	1	0.0	1.4	1.4	0.0
42	EA	0.4	0.4	0.0	0	0	0	1	0.0	4.0	3.9	1.1
43	XEA	0.4	0.4	0.0	0	0	0	1	0.0	1.2	1.2	0.0
44	XEA	0.4	0.4	0.0	0	0	0	1	0.0	0.3	0.3	0.0
45	XEA	0.4	0.4	0.0	0	0	0	1	0.0	0.1	0.1	0.0
46	EA	0.4	0.4	0.0	0	0	0	1	0.0	2.4	0.3	0.1
47	XEA	0.3	0.3	0.0	0	0	0	1	0.0	0.7	0.7	0.0
48	XEA	0.3	0.3	0.0	0	0	0	1	0.0	0.0	0.0	0.0
49	EA	0.3	0.3	0.0	0	0	0	1	0.0	0.5	0.5	0.5
50	EA	0.3	0.3	0.0	0	0	0	1	0.0	0.4	0.3	0.3
AVERAGE TOP 50		1.0	0.98	0.03	0.38	0.12	0.26	1.22	0.14	1.05	0.82	0.30
AVERAGE		0.3	0.31	0.01	0.10	0.03	0.07	1.06	0.04	0.77	0.67	0.15

Note: For confidentiality reasons bank names have been anonymized. The results in this table are ranked by CI index. CI refers to contagion index at euro area scale and amounts represent capital losses to all banks in percent of entire banking system's total capital. This index is further decomposed into the respective contributions by credit (CI CR) and funding (CI FU) shocks. Defaults refer to the number of defaults a bank has induced in the system. Rounds indicate the maximum number of rounds the simulation required until no additional defaults in the system, whereas amplification ratio is the ratio of losses in subsequent rounds to losses in the initial round. The sacrifice ratio indicates the ratio of systemic losses caused by a bank over the cost of rescue package to fully recapitalize the bank.

4.1.1 Amplification Effects

One powerful feature of our framework is its ability to capture cascade effects due to an initial distress event. In most cases, the contagion does not spread beyond the direct counterparties in the first round. At most, the contagion cycle ends after a second round of failures, and overall has limited repercussions on the system as a whole. There are only two banks with an amplification effect larger than 1 and whose failure causes losses 4.3 and 1.4 times more in subsequent rounds compared to the initial round.

4.1.2 Sacrifice ratio

In this exercise, four failures warrant an intervention in the form of a rescue package by national authorities. The average sacrifice ratio is close to 0.3 for the top-50, whereas for the top-10 most systemic banks is equal to 0.13. The latter is lower than the former because i) global banks tend to have most of their exposures outside the domestic interbank market, thereby implying a lower numerator of the sacrifice ratio than a bank more domestic-oriented, ii) global banks tend to have a larger denominator than the more domestic-oriented ones due to higher capital requirements. However, if supervisors take the perspective of a euro area authority, the average ratio of the top-50 increases up to 0.82, and five more interventions are justified. In this respect, six out of nine defaults originate from entities located within the euro area and, thus, can be resolved within the realm of the Single Resolution Mechanism. The other three interventions should be granted to extra-euro area banks, and given their respective contagion to the euro area banking system, it might be instructive to monitor the evolution of such costly spillovers and cooperate closely with international authorities as needed.

In the end, a global perspective increases the number of interventions up to eleven, thereby highlighting how international cooperation is necessary to reduce negative externalities to the whole financial system

4.1.3 Vulnerability

Having investigated the various aspects of contagion, it is important to understand its complementary interface, i.e. which banks are the most vulnerable and how contagion affects them. Hence, banks are ranked by vulnerability index at global scale.

Table 4: Vulnerability Measures

Vulnerability		GLOBAL SCALE			Defaults			Amplification	Contribution	EURO AREA		
RANK	**Country**	**VI**	**VI CR**	**VI FU**	**ToT**	**Solv.**	**Liq.**	**Ratio**	**Ratio**	**VI**	**VI CR**	**VI FU**
1	EA	1.8	0.7	1.2	2	2	0	0.0	0.9	1.6	0.7	1.0
2	EA	1.4	1.4	0.0	0	0	0	0.0	0.7	1.0	1.0	0.0
3	EA	1.1	1.1	0.0	0	0	0	0.0	1.5	1.6	1.6	0.0
4	EA	1.0	1.0	0.0	0	0	0	0.0	0.8	0.8	0.8	0.0
5	EA	0.9	0.9	0.0	0	0	0	0.0	1.1	1.0	1.0	0.0
6	XEA	0.8	0.8	0.0	0	0	0	0.4	1.1	0.9	0.9	0.0
7	EA	0.8	0.8	0.0	0	0	0	0.0	0.6	0.4	0.4	0.0
8	EA	0.7	0.7	0.0	0	0	0	0.0	0.9	0.6	0.6	0.0
9	EA	0.6	0.6	0.0	0	0	0	0.0	0.4	0.3	0.3	0.0
10	EA	0.6	0.5	0.1	2	0	2	0.0	2.1	1.3	1.1	0.2
AVERAGE TOP 10		**1.0**	**0.8**	**0.1**	**0.4**	**0.2**	**0.2**	**0.0**	**1.0**	**0.9**	**0.8**	**0.1**
11	EA	0.6	0.6	0.0	0	0	0	0.2	1.4	0.9	0.9	0.0
12	EA	0.5	0.5	0.0	0	0	0	0.0	0.7	0.4	0.4	0.0
13	EA	0.5	0.5	0.0	0	0	0	0.0	0.6	0.3	0.3	0.0
14	EA	0.5	0.5	0.0	0	0	0	0.0	0.8	0.4	0.4	0.0
15	EA	0.5	0.5	0.0	0	0	0	0.1	1.2	0.6	0.6	0.0
16	EA	0.4	0.4	0.0	0	0	0	0.1	1.0	0.4	0.4	0.0
17	EA	0.4	0.4	0.0	0	0	0	0.0	1.2	0.5	0.5	0.0
18	EA	0.4	0.4	0.0	3	3	0	0.0	1.3	0.5	0.5	0.0
19	EA	0.4	0.4	0.0	0	0	0	0.0	1.8	0.8	0.8	0.0
20	EA	0.4	0.4	0.0	0	0	0	0.0	1.0	0.4	0.4	0.0
21	EA	0.4	0.4	0.0	0	0	0	0.0	0.7	0.3	0.3	0.0
22	EA	0.4	0.4	0.0	0	0	0	0.0	2.1	0.8	0.8	0.0
23	EA	0.4	0.4	0.0	0	0	0	0.0	0.8	0.3	0.3	0.0
24	EA	0.4	0.4	0.0	0	0	0	0.0	1.0	0.4	0.4	0.0
25	EA	0.4	0.4	0.0	0	0	0	0.0	2.1	0.7	0.7	0.0
26	EA	0.4	0.4	0.0	0	0	0	0.0	1.6	0.6	0.6	0.0
27	EA	0.3	0.3	0.0	0	0	0	0.0	0.9	0.3	0.3	0.0
28	EA	0.3	0.3	0.0	0	0	0	0.0	1.0	0.4	0.4	0.0
29	EA	0.3	0.3	0.0	0	0	0	0.0	1.2	0.3	0.3	0.0
30	EA	0.3	0.3	0.0	0	0	0	0.0	0.6	0.2	0.2	0.0
31	EA	0.3	0.3	0.0	0	0	0	0.0	1.8	0.5	0.5	0.0
32	EA	0.3	0.2	0.1	4	0	4	0.0	0.1	0.0	0.0	0.0
33	EA	0.3	0.3	0.0	0	0	0	0.0	0.7	0.2	0.2	0.0
34	EA	0.3	0.1	0.1	4	0	4	0.0	0.2	0.0	0.0	0.0
35	EA	0.3	0.3	0.0	0	0	0	0.0	0.9	0.2	0.2	0.0
36	EA	0.3	0.3	0.0	0	0	0	0.0	0.8	0.2	0.2	0.0
37	EA	0.2	0.2	0.0	0	0	0	0.0	2.1	0.5	0.5	0.0
38	XEA	0.2	0.2	0.0	0	0	0	0.9	1.3	0.3	0.3	0.0
39	EA	0.2	0.2	0.0	0	0	0	0.0	1.8	0.4	0.4	0.0
40	EA	0.2	0.2	0.0	0	0	0	0.0	0.0	0.0	0.0	0.0
41	EA	0.2	0.2	0.0	0	0	0	0.0	1.1	0.2	0.2	0.0
42	EA	0.2	0.2	0.0	0	0	0	0.0	2.1	0.4	0.4	0.0
43	EA	0.2	0.2	0.0	0	0	0	0.0	0.8	0.2	0.2	0.0
44	EA	0.2	0.2	0.0	0	0	0	0.0	1.9	0.4	0.4	0.0
45	EA	0.2	0.2	0.0	0	0	0	0.0	1.3	0.3	0.3	0.0
46	EA	0.2	0.2	0.0	0	0	0	0.0	0.8	0.2	0.2	0.0
47	EA	0.2	0.2	0.0	0	0	0	0.0	1.2	0.2	0.2	0.0
48	EA	0.2	0.2	0.0	0	0	0	0.0	0.8	0.2	0.2	0.0
49	EA	0.2	0.2	0.0	0	0	0	0.0	1.3	0.3	0.3	0.0
50	EA	0.2	0.2	0.0	0	0	0	0.0	0.6	0.1	0.1	0.0
AVERAGE TOP 50		**0.45**	**0.42**	**0.03**	**0.3**	**0.1**	**0.2**	**0.03**	**1.1**	**0.5**	**0.4**	**0.0**
AVERAGE		**0.14**	**0.13**	**0.01**	**0.1**	**0.0**	**0.1**	**0.05**	**1.3**	**0.2**	**0.1**	**0.0**

Note: For confidentiality reasons bank names have been anonymized. VI refers to vulnerability index and amounts represent average capital losses across all independent simulations in percent of a bank's capital. The vulnerability index is further decomposed into the respective contributions by credit (VI CR) and funding (VI FU) shocks. VI from Euro Area (VI EA) is computed with respect to average losses caused by banks in respective groups. Defaults refer to the number of defaults a bank has experienced given the hypothetical (exogenous) defaults of each other bank in the system. Amplification ratio is is the ratio of losses in subsequent rounds to losses in the immediate round. The results in this table are ranked by VI Global Scale.

Focusing on the banks with the 50 highest vulnerability scores, they are almost all from within the euro area. This is due to the fact that the large exposures dataset, as emphasized in section 2, mostly captures exposures from euro area banks, and for this precise reason, we adopt a euro area centric view. Although, this index is computed as the share of losses experienced by a bank over the bank's capital base, and not in % of the system capital, the distribution of losses also for this index follows a power-law distribution.

As previously emphasized, funding risk is concentrated with few banks, whereas losses due to credit risks are spread over the entire sample. Consistently, out of 15 defaults experienced by the top-50 most vulnerable banks, liquidity defaults accounts for 2/3 of failures, while solvency defaults account only for 1/3. Cascade effects seem to play a minor role in terms of loss amplification and induced defaults. None of the banks defaulting shows a positive amplification ratio, which is concentrated to a few entities.

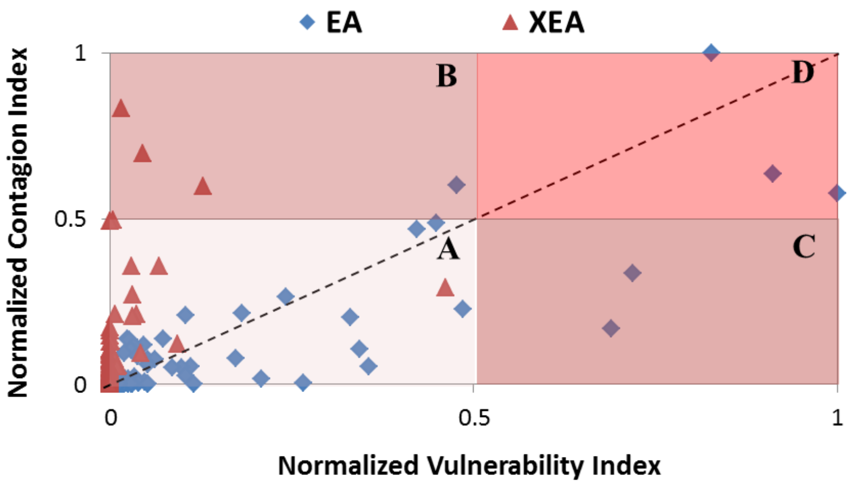
We also report for comparative purpose, the euro area based vulnerability index and its regional contribution in order to disentangle which banks may be most vulnerable from shocks arising from within and outside the euro area banking system. On average, losses produced from within the euro area are 1.3 time higher than the amount of losses experienced from entities located outside the euro area. Whereas, for the top-10 most vulnerable banks externally-driven losses are at least as important as euro area induced losses, reflecting the international profile of this group of institutions.

In Figure 12, a systemic risk map combines information from both indexes in order to allow an easy identification of threats to euro area financial stability.[26] In this picture, the contagion and vulnerability indexes are normalized and reported in absolute terms, i.e. total amount of losses induced and experienced by each bank, respectively. Figure 12 is divided into four quadrants capturing different degrees of banks' systemic footprints. Banks in the north-west quadrant (B) are those whose default would induce the greater amount of losses to the euro area banking system, while those lying in the south-east quadrant (C) are those most vulnerable to a default event. Banks located in the north-east

[26] The vulnerability index is here reported in absolute terms, i.e. considering the EUR value of capital depletion, and not as a % of the capital base.

quadrant (D) are both highly contagious and vulnerable. These metrics provide a useful monitoring tool to assess vulnerabilities in the euro area banking system due to interconnectedness.

Figure 12: Systemic-Risk Map



Note: Contagion and vulnerability indexes are normalized by dividing each index for the entity's maximum value.

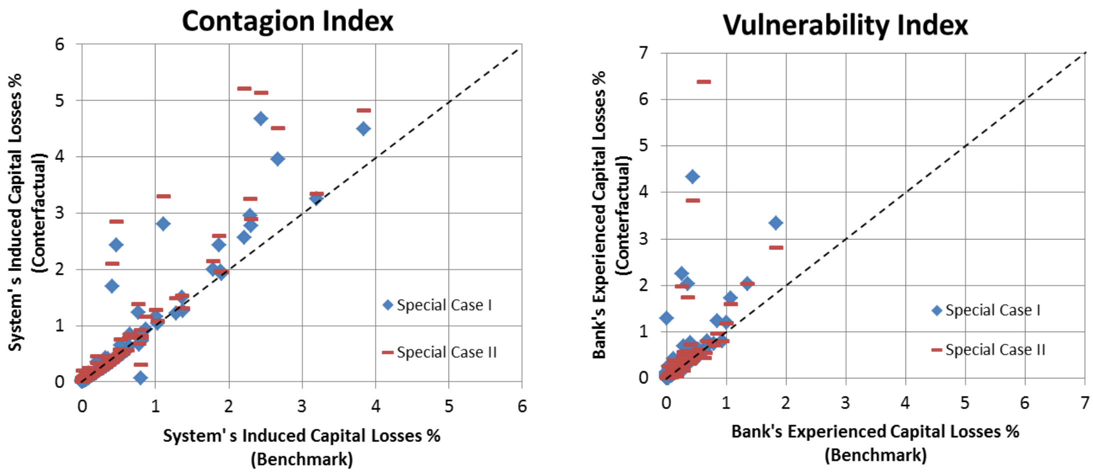
4.2 Bank-Specific Calibration

Parameters and model heterogeneity renders a different picture compared with homogeneous parameters ($\lambda, \rho, \gamma, \theta, \delta$) approximated as sample averages uniformly applied to all banks (Special Case I). This difference is even more marked when we don't consider the bank-specific liquidity coverage ratio (γ) and the liquidity default assumptions, respectively by setting $\gamma = 0$ and $\theta = \infty$ (Special Case II).[27] As shown in Figure 13, in both cases losses are larger than in the bank-specific calibration (benchmark case). On the one hand - special case I - using average parameters cancels all the losses coming from funding risk (See Table 1A Appendix). This is due to the fact that the liquidity buffer (γ) is large enough to cover all short-term funding needs. On the other hand, a bank-average calibration neglecting the liquidity buffer (γ) and the constraint based on the pool of available for sale assets (θ) results in an over-estimation of funding

[27] For computing fire sales losses, we now use a lower discount rate than the average of the bank-specific one because assets available for sales are not limited to the pool of non-HQLA assets, but comprehend also HQLA assets which, by definition, face lower haircuts. The former average was set close to 57.5% (as shown in figure 9), while now it stands to 26%.

risk. This is due to the assumption that each funding shortfall is directly transformed via fire sales into a solvency risk.

Figure 13: Bank-Specific Calibration



Note: Benchmark refers to results presented in section 4.1. Special case I sets $(\lambda, \rho, \gamma, \theta, \delta)$ equal to the average of the sample, while special case II sets (λ, ρ, δ) equal to the average of the sample and $\gamma = 0$ and $\theta = \infty$. We use the same distress threshold as in the benchmark case.

These findings highlight that bank-heterogeneity is an essential determinant of liquidity contagion, since weak nodes are those channels amplifying the initial shock and creating cascade effects. Moreover, by applying average parameters credit risk increases. The intuition behind this effect is that banks with larger and riskier exposures tend to ask for a higher collateral amount, which results in a counterbalancing-risk behavior and a lower exposure-specific LGD vis-à-vis riskier counterparties.

Overall, the results from this exercise support the importance of calibrating the model with bank-level specificities and how the inclusion of prudential regulations into the model parameters such as the HQLA buffer (λ) is essential to more properly estimate liquidity risk. Model and parameter heterogeneity lead to significant corrections and overall changes in the CI and VI indexes as well as in bank-specific scores. In addition, this exercise clearly highlights the role played by weak nodes in amplifying contagion, and how neglecting them may lead to estimation bias.

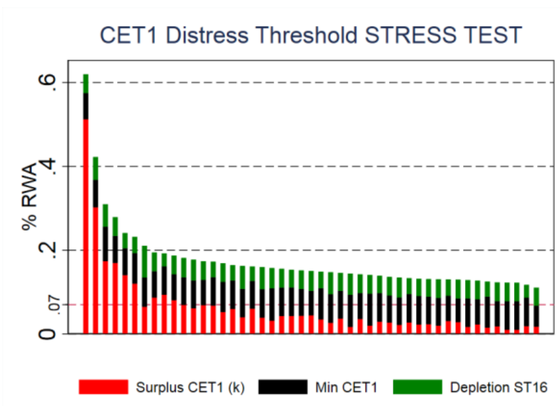
4.3 Macro Stress Test Scenarios

The framework has so far been applied as an exercise that simulated the hypothetical failure of each bank separately. Bank defaults may occur for purely institution-specific reasons. However, often bank defaults (or distress) happen against the background of more widespread stress in the financial system. Under such stressed circumstances the contagion potential from one bank defaulting might be more pronounced as also the banks' counterparts are in a weakened position. To explore the contagion risk under a generalized financial stressed situation, we incorporate the EBA 2016 stress test adverse scenario in our framework.[28]

In this exercise, as shown in equation (20), we recalibrate the capital surplus ($k_i^{DS\_ST16}$) in line with the capital depletion (c_i^{ST16}) that resulted from the 2016 EBA Stress Test of EU banks under an adverse scenario (Figure 14).[29]

$$k_i^{DS\_ST16} = k_i^{DS} - c_i^{ST16} \qquad (20)$$

Figure 14: Distress Threshold – Stress Test 2016's Capital Depletion



Source: COREP Supervisory Data Templates C.01 – C.03, and Bankscope.
Note: The sum of minimum CET1, surplus CET1 and ST16 gives total CET1. ST16 refers to the capital depletion due to the 2016 stress test's results. For confidentiality reasons, the chart shows surplus and minimum CET1 as average among three banks following total capital decreasing ordering.

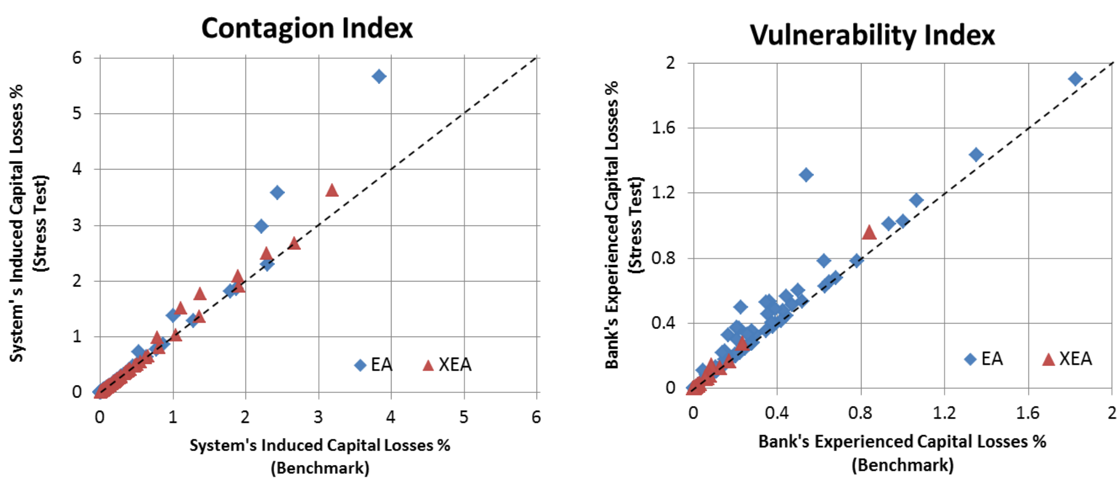
Overall, as shown in Figure 15, the weakened solvency position of euro area banks results in a disproportional increase of the contagion index. The top-10 most systemic

[28] As an alternative to assuming a macro shock, we could implement a multiple default scenario approximating a severe shock causing near collapse of the banking system in several major economies (i.e. Global Financial Crisis).

[29] We apply the average capital depletion to those banks not included in the EBA exercise.

banks increase their average losses caused at aggregate level by 1.25 times. In addition, accounting for an adverse macro scenario reshapes the ranking of the most systemic banks. In contrast, the vulnerability ranking is more affected at the center of the distribution, with the most vulnerable banks preserving their position. Also concerning this indicator, the effects seem to suggest non-linearities as shown by uneven changes across banks. Overall, the average number of induced defaults rises by a factor of 3.3 (from 0.1 to 0.34), impacting consistently both the average top-50 amplification ratio and the sacrifice ratio, which respectively increase from 0.05 to 0.25 and from 0.52 to 0.61 (for the euro area authority), with 2 additional cases of positive system-wide returns from banks' recapitalization.

Figure 15: Non-linear Effects of a Stress Test Scenario



Note: Benchmark refers to results presented in section 4.1.

4.4 Sensitivity Analysis

In this section we test the sensitivity of the results to a range of parameter assumptions so as to disentangle the key determinants of contagion and vulnerability of the euro area banking system.

The first sensitivity analysis tests the difference between a distress and a default threshold as described respectively in equation (19a and 19b). As can be observed in Figure 16 (Appendix), on average the affected banks operate with a capital surplus based on a default threshold which is 1% higher than the capital surplus based on a distress threshold (in RWA terms), with some outliers close to 3% (panel a). Nonetheless, as we can see from panel (b) this difference does not produce any relevant variation in the contagion and vulnerability indexes. The explanation for this finding is that the most systemic banks are also the ones facing the highest macroprudential buffer requirements ($SRB_i, GSII_i, OSII_i$) and generally did not fail in the benchmark exercise with a distress threshold, which is by construction smaller than the default threshold. Moreover, the CCyB buffer is currently of a small magnitude, thereby reducing the capital surplus of the distress threshold by little.

A second robustness check aims to verify whether changing the capital base from CET1 to own funds (total capital) may affect the capital surplus based on the distress threshold in a sizeable manner. As reported in Figure 17 panel (a) in the appendix, banks may face both a decrease or an increase in the capital surplus depending on whether the increased amount of minimum capital requirements (from 4.5% CET1 to 8% Own Funds) outweighs the increased amount of capital included into own funds, i.e. additional tier 1 and tier 2 instruments. Overall, the results seem to be almost invariant to the selection of the capital base. In both exercises, the findings remain unchanged relative to the benchmark case.

The third exercise aims to test the sensitivity of the results to a deterioration of banks' liquidity position. In this respect, the key liquidity parameters, respectively the funding shortfall (ρ_i), the net liquidity position (γ_i) and the pool of assets available for sales (θ_i) are adjusted to intensify a liquidity shock conditional on a default event. As we can see from panel (a) of Figure 18 (appendix) an increase of the short-term funding from an average of 35% (one month in the benchmark case) to 40% (3 months average) or alternatively an increase of short-term funding up to 50% produces a negligible effect on the contagion index, with only two banks on the contagion side facing a relevant positive adjustment.[30] This implies that the current LCR ratio (γ_i) is large enough to cover the additional short-term liquidity needs. Next, we suppose a reduction of 20% and 40% in the net liquidity position (γ_i) for instance due to a sudden depletion of the buffer of HQLAs or due to a higher run off rate of deposits (panel b). In this case, we notice that results are almost unaffected for both indexes, implying that the bank-specific liquidity

[30] The average funding shortfall increases from 35% to 40% when considered 3 months as short-term liabilities.

buffer is well above the threshold needed to cover short-term liquidity needs. Finally, we assume that the pool of assets available for sales faces a haircut of 20% and 40% respectively (panel c). Results are unchanged because no other banks, except those previously triggering the fire sales stage, are liquidity constrained and therefore no additional losses or failures are accounted in the system given this assumption.[31]

The fourth sensitivity analysis aims at capturing the role played by the network structure. In achieving this, we exploit additional granular exposure-level information from COREP template C.28 regarding bilateral linkages. Hence we test the sensitivity of the contagion and vulnerability indexes to a network structure based on total gross amounts (including exemptions). As we can see in Figure 19, when we consider the network structure based on gross amounts (€ 1.120 bn) both contagion and vulnerability indexes, as expected, strongly increase. These effects seem to be strong and distributed unevenly pointing to non-linear effects. Several banks move from the bottom to the top of the contagion index, depleting almost 3-4% of the capital of the system given their default. Regarding the vulnerability index, the effects are even more pronounced than the contagion index, and the largest increase is about a factor of 55, depleting on average 33% of the capital base.

The fifth exercise consists of testing the sensitivity of the results to the interaction of different dimensions as in Kok and Montagna (2016): liquidity, solvency and network topology. In this respect, we assume first a full-liquidity shock affecting all parameters as in the benchmark case of the third sensitivity analysis, but contemporaneously: ($\rho_i =$ 40%; $\Delta\gamma_i = -20\%$; $\Delta\theta_i = -20\%$). Then we decrease by 20% the capital surplus, and we proportionally increase by 30% the exposure amounts which correspond to the gross amount presented in the fourth sensitivity analysis (€ 1.120 billion). As we can see from Figure 20 (appendix) the interplay of liquidity parameters pushes up the contagion and vulnerability indexes of some specific banks, but does not result in a relevant system-wide increase. When this effect is combined with a decreased capital surplus, more indices increase, but also in this case it does not produce a systemic-wide effect. When

[31] The vulnerability index decreases for some selected banks because now those banks can sell a less amount of assets and therefore will face a lower amount of losses via fire sales. Nevertheless, the number of liquidity defaults remains unchanged.

we also stretch the network structure we are able to capture, this time, a quasi-linear effect on contagion and vulnerability indexes. The few non-linear effects are produced by the interaction of liquidity and solvency parameters. This exercise once more highlights the role played by tipping points within a network and how bank-specific and exposure-specific characteristics may determine non-linear amplification effects resulting in a higher degree of systemic-risk.

Finally, we compare our model-based estimates of contagion and vulnerability indices to market data-based measures of individual banks' systemic footprint. We use the SRISK index based on Global Dynamic Marginal Expected Shortfall (MES) retrieved from V-lab and based on Acharya et al. (2012).[32] For this purpose, we download and adjust the SRISK index for the European Union such that it overlaps with our sample of euro area banks. By doing this, we end up with 40 banks.[33] Then we construct a SRISK index based on our model-based estimates by dividing the numerator of the vulnerability index (total losses experienced by each bank) by the total losses experienced by the system. By doing this, we are able to derive the proportional contribution of each firm's SRISK to the total positive SRISK of the euro area banking system. Figure 21 depicts both SRISK index and the ranking based on the SRISK index. Both measures display a high correlation with VI of 0.85 for the SRISK index and 0.74 for the SRISK ranking, respectively. As can be seen in the bottom left of the SRISK ranking, for the top-10 banks our balance-sheet based approach captures the very same banks of the SRISK approach based on MES.

Overall, we find both similarities and divergences between market-based measures such as SRISK and balance sheet based measures such as our approach. Notwithstanding the correspondence (high correlation) between our VI measure and SRISK is reassuring, we identify notable differences for individual banks in the middle of the distribution. This is potentially due to our modelling strategy which takes into account bank-specific characteristics which are only implicitly reflected in the market-based measures such as SRISK.

[32] See also Acharya et al. (2017).
[33] Differences in the sample are due to the fact that Acharya et al. (2010) work on a solo basis and they don't include banks for which market-data are not available. The SRISK estimates are based on a 40% fall of the broad market index and a 8% capital requirement.

5. Reducing contagion risk by fine-tuning prudential measures

The modelling framework can also be used to conduct ex ante impact analysis of prudential policy measures based on counterfactual analyses. By exploiting the breakdown of the vulnerability index into credit and funding risks, we are able to target banks with specific liquidity and capital vulnerabilities that may give rise to contagion.

Our findings suggest that regulators should look at the interplay of network topology and bank-specific characteristics in addition to setting prudential requirements based on individual supervisory assessments of each bank in isolation. Tipping points shifting the financial system from a less vulnerable state to a highly vulnerable state are a non-linear function of the combination of network structures and bank-specific characteristics.[34] Therefore, policies aiming at reducing systemic risk externalities related to interconnectedness should focus on increasing the resilience of weak nodes in the system, thereby curbing potential amplification effects due to cascade defaults, and on reshaping the network structure in order to set a ceiling to potential losses.

As we show below, this requires a bank-specific calibration of prudential buffers both targeting solvency and liquidity defaults so as to minimize amplification effects due to contagion. Second-round default events are the key determinant of non-linear effects in loss amplification, thereby becoming a natural candidate as an intermediate policy target for macroprudential supervisors. In other words, the macroprudential regulator could aim at reducing the role played by the network structure in terms of spreading contagion and exposing the vulnerability of banks to shocks hitting the network. This paper proposes a methodology to capture such amplification effects as reflected in the contagion and vulnerability indexes (Figure 12) and their determinants (Tables 3 and 4). Moreover, as we illustrate below, the CoMap methodology can be used to run counterfactual simulations to study the effectiveness of different prudential actions in reducing contagion potential in the network.

[34] See also Battiston et al. (2009), Battiston and Caldarelli (2012) and Aikman et al. (2018).

For illustrative purposes, our counterfactual (macro) prudential simulations consist of (i) increasing the buffer of HQLA assets (γ_i), (ii) increasing the pool of available for sale assets (θ_i), and/or (iii) increasing the CET1 capital surplus (k_i^{DF}). The three distinct policy measures aim at assessing the effectiveness of a single and equal increase in each of the parameter in terms of reducing the number of banks experiencing a liquidity or solvency default in Table 8.

Specifically, we consider a mix of the three policy measures, which is based on a simple optimization problem for which we want to minimize the vulnerability level (VL) - number of defaults experienced - so as to reduce the losses incurred due to second-round effects (equation 21). This optimization problem is subject to an inequality constraint which establishes that the sum of the parameters may not be larger than a certain buffer (F) and each parameter should be at least equal to or higher than the starting value $\bar{\gamma},\ \bar{\theta}\ ,\overline{k^{DF}}$ derived by the bank-specific calibration.

$$\min VL(\gamma_i, \theta_i, {k_i^{DF}}_i) \tag{21}$$

$$s.t.\quad \vartheta_1\, k_i^{DF} + \vartheta_2\, \gamma_i + \vartheta_3\, \theta_i \leq F \quad ; \quad k_i^{DF} \geq \overline{k^{DF}}, \quad \gamma_i \geq \bar{\gamma}, \quad \theta_i \geq \bar{\theta}.$$

For simplicity, we set $\vartheta_1 = \vartheta_2 = \vartheta_3 = 1$.[35] Figure 21 (panel a) presents the vulnerability and contagion levels for the top-80 and top-40 banks with the highest number of defaults experienced and induced, respectively. For the presentation of results, the number of defaults is divided into four buckets capturing twenty (ten) banks each in a descending order from most vulnerable (contagious) to less vulnerable.[36] The benchmark results are reported for comparative purposes.

The first exercise (LCR adj.) tests the effectiveness of an increase in the liquidity buffer (γ_i) by 25 billion[37] so as to increase the LCR ratio and better absorb the funding shortfall induced by a default event. Since we are able to disentangle which banks suffer

[35] For purely illustrative purposes, we assume (for simplicity) that the cost of increasing one buffer is invariant across type of buffers.
[36] It was preferred to display the top-80 instead of the top-50 in order to capture all banks defaulting.
[37] The reasoning is that as initial policy rule we assume that banks experiencing a liquidity default would increase the HQLA buffer up to the average of the sample (as depicted in Figure 8). This initial condition increases the total amount of HQLA assets in the system by 25 billion. This policy rule is commonly used in the literature, for instance see Gai et al. (2011). For the following exercises, this amount is shared across the treated banks following a weighted average calculation based on total assets.

liquidity and solvency defaults, we threat with this policy experiment 8 banks experiencing a default event. This experiment decreases the number of defaults by 16 units (red bars) out of 20 reported initially in the benchmark case (black bars). The effectiveness of this treatment is relatively high, since the 4 remaining failures are all solvency driven.

The second exercise (Pool adj.) resembles the first exercise and tests the effectiveness in curbing liquidity driven defaults by increasing the pool of assets available for sale by 25 billion. As captured by the blue bars, this policy rule is less effective than an equal increase of the HQLA buffer, nevertheless it still reduces the number of liquidity driven defaults by 11 units.

The third exercise (CET1 adj.) increases the average capital surplus by 25 billion. Applying this policy measure reduces the number of defaults by only 6 units, although the number of solvency driven defaults gets to 0.

The optimal policy mix set up by the minimization of the vulnerability level is able to bring the total number of defaults among the top-80 most vulnerable banks to 0. Given the set-up of the model, as described in equation (21), the most effective allocation is divided between an increase in the liquidity buffer (γ_i) for those banks facing liquidity driven defaults and an increase in the CET1 capital surplus for those banks vulnerable to facing capital shortfalls. No fund is allocated to the pool of assets because each amount used to absorb the funding shortfall will be discounted by a bank-specific discount rate, leading to a less effective outcome than in the case of an equal increase in the buffer of HQLA assets to which no discount rate is applied by assumption.[38]

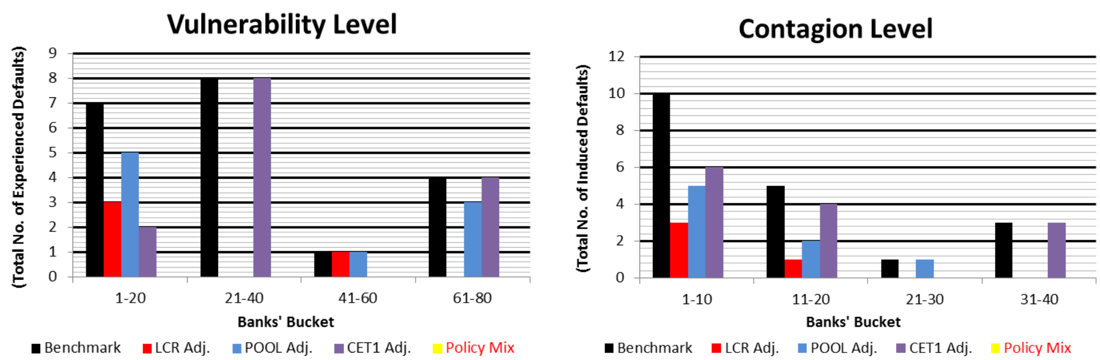
Overall, the policy mix is able to bring the contagion level induced by the top-40 most systemic banks to zero. However, as shown in panel (b) of Figure 21, which reports the vulnerability and contagion indexes, the scale of losses induced and experienced even after the policy mix treatment still presents a fat-tailed distribution. This emphasizes that decreasing the number of cascade defaults reduces contagion and vulnerability indexes

[38] A different cost structure than $\vartheta_1 = \vartheta_2 = \vartheta_3 = 1$ would affect the optimal policy mix.

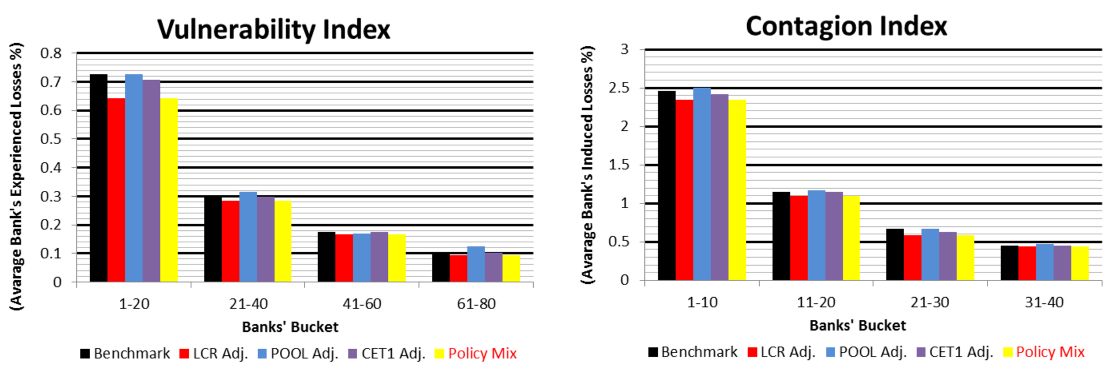
by the contribution of amplification effects, which in our set-up are limited. In this regard, first round effects dominate losses incurred due to cascade defaults.[39]

Figure 21: Comparative Statics of Policy Options

Panel (a)



Panel (b)



Note: Benchmark refers to results presented in section 4.1.

A final remark on the counterfactual policy simulations is that they focus solely on the benefits related to curbing contagion risk in the system by modifying the network structure and making banks more resilient. What is however not considered are the potential costs of imposing more stringent requirements on banks (e.g. requiring higher liquidity and or capital buffers). In reality, policy makers need to conduct a cost-benefit analysis taking into account also the costs of doing so; for instance, in terms of lower intermediation activity in the interbank market and other market segments where banks interact.

[39] This finding is in line with the literature; see e.g. Upper (2011) and Hüser (2015).

Conclusion

Our euro-centric systemic risk assessment based on the network of euro area banks' large exposures within the global banking system highlights that the degree of bank-specific contagion and vulnerability depends on network specific tipping points affecting directly the magnitude of amplification effects. This leads to the clear-cut conclusion that the identification of such tipping points and their determinants is the essence of an effective micro and macro prudential supervision. The current financial regulations seek to limit each institution's risk in isolation underestimating the systemic risk contribution to the overall fragility.

In this paper, we argue that in isolation and with linear variations, bank-specific characteristics seem to play a less relevant role than the network structure, whereas what really determines a system shift comes from their non-linear interaction, for which both are equally important. In a variety of tests, heterogeneity in the magnitude of bilateral exposures and of bank-specific parameters is detected as a key driver of the total number of defaults in the system. Unless systemic risk externalities are internalized by each bank in the network, bank recapitalizations may be still convenient from a cost-return trade-off of a global or European central planner. It follows that international cooperation is essential to limit the ex-ante risk and reduce the ex-post system-wide losses striving for a Pareto efficient outcome

Several extensions of our work should be explored in the future. The results are network and model dependent based on an incomplete set of bilateral exposures. Therefore, both dimensions need to be extended so as to include additional channels of contagion and in turn improve the loss estimates of an extreme event. As a natural step work should be done to incorporate i) euro area less significant institutions to complete the euro area banking system, ii) financial corporations to model the complex interactions within the financial system, and iii) exposures to real economy so as to capture feedback loops. Moreover, we could complete the extra-euro area network by imputing missing bilateral linkages by generating random networks consistent with partial information as in Halaj and Kok (2013). Without changing the model assumptions, enlarging the dataset dimension would lead to closer-to-reality second-round amplification effects. Next, the modelling strategy may include a confidence channel so as to capture liquidity-hoarding behaviors. This feature should bring funding risks to the forefront and determine a more balanced contribution to loss estimation than the actual, which is mainly credit risk driven. While we estimate fire-sales losses using a static balance-sheet approach, another way to model them is dynamically by exploiting information on cross-holdings of assets and derive the discount rate endogenously à la Cont and Schaanning (2017). Finally, we should investigate the role of additional prudential requirements currently missing in our framework such as a leverage ratio and a net stable funding ratio which in 2019 will become binding.

Uncertainty surrounding the global financial network requires regulators to handle an ever complex set of information so to be prepared in case such an adverse event takes place. Nevertheless, networks are adaptive and so the policy mix needs to be. We have provided a framework to capture few features of such complexity, and many more need to be modelled to prune the fog of uncertainty, and take a decision when instability suddenly arises.

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Appendix

Data Infrastructure

Regarding the data reporting requirements, institutions should provide the name, Legal Entity Identifier (LEI code), country, sector, and NACE classification of the counterparty.[40] This qualitative information is not always fulfilled, especially for exposures to group of connected clients which cover approximately half of the data sample. In addition, LEI codes are often missing and not every institution owns a LEI code. This implies that identifying exposures vis-à-vis the very same counterparty across countries can only take place through the counterparty's name. However, the counterparty's name is often reported differently by different reporting institution and in different languages according to the reporting country. For that reason, to exploit the large exposures data and analyze the complex network of euro area banks' large exposures a reconciliation (or mapping) of counterparty names is necessary. Furthermore, to complete the set of inputs for the modelling framework (section 3) is required to link large exposures information with additional data sources.

In achieving this, we have developed an advanced algorithm defined as the Stata Mapping Code (SMC), which aims at mapping counterparties' names as well as filling data reporting deficiencies regarding missing and misleading counterparty's details (e.g. LEI codes, country and sector)[41].

At our reference date (Q3 2017), before applying the SMC, there were almost 34.080 exposures of which 9.880 reported from euro area less significant institutions (LSIs). Out of the 24.200 remaining exposures reported by euro area significant institutions (SIs), 15.363 are from institutions which are subsidiaries of the group, while the remaining 8.837 are from euro area consolidated group of SIs. These are the reporting institutions

[40] The guidelines by the European Banking Authority (EBA) include common reporting templates and guidance in relation to large exposures (LE) reporting within the COREP framework. There are three templates included in the LE reporting framework that constitute the main source of data in establishing bank network. These are: LE1 (C. 27.00) identification of the counterparty; LE2 (C. 28.00) exposures to individual client and group of connected clients; LE3 (C. 29.00) detail of the exposures to individual clients within groups of connected clients; LE4 (C. 30.00) and LE5 (C. 31.00): detail the information regarding the maturity buckets to which the expected maturing amounts of the ten largest exposures to institutions as well as the ten largest exposures to unregulated financial sector entities shall be allocated, respectively for table C.28.00 and C.29.00.

[41] The SMC follows a four-step approach. The step (1) aims at reconciling counterparties' names using fuzzy match commands based on a set of names' similarities, existing LEI codes or combination of counterparty-specific keywords and counterparty details such as country or sector of belonging. Step (2) cross-merges the dataset by counterparties' names and LEI codes in order to exploit existing counterparties' information so as to fill missing LEI codes, country and sectoral details. Step (3) enhances further data quality by retrieving the missing counterparty information from the following sources: gleif.org, Bloomberg or Bankscope. In the end, step (2) is repeated to complete the cycle. This cycle is repeated up to the point no information is added to the system. Two cycles are sufficient to cover most of the improvements.

on which we base this study; that is, the 107 euro area significant institutions at the highest level of consolidation.[42]

In this regard, before applying the SMC, 5.833 individual counterparties were identified, while after the algorithm mapping counterparty names was implemented the number reduces by 1.353 units. Furthermore, the SMC by cross-merging information already existing within the dataset and by adding missing information retrieved from Bloomberg and Bankscope, is able to increase data availability on counterparties' details on average by 40%[43]. The coverage of LEI codes increases from 30% to 69%, the country dimension from 68% to 97%, sectors from 57% to 94%, and NACE codes from 34% to 81%.

Specifically, regarding the counterparty sector of interest - credit institutions - we identify 2.189 large exposures towards 498 unique counterparties, of which 77 are euro area significant institutions (SIs), 155 non-euro area credit institutions, 238 euro area less-significant institutions (LSIs), 21 are state development banks (SDBs), while 7 are international organizations (IOs). In our study, we focus on large exposures between reporting SIs and the first two counterparty groups, that is, SIs and non-euro area credit institutions. Therefore, we drop from the sample of exposures LSIs, SDBs, and IOs. We do this because for the modelling framework we need precise information about the capital base and RWAs that are often not available for state development banks and international organizations, as well as because exposures to SDBs and IOs are often riskless. The inclusion of LSIs in the counterparty sample would be consistent only if we include LSIs on the reporting side too. However, given the large number of LSI reporting entities, we leave the LSI dimension for a future investigation.

[42] For the sake of clarity, euro area SIs are 118 as cut-off date January 2018. However, since we work with consolidated banking groups, large exposure amounts comprehend the exposures from its subsidiaries, i.e., from other SIs. For instance Unicredit Austria is a significant institution which belongs to Unicredit spa. In this respect, the number of individual SIs decrease from 118 to 107 because of the consolidated approach. See SSM' list of supervised entities, cut-off date January 2018:
https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.list_of_supervised_entities_201802.en.pdf

[43] We aim at having complete information about the counterparties for two main reasons: (1) LEI codes are necessary to link the dataset with complementary sources of information about bank balance sheet data and in turn calibrate the bank-specific model's parameters; (2) country codes are necessary to disentangle the geographical contribution to systemic risk.

Table A1: Top 30 Most Contagious and Vulnerable Banks – Special Cases

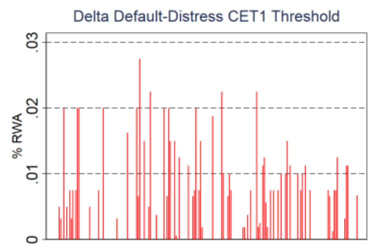
Contagion		Model-Parameter Heterogeneity							Special Case 1							Special Case 2				
		Bank-Specific Perameters							Average Parameters							Average Parameters (θ = ∞ and γ = 0)				
		Defaults			Euro Area			Amp.	Defaults			Euro Area			Amp.	Defaults	Euro Area			Amp.
RANK	Country	Solv.	Solv.	Liq.	CI	CI CR	CI FU	Ratio	Defaults	Solv.	Liq.	CI	CI CR	CI FU	Ratio	ToT	CI	CI CR	CI FU	Ratio
1	EA	0	0	0	3.8	3.8	0.0	0.0	2	2	0	4.5	4.5	0.0	0.2	2	4.8	4.5	0.3	0.2
2	XEA	3	1	2	3.2	3.1	0.1	0.1	2	2	0	3.3	3.3	0.0	0.0	2	3.3	3.3	0.1	0.0
3	XEA	1	1	0	2.7	2.3	0.4	0.5	5	5	0	4.0	4.0	0.0	1.1	5	4.5	4.0	0.6	1.3
4	EA	2	2	0	2.4	2.4	0.0	0.0	6	6	0	4.7	4.7	0.0	1.1	6	5.1	4.7	0.5	1.1
5	EA	0	0	0	2.3	2.3	0.0	0.0	1	1	0	2.8	2.8	0.0	0.0	1	2.9	2.8	0.1	0.0
6	XEA	3	0	3	2.3	2.1	0.2	0.2	1	1	0	2.9	2.9	0.0	0.1	1	3.2	2.9	0.3	0.2
7	EA	1	0	1	2.2	2.1	0.1	0.0	0	0	0	2.6	2.6	0.0	0.0	6	5.2	4.2	1.0	1.2
8	XEA	0	0	0	1.9	1.9	0.0	0.0	0	0	0	1.9	1.9	0.0	0.0	0	2.0	1.9	0.0	0.0
9	XEA	0	0	0	1.9	1.9	0.0	0.0	0	0	0	2.0	2.0	0.0	0.0	0	2.0	2.0	0.0	0.0
10	EA	0	0	0	1.9	1.9	0.0	0.0	1	1	0	2.4	2.4	0.0	0.0	1	2.6	2.4	0.2	0.0
11	EA	1	1	0	1.8	1.8	0.0	0.0	1	1	0	2.0	2.0	0.0	0.0	1	2.2	2.0	0.2	0.0
12	XEA	1	0	1	1.4	1.2	0.2	0.1	0	0	0	1.3	1.3	0.0	0.0	0	1.3	1.3	0.1	0.0
13	XEA	2	0	2	1.4	1.3	0.1	0.3	0	0	0	1.5	1.5	0.0	0.0	0	1.5	1.5	0.0	0.0
14	EA	0	0	0	1.3	1.3	0.0	0.0	0	0	0	1.2	1.2	0.0	0.0	0	1.5	1.2	0.3	0.0
15	XEA	0	0	0	1.1	1.0	0.1	0.0	5	5	0	2.8	2.8	0.0	2.5	5	3.3	2.8	0.5	2.8
16	XEA	0	0	0	1.0	1.0	0.0	0.0	0	0	0	1.0	1.0	0.0	0.0	0	1.1	1.0	0.0	0.0
17	EA	0	0	0	1.0	1.0	0.0	0.0	1	1	0	1.2	1.2	0.0	0.0	1	1.3	1.2	0.1	0.0
18	EA	0	0	0	0.9	0.9	0.0	0.0	0	0	0	0.9	0.9	0.0	0.0	0	1.2	0.9	0.2	0.0
19	EA	1	0	1	0.8	0.8	0.0	0.1	0	0	0	0.7	0.7	0.0	0.0	1	0.8	0.7	0.1	0.0
20	XEA	0	0	0	0.8	0.8	0.0	0.0	0	0	0	0.8	0.8	0.0	0.0	0	0.8	0.8	0.0	0.0
21	XEA	0	0	0	0.8	0.8	0.0	0.0	0	0	0	0.8	0.8	0.0	0.0	0	0.9	0.8	0.1	0.0
22	EA	1	1	0	0.8	0.4	0.4	4.3	0	0	0	0.1	0.1	0.0	0.0	0	0.3	0.1	0.2	0.0
23	XEA	0	0	0	0.8	0.8	0.0	0.0	0	0	0	0.7	0.7	0.0	0.0	0	0.7	0.7	0.0	0.0
24	EA	0	0	0	0.8	0.8	0.0	0.0	0	0	0	1.2	1.2	0.0	0.0	0	1.4	1.2	0.1	0.0
25	XEA	0	0	0	0.7	0.7	0.0	0.0	0	0	0	0.8	0.8	0.0	0.0	0	0.8	0.8	0.0	0.0
26	EA	0	0	0	0.6	0.6	0.0	0.0	0	0	0	0.6	0.6	0.0	0.0	0	0.8	0.6	0.2	0.0
27	XEA	0	0	0	0.6	0.6	0.0	0.0	0	0	0	0.6	0.6	0.0	0.0	0	0.6	0.6	0.0	0.0
28	XEA	0	0	0	0.6	0.6	0.0	0.0	0	0	0	0.5	0.5	0.0	0.0	0	0.5	0.5	0.0	0.0
29	EA	0	0	0	0.5	0.5	0.0	0.0	0	0	0	0.7	0.7	0.0	0.0	0	0.8	0.7	0.1	0.0
30	EA	0	0	0	0.5	0.4	0.1	0.0	0	0	0	0.5	0.5	0.0	0.0	0	0.6	0.5	0.1	0.0
AVERAGE TOP 30		**0.53**	**0.20**	**0.33**	**1.43**	**1.37**	**0.05**	**0.19**	**0.83**	**0.83**	**0.00**	**1.70**	**1.70**	**0**	**0.17**	**1.07**	**1.93**	**1.75**	**0.18**	**0.23**

Vulnerability		Model-Parameter Heterogeneity							Special Case I							Special Case II				
		Bank-Specific Perameters							Average Parameters							Average Parameters (θ = ∞ and γ = 0)				
		Defaults			Global			Amp.	Defaults			Global			Amp.	Defaults	Global			Amp.
RANK	Country	ToT	Solv.	Liq.	VI	VI CR	VI FU	Ratio	ToT	Solv.	Liq.	VI	VI CR	VI FU	Ratio	ToT	VI	VI CR	VI FU	Ratio
1	EA	2	2	0	1.8	0.7	1.2	0.0	4	4	0	2.8	2.8	0.0	0.1	5	3.3	2.9	0.4	0.1
2	EA	0	0	0	1.4	1.4	0.0	0.0	0	0	0	2.0	2.0	0.0	0.0	0	2.0	2.0	0.0	0.0
3	EA	0	0	0	1.1	1.1	0.0	0.0	0	0	0	1.6	1.6	0.0	0.6	1	1.7	1.7	0.0	0.7
4	EA	0	0	0	1.0	1.0	0.0	0.0	1	1	0	1.2	1.2	0.0	0.0	1	1.2	1.2	0.0	0.0
5	EA	0	0	0	0.9	0.9	0.0	0.0	0	0	0	0.8	0.8	0.0	0.0	0	0.8	0.8	0.0	0.0
6	XEA	0	0	0	0.8	0.8	0.0	0.4	0	0	0	1.0	1.0	0.0	0.6	0	1.2	1.1	0.2	0.8
7	EA	0	0	0	0.8	0.8	0.0	0.0	0	0	0	0.7	0.7	0.0	0.0	0	0.8	0.7	0.0	0.0
8	EA	0	0	0	0.7	0.7	0.0	0.0	0	0	0	0.8	0.8	0.0	0.0	0	0.8	0.8	0.0	0.0
9	EA	0	0	0	0.6	0.6	0.0	0.0	0	0	0	0.6	0.6	0.0	0.0	0	0.7	0.6	0.1	0.1
10	EA	2	0	2	0.6	0.5	0.1	0.0	0	0	0	0.4	0.4	0.0	0.0	0	0.6	0.4	0.2	0.0
11	EA	0	0	0	0.6	0.6	0.0	0.2	6	6	0	6.4	6.4	0.0	0.9	7	7.0	6.4	0.6	0.9
12	EA	0	0	0	0.5	0.5	0.0	0.0	0	0	0	0.6	0.6	0.0	0.4	0	0.6	0.6	0.0	0.4
13	EA	0	0	0	0.5	0.5	0.0	0.0	0	0	0	0.4	0.4	0.0	0.0	0	0.5	0.4	0.0	0.0
14	EA	0	0	0	0.5	0.5	0.0	0.0	0	0	0	0.5	0.5	0.0	0.1	0	0.6	0.5	0.0	0.1
15	EA	0	0	0	0.5	0.5	0.0	0.1	0	0	0	0.5	0.5	0.0	0.2	0	0.6	0.5	0.0	0.2
16	EA	0	0	0	0.4	0.4	0.0	0.1	5	5	0	3.8	3.8	0.0	1.0	6	4.3	4.3	0.0	1.2
17	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.4	0.4	0.0	0.0	0	0.5	0.4	0.1	0.1
18	EA	3	3	0	0.4	0.4	0.0	0.0	3	3	0	0.4	0.4	0.0	0.0	3	0.4	0.4	0.0	0.0
19	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.5	0.5	0.0	0.0	0	0.5	0.5	0.0	0.0
20	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.7	0.7	0.0	0.0	0	0.8	0.7	0.0	0.0
21	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.3	0.3	0.0	0.0	0	0.4	0.3	0.1	0.1
22	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.3	0.3	0.0	0.0	0	0.3	0.3	0.0	0.0
23	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.4	0.4	0.0	0.1	0	0.4	0.4	0.1	0.2
24	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.3	0.3	0.0	0.0	0	0.3	0.3	0.0	0.0
25	EA	0	0	0	0.4	0.4	0.0	0.0	0	0	0	0.6	0.6	0.0	0.0	0	0.7	0.6	0.1	0.0
26	EA	0	0	0	0.4	0.4	0.0	0.0	7	7	0	1.7	1.7	0.0	0.7	8	2.0	1.9	0.1	0.9
27	EA	0	0	0	0.3	0.3	0.0	0.0	0	0	0	0.3	0.3	0.0	0.0	0	0.4	0.4	0.0	0.0
28	EA	0	0	0	0.3	0.3	0.0	0.0	0	0	0	0.3	0.3	0.0	0.1	0	0.4	0.3	0.0	0.1
29	EA	0	0	0	0.3	0.3	0.0	0.0	1	1	0	0.3	0.3	0.0	0.0	1	0.4	0.3	0.0	0.0
30	EA	0	0	0	0.3	0.3	0.0	0.0	0	0	0	0.6	0.6	0.0	0.6	0	0.7	0.6	0.1	0.6
AVERAGE TOP 30		**0.23**	**0.17**	**0.07**	**0.60**	**0.56**	**0.04**	**0.02**	**0.90**	**0.90**	**0.00**	**1.05**	**1.05**	**0.00**	**0.18**	**1.07**	**1.16**	**1.09**	**0.08**	**0.22**

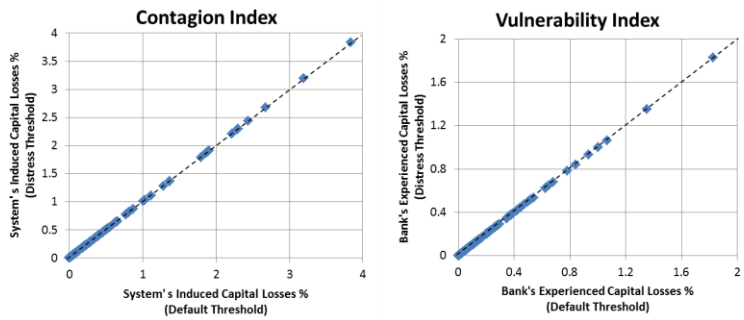
Note: Special case I sets $(\lambda, \rho, \gamma, \theta, \delta)$ equal to the average of the sample, while special case II sets (λ, ρ, δ) equal to the average of the sample and $\gamma = 0$ and $\theta = \infty$. CI EA refers to contagion index and amounts represent capital losses to EA banks in percent of EA banking system's total capital buffer. This index is further decomposed into the respective contributions by credit (CI EA CR) and funding (CI EA FU) shocks. VI refers to vulnerability index and amounts represent average capital losses across all independent simulations in percent of a bank's capital buffer. The vulnerability index is further decomposed into the respective contributions by credit (VI CR) and funding (VI FU) shocks. The results in the tables are ranked respectively according to CI EA and VI based on the benchmark model with bank-specific parameters

Figure 16: Distress vs Default CET1 Thresholds

Panel (a)



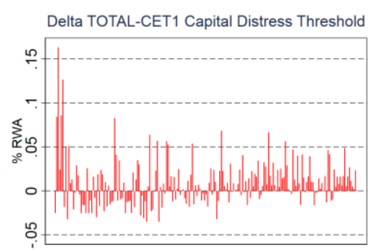
Panel (b)



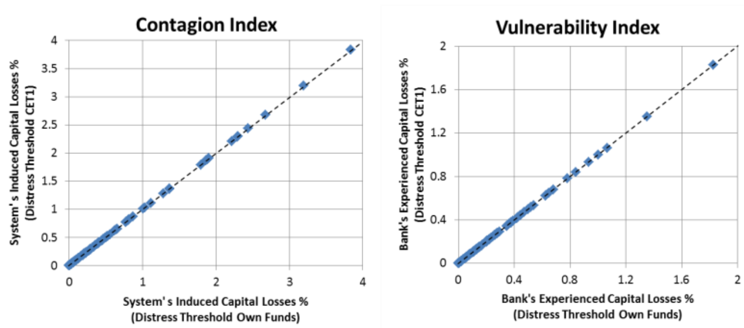
Note: Panel (a) is ordered according to CET1 distress threshold. For confidentiality reasons, the chart shows statistics as average among three banks.

Figure 17: CET1 Distress Threshold vs Total Capital Distress Threshold

Panel (a)



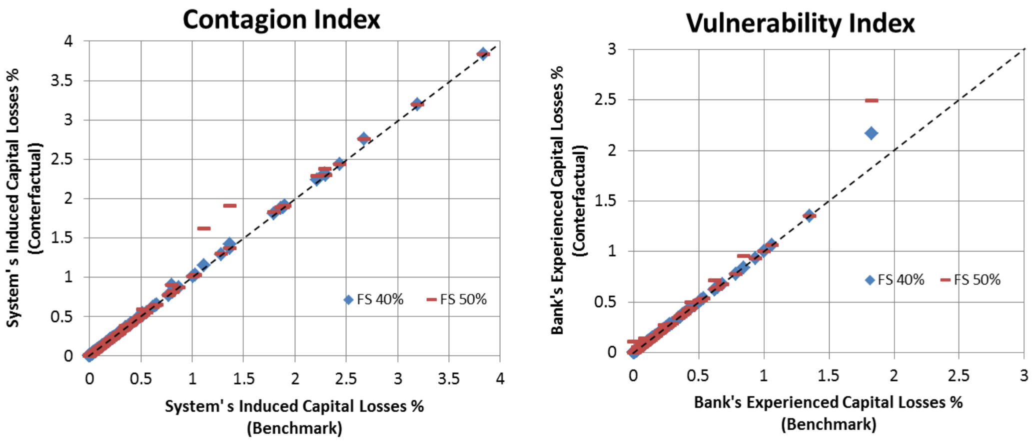
Panel (b)



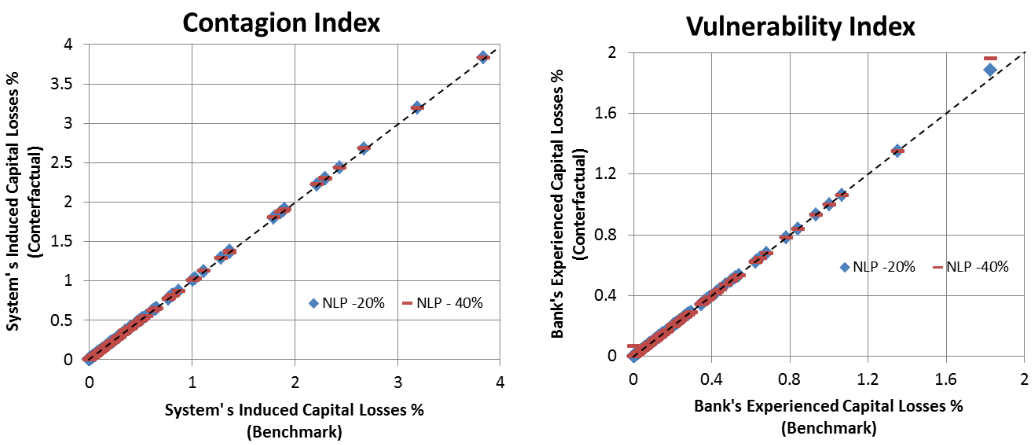
Note: Panel (a) is ordered according to CET1 distress threshold. For confidentiality reasons, the chart shows statistics as average among three banks.

Figure 18: Sensitivity to Funding Parameters

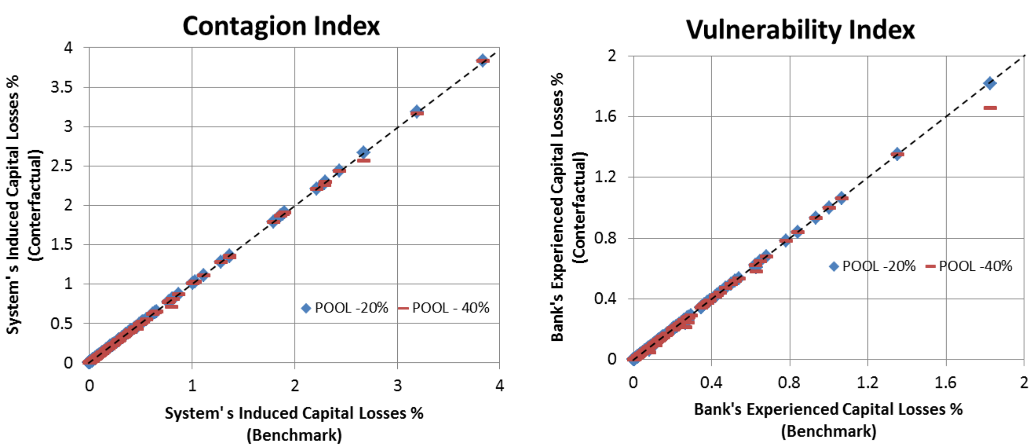
Panel (a): Funding Shortfall



Panel (b): Net Liquidity Position

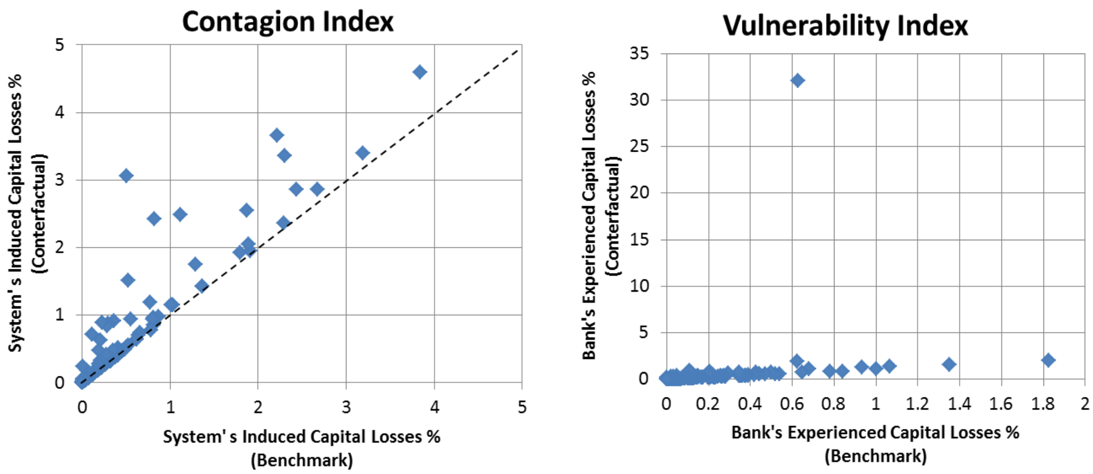


Panel (c): Pool of assets



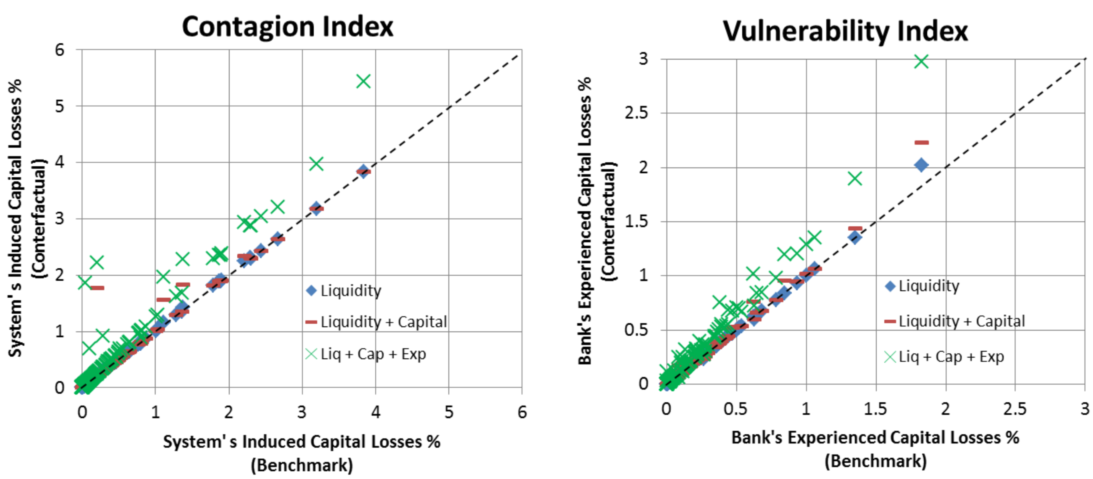
Note: Benchmark refers to results presented in section 4.1.

Figure 19: Network Structure Sensitivity Based on Gross Exposures



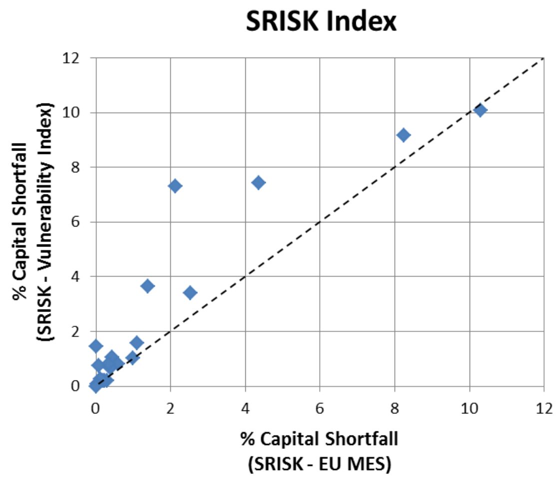
Note: Network Structured is based on the statistics presented in table 1 regarding gross exposures amounts before taking into account exemptions. Benchmark refers to results presented in section 4.1.

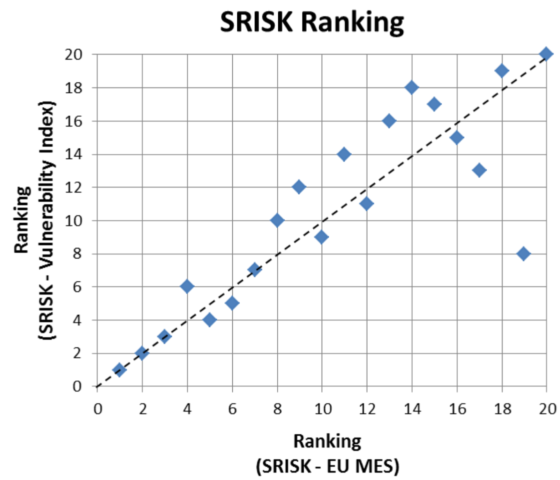
Figure 20: Multi-Factor Sensitivity



Note: The liquidity scenario has been modelled as ($\Delta\rho_i = 40\%$; $\Delta NLP_i = -20\%$; $\theta_i = -20\%$), the capital scenario includes a 20% decrease in the capital surplus, while in the third scenario (network) exposure amounts increase by 30% up to which (€ 1.120 billion).

Figure 21: SRISK Ranking Comparison





Note: Regarding the SRISK ranking, bank number 1 is the one with the highest SRISK estimate, i.e. the one in the top-right corner of the SRISK Index. MES based SRISK estimates for European banks have been retrieved from vlab.stern.nyu.edu. For confidentiality reasons, the chart shows statistics as average among three banks.